Dissecting Climate Risks: Are they Reflected in Stock Prices?*

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Abstract

We provide first-time evidence on whether market-wide physical or transition climate risks are priced in U.S. stocks. Textual and narrative analysis of Reuters climate-change news over 1 January 2000-31 December 2018, uncovers four novel risk factors related to natural disasters, global warming, international summits, and U.S. climate policy, respectively. Only the climate-policy factor is priced, especially post-2012. The documented risk premium is consistent with investors hedging the imminent transition risks from government intervention, rather than the direct risks from climate change itself.

JEL classification: C63; E58; G12; G18; Q5

Keywords: Physical risks; Transition risks; Latent Dirichlet Allocation; Cross-section of stock returns; Textual analysis

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1 Introduction

Are climate risks priced in the stock market? If so, are the direct risks from climate change itself or government intervention what is being priced? Stroebel and Wurgler (2021) document that these two types of risks are distinct from an investors' perspective.[1] To address these questions, we dissect climate news and provide separate daily proxies for *market-wide* physical risks, e.g. risks stemming from natural disasters and rising temperatures, and transition risks, e.g. risks stemming from government intervention via carbon taxation and incentives to develop green technologies. We then examine whether these are reflected in U.S. stocks and propose intertemporal hedging of transition risks as an economic explanation for the results, which we validate by a series of tests. To the best of our knowledge, this is the first study that examines whether it is market-wide transition risks or physical risks that are priced in the U.S. stock market. The results have important implications for policy makers and investors. Our study builds on Engle et al. (2020), who carry out textual analysis of news to construct a market-wide measure of climate risk, which aggregates *all* dimensions of climate risk.

To dissect climate risks and construct our market-wide climate-risk factors, we employ the Latent Dirichlet Allocation (LDA, Blei et al. (2003)), a method of textual analysis. LDA was first introduced in economics by Hansen et al. (2017), and has recently been applied to finance (e.g., Hanley and Hoberg (2019), Bandiera et al. (2020) and Bellstam et al. (2020)). LDA classifies the news corpus into categories, termed 'topics', where each topic contains a set of words ranked by their frequency. Then, the user labels each category based on the frequency and type of words being included. In addition to topics, LDA also delivers topic shares, which is the share of an article's text associated with any given topic. Given that articles are time-stamped, summing the shares of a particular topic across all articles, forms a time series of the intensity of news coverage for any given topic.

[1]This question is timely in light of views expressed recently by some important stock market participants. For some, natural disasters do not matter; Stuart Kirk, the former Global Head of Responsible Investing, at HSBC Asset Management, stated *"Who cares if Miami is six metres underwater in 100 years?"* (Moral Money Financial Times Conference May 19, 2022). Others, state that investors care about climate risks only when policy makers intervene, e.g., Tariq Fancy, the former CIO at BlackRock stated *"If I was on a panel and someone asked me what's the best way to tackle climate change?...The truth is someone is better off calling their congressperson"* (Guardian, March 30, 2021).

We apply LDA to the articles that contain the words "climate change" and "global warming", published over January 1st 2000 – December 31st 2018 in Refinitiv News Archive, a leading provider of information to the financial sector. Our corpus of articles is heterogeneous, encompassing various dimensions of climate risk. It contains news ranging from the political debate on climate-change legislation in different countries to news on natural disasters, scientific evidence on the rise in global temperatures, and corporate actions related to climate change. We single out four relevant topics which have a clear interpretation in terms of physical and transition risks, and which are potentially relevant to the U.S. stock market: the occurrence of natural disasters, global warming, U.S. climate policy (actions and debate), and international summits on climate-change. We consider news on the first two topics to be directly informative about the physical risks from climate change, whereas news about the last two topics are mostly informative about transition risks.[2] We interpret the daily time series of the estimated intensity of media news coverage for each topic as the respective climate risk factor; the disclosure of such news reveals risks for firms and investors (see Engle et al. (2020) and Section 4 on the link between news coverage and risk).

Next, we investigate whether each one of our four textual factors is priced in the universe of U.S. common stocks via portfolio sorts. In contrast to regression-based asset pricing tests, portfolio sorts constitute a non-parametric approach to testing for the significance of asset pricing factors and capture any non-linear relation between expected returns and factors (Bali et al. (2016)). For any given climate risk factor, we examine whether a long-short spread value-weighted portfolio constructed by going long in the portfolio which includes stocks with the greatest climate betas and short in the portfolio which includes stocks with the smallest climate betas, earns a statistically significant average return, once we control for other risk factors. To test the robustness of our results, we sort stocks in decile and quintile portfolios, separately, and we use alternative specifications to estimate stocks' climate betas and the spread portfolios' alphas.

We find that only the U.S. climate policy factor is priced. The spread portfolio formed

[2] Natural disasters and global warming may also *indirectly* reflect transition risks, as policymakers are more likely to take legislative action as the occurrence of extreme natural events alerts them to the reality of climate change. In this paper, we term that a topic reflects physical or transition risk, based on its *direct* effect.

on the U.S. climate policy factor earns a statistically significant positive alpha, for almost all models used to estimate climate betas and alphas. There is no evidence that the risks elicited by news about the occurrence of natural disasters, the rise in temperatures, and the debate in international summits are priced. Our findings suggest that it is only the imminent risk of government intervention that is priced in the stock market, and not the direct risks from climate change itself. This is consistent with the survey results in Krueger et al. (2020) and Stroebel and Wurgler (2021); the average respondent believes that equity valuations do not reflect the physical risks and that climate policy risks are of first order importance relative to physical risks.

We attribute the positive risk premium of the U.S. climate-policy textual factor to an intertemporal hedging motive (Merton (1973); for applications of the same argument to explain the sign of documented risk premiums, see also Bali et al. (2017), Huynh and Xia (2021) and Pastor et al. (2021)). To establish our argument, we hypothesize that news coverage of the U.S. political debate on climate policy has typically reassured investors that transition risks would not materialize. If this is the case, an increase in this factor signals a fall in transition risks and thus good news to the economy. Conversely, a decrease in this factor translates to bad news, and hence it deteriorates the investors' opportunity set. To hedge against such an unfavorable shock, investors would buy (short sell) stocks with negative (positive) climate betas, thus increasing (decreasing) their prices and reducing (increasing) their return. As a result, the long-short portfolio (i.e., high climate beta stocks minus low climate beta stocks) would yield a positive alpha, as we find.

We verify our hedging argument by following two sequential steps to ensure that our conjectured interpretation of fluctuations in the factor holds. First, we examine whether the climate policy textual factor is priced by conducting a subsample analysis. We split our sample on November 6$^{\text{th}}$ 2012. Over the period that follows this date, characterized by the second term of Obama's administration and the one of Donald Trump, our hypothesis that news has typically signalled a reduction in transition risks is most likely to hold true.[3] We find that the statistical significance of the positive risk premium of the climate

[3] During Obama's second term in Office, the lack of a majority in the House of Representatives, and then also in the Senate after November 2014, forced the Democratic administration to find common grounds with the Republicans in order to resolve the political impasse. As a result, Obama's administra-

policy textual factor hinges exclusively on this latest part of the sample, i.e., November 6th 2012 to December 31st 2018. This is consistent both with our hedging explanation of the documented positive premium for climate-policy risk and with previous findings in the literature, that investors have become aware of climate change risks only in the most recent years (Krueger et al. (2020), Painter (2020), Bolton and Kacperczyk (2021), Goldsmith-Pinkham et al. (2021)).[4]

Second, instead of using the textual factor, we conduct the same asset pricing tests by constructing and using a *narrative* U.S. climate-policy factor; we obtain the latter by performing a narrative analysis on the textual factor to identify the content of climate change news (for a seminal application in economics, see Romer and Romer (2010)).[5] We collect all articles which load with more than 40% on the topic. This yields 3,500 articles. We read each article, and mark it according to whether it reflects an increase or a decrease in transition risks. By construction, an increase in this narrative factor reflects an increase in transition risks. We find that transition risks decrease in the post-November 2012 period, in line with our hypothesis and interpretation of the textual factor. In addition, we find that the narrative factor is priced in the post-November 2012 period by carrying a *negative* risk premium. This again confirms the hedging explanation of the documented positive risk premium of the U.S. climate policy textual factor. Stocks which are positively (negatively) correlated with the textual (narrative) factor are riskier because a decrease (increase) in the factor signals an increase in transition risks. To hedge the risk of the textual (narrative) factor, investors buy stocks with negative (positive) climate betas, thus increasing their prices and lowering their returns. As a result, the long-short spread portfolio formed with respect to the textual (narrative) factor will yield

tion was unable to pass any significant climate change legislation through Congress. Trump continued to unravel any progress made by the Obama administration on climate change issues (e.g., the appointment of Scott Pruitt, a notorious climate change denialist, as head of the Environmental Protection Agency), ultimately withdrawing from the International Paris Agreement. This news is "good" for the economy in the short run. The realization of transition risks entails a temporary negative impact on production, the price that needs to be paid to curb climate change.

[4]As a robustness test, we have also checked that the U.S. policy factor carries a positive premium after the victory of Donald Trump in the presidential elections of November 8th, 2016.

[5]An alternative approach to decide on whether the content of climate change related news has a positive or negative meaning, would be to apply a sentiment correction using dictionary based methods (e.g., Apel et al. (2021), Ardia et al. (2022), Bua et al. (2022)). However, these may result in misclassification of the content of news (for a discussion of these biases in financial applications, see Loughran and McDonald (2011)).

a positive (negative) alpha. In line with the with the theoretical results of Pastor et al. (2021) and Baker et al. (2022) and the findings of Engle et al. (2020), Alekseev et al. (2022) and Ardia et al. (2022), and in contrast to common priors, we find that investors do not hedge climate policy risk by necessarily using 'green' firms. This is also consistent with the findings of Cohen et al. (2020) that some brown firms are innovators of green technology and hence investors may use them as a hedging tool.

We also document that our textual and narrative policy factors genuinely reflect climate risks and do not confound the effects of other sources of uncertainty induced by government's intervention, like economic policy uncertainty or political uncertainty; both types of risk have been documented to affect stock prices (Pastor and Veronesi (2013), Bali et al. (2017)). In line with Bali et al. (2017), we conduct bivariate conditional portfolio sorts and we find that our climate policy factors are priced even once we control for the other two types of policy uncertainty.

Finally, we carry out one additional robustness test, by creating narrative factors also for the articles related to natural disasters, global warming and international summits, respectively. This analysis confirms that even after controlling for the informational content of each relevant article, the associated risk factors are still not priced in the cross section of U.S. stock returns. Importantly, the patterns of the narrative factors are consistent with those of the corresponding textual factors. The analysis based on the textual and narrative factors constitutes a two-step approach which validates the provided factors and the results of the analysis (for an alternative two-step procedure, see Hanley and Hoberg (2019)).

2 Literature review

Our paper contributes to the growing empirical literature on climate finance with respect to the measurement of climate risks and their effects on asset prices, by taking a textual approach (for a detailed survey, see Giglio et al. (2021a)). This literature finds mixed results depending on the variable used to proxy the risk stemming from climate change and the asset class, or even the segment in the asset class, under scrutiny.[6]

[6]Baldauf et al. (2020) find little evidence that the flood risk due to sea-level rise is incorporated in coastal real estate prices, whereas Bernstein et al. (2019) and Giglio et al. (2021b) find opposite

Focusing on the cross-section of individual stocks, which our paper also employs, it is not obvious in advance whether climate risks are priced, given investment practices. On the one hand, some institutional investors may not regard climate risks as important as other financial risks and/or they may find them difficult to price and hedge (Krueger et al. (2020)). For instance, the fraction of "green" investors (Heinkel et al. (2001)) and trading constraints to "decarbonizing portfolios" (Bessembinder (2017)) are factors to consider. On the other hand, climate risks incorporated in legislation may affect the profitability and operation of firms (Bartram et al. (2022), Ramadorai and Zeni (2021)), and thus stock valuations. Pastor et al. (2022) document that stocks of green firms outperform those of brown firms. Oestreich and Tsiakas (2015), Hsu et al. (2022), Bolton and Kacperczyk (2021) and Bolton and Kacperczyk (2022) find that climate risk are priced, when proxied by carbon emissions, whereas Görgen et al. (2019) find opposite results, when using a composite measure of carbon emissions and environmental firm rating.

Our finding that the U.S. stock market prices the risks elicited by the U.S. political debate on climate change is consistent with the results of Barnett (2019), Hsu et al. (2022), Bolton and Kacperczyk (2021), Bolton and Kacperczyk (2022), Ramelli et al. (2021), Seltzer et al. (2020), and Ilhan et al. (2021), who document that climate policy uncertainty related to the treatment of carbon emissions is priced in the stock, bond, and option markets; our textual climate-policy factor loads heavily on topics related to energy production and emissions. Our results also relate to Pastor et al. (2021): in their model, the stocks of firms which pollute more (brown firms) than others (green firms) command a greater expected return because investors use green assets to hedge climate risks. Our findings support the hypothesis that hedging generates a climate-policy risk premium, but also suggest that when choosing stocks to hedge climate risks, investors do

results. Painter (2020) and Goldsmith-Pinkham et al. (2021) find that the risk of sea level rise is priced by municipal bonds, especially in the longer maturities. Seltzer et al. (2020) and Duan et al. (2021) find that environmental regulatory uncertainty and carbon risk are reflected in corporate bond prices, respectively. Ilhan et al. (2021) find that out-of-the-money options are relatively more expensive for carbon intensive firms and Cao et al. (2021) find that the implied volatilities of at-the-money options are higher for underlying stocks with lower environmental scores. Bansal et al. (2017) find that temperature changes carry a negative risk premium for a specific set of stock portfolios. Manela and Moreira (2017) find that natural disasters do not account for the variation in the market risk premium. Hong et al. (2019) find that the increasing risk of droughts caused by global warming is not efficiently discounted by food stock prices.

not simply classify between green and brown firms.[7]

Our paper also contributes to the literature that applies textual analysis to finance (for reviews, see Das (2014), Loughran and McDonald (2016), Gentzkow et al. (2019), and Loughran and McDonald (2020)). In the context of textual analysis in climate finance, we contribute to the construction of *market-wide* textual climate measures. Most closely related to our paper are Engle et al. (2020) and the concurrent study of Ardia et al. (2022). A common feature shared by these and our study is that they all provide market-wide 'raw' textual climate change risk factors, as well as sentiment-corrected factors to identify whether news have a positive or negative content for the economy. On the other hand, the proposed risk factors differ in several dimensions with respect to their construction and this explains the low correlations between them reported by Ardia et al. (2022).[8, 9] Regardless of these differences, the focus of the three papers differs. Engle et al. (2020) use textual analysis for the purposes of constructing climate hedging portfolios, Ardia et al.

[7]There is a growing theoretical literature on climate risks and asset pricing. Bansal et al. (2017) employ a long-run risk setting which yields risk premia as a function of shifts in temperature and temperature-related risks. Barnett (2019) develops a general equilibrium model to study the effect of climate-policy uncertainty on oil prices and oil production. Barnett et al. (2020) show the effect of climate uncertainty on the social planner's stochastic discount factor. Giglio et al. (2021b) present a model which relates the term structure of risk premia to the probability of natural disasters. Pastor et al. (2021), Pedersen et al. (2021), and Zerbib (2022) provide asset pricing models with an environmental-social-governance (ESG) factor which can also accommodate climate risk, and Heinkel et al. (2001) show the effect of green investors to expected returns. Albuquerque et al. (2018) show a mechanism through which corporate social responsibility affects systematic risk.

[8]First, Engle et al. (2020) and Ardia et al. (2022) factors are constructed by using climate change dictionaries (see also Apel et al. (2021) and Bua et al. (2022) for dictionary-based textual climate risk factors). Ardia et al. (2022) also provide factors by using a topic-textual model, as we do, yet the employed topic models differ; these are more advanced textual methods compared to papers which construct textual climate factors based on counting climate-related words from newspapers and online sources (e.g., Donadelli et al. (2020), Gavriilidis (2021), Basaglia et al. (2022), Meinerding et al. (2022)). Second, Engle et al. (2020) textual factors do not dissect climate changes risk in its various dimensions, whereas Ardia et al. (2022) and our factors do so. Third, all three papers provide sentiment-corrected factors, yet the method to mark whether climate news reflects concerns or positive news for the economy differs. Engle et al. (2020) and Ardia et al. (2022) are based on dictionaries, whereas we mark the content of each article manually. Fourth, the two papers use innovations of their factors, whereas we use the levels of our factors; the choice depends on the research question and the assumptions one wishes to make.

[9]Interestingly, Alekseev et al. (2022) document that that the returns of their hedging strategy are correlated with the innovations of Engle et al. (2020), Ardia et al. (2022) and our factors, yet this speaks to the robustness of the effectiveness of their hedging scheme with respect to alternative measures of climate risks rather than to the similarity of the factors. Echoing this, Chini and Rubin (2022) use alternative climate hedging strategies to hedge against the innovations of the same climate textual factors. They find that the hedging effectiveness differs depending on the employed factors, with the returns of their strategy being mostly correlated with our factors. Again, this does not imply something about the superiority of any of the employed factors.

(2022) focus on testing the predictions of Pastor et al. (2021) model, whereas we focus on which types of climate change risks are priced in the cross-section of U.S. equities. Our paper is also similar in spirit to Huynh and Xia (2021) who use the Engle et al. (2020) textual factor to examine whether market-wide climate risks are priced in the corporate bond market. They find that they are, and they also attribute this to an intertemporal hedging motive.[10]

3 Data and textual analysis

3.1 Stock market data and other related variables

We obtain daily stock prices, stock characteristics, and daily closing bid and ask stock prices, from the Center for Research in Security Prices (CRSP) and Compustat via the Wharton Research Data Services (WRDS). Our stock universe consists of all U.S. common stocks trading at NYSE, NASDAQ, and AMEX (CRSP share codes 10 and 11). Our sample is unbalanced and spans January 1st 2000 – December 31st 2018. For each day, we have on average about 4,700 returns from a total of 10,498 listed firms in our sample. We adjust returns for delisted firms as in Shumway (1997).

We obtain daily data on equity risk factors and the synthetic-stock difference (SSD) measure of Hiraki and Skiadopoulos (2023) from Kenneth French's and George Skiadopoulos websites, respectively. We obtain data on the Chicago Board Options Exchange (CBOE) Volatility index (VIX) and on the NBER based recession indicator from CBOE's and Federal Reserve Economic Data (FRED) of the Federal Reserve Bank of St. Louis websites, respectively. We also obtain yearly firm-level data on ESG scores and carbon dioxide (CO_2) emissions from Refinitiv. We obtain the total ESG and the environmental pillar 'E' score and the total direct and indirect CO_2 emissions intensities.

[10]There is a series of concurrent papers which apply textual analysis at a *firm*-level to construct climate factors. Hassan et al. (2019) use conference calls to construct a climate policy risk factor, among the other types of political risks they consider. Li et al. (2020) and Sautner et al. (2022a) construct factors by applying textual analysis to conference calls of publicly-listed firms and study their relation with firms' characteristics rather than on whether they are priced. Berkman et al. (2021) and Kölbel et al. (2022) construct climate textual factors by applying textual analysis to 10-K reports, and they examine their effect to firm valuation and the term structure of credit default swaps, respectively. Sautner et al. (2022b) examine whether the Sautner et al. (2022a) factors are priced in the universe of S& P 500 stocks and they find mixed results depending on how the stock's expected return is estimated.

The latter two variables are measured as Scope 1 plus Scope 2 CO_2 equivalent emissions to revenues USD in million and Scope 3 CO_2 equivalent emissions to revenues USD in million, respectively.

3.2 News articles from Reuters

Our sample consists of more than 13 million articles from Refinitiv News Archive published from January 1st 2000 to December 31st 2018. Reuters news reaches one billion individuals each day, and its associated trading platform Eikon has a 34% market share for the delivery of financial information.[11] Reuters is thus a key player in this market, affecting stock market prices via the dissemination of news.

We restrict the analysis to news articles written in English and we apply filters to remove entries that summarize different unrelated news, or simply report tables of stock market returns. If there are subsequent corrections to an article, we use the first version of the article within a 12-hour period, and in case of additions to an article within a trading day, we use the article with the longest body text.[12] After this initial procedure, we end up with a sample consisting of roughly seven million articles. This sample contains articles within a diverse set of topics, including sports, technology, politics, finance, among others. Given our focus on climate risk, we discard irrelevant articles by retaining only the news in which the bigrams "*climate change*" or "*global warming*" occur at least once. This yields a final sample consisting of roughly $34,000$ articles.

This textual corpus comprises a very heterogeneous set of articles related to climate change. Some articles reflect climate change views expressed in the domestic political debate over different geographical locations in the U.S. and internationally; others reflect corporate views or marketing initiatives across the globe related to climate change; others report news about scientific research and on the effects of emissions on global warming; some news may report on the realizations of extreme meteorological events; finally, some news may be only incidentally related to climate change. To group the heterogeneous

[11] https://www.thomsonreuters.com/content/dam/openweb/documents/pdf/reuters-news-agency/fact-sheet/reuters-fact-sheet.pdf

[12] As soon as a news item occurs, Reuters publishes a breaking news alert, often consisting of a single sentence. The body of the article is then added within a few minutes. In our corpus, we observe both entries separately, but we use only the second, updated version in the analysis.

news into specific climate-subcategories, we conduct textual analysis by employing the Latent Dirichlet Allocation (LDA). We describe the method in the following section.

3.3 Latent Dirichlet Allocation: Concepts and estimation

LDA (Blei et al. (2003)) is one of the most commonly employed topic models in textual analysis (Zhao et al., 2015). It is a textual method which takes a collection of articles and the number of unique words (termed vocabulary) contained in these articles, as inputs. In our case, we have 33,735 articles and a vocabulary of 6,158 unique words that appear across all articles. LDA delivers two outputs. First, it decomposes the entire textual corpus into categories (termed topics); the number of topics is set by the user. A topic is a probability distribution over the unique words: it reflects how frequently each unique word appears in a topic. Second, LDA expresses every article as a probability-weighted average of topics, the weights termed topic shares. Each topic share shows the percentage of the given article associated with the respective topic, i.e., the intensity by which a topic appears in that article. Summing these topic shares across all the articles published in a given day, delivers a measure of the intensity of news coverage for a given topic in a given day. Given that articles are time stamped, LDA ultimately allows us to recover time series of news coverage by climate topic. These time series will be our textual climate risk factors, as we will discuss in Section 4.

LDA is an unsupervised machine learning method, i.e., it is the method, rather than the user, which dissects textual heterogeneity in topics. This is in contrast to dictionary methods, where it is the user who labels the topics in advance, by specifying the words that are most likely to characterize it. Once LDA delivers the topics, the user labels them based on the words that appear most frequently. This is useful for our purpose because in the context of climate change news, words like "pollution", could feature in articles covering different themes, ranging from scientific research and corporate announcements, to natural disasters and climate-change legislation.

To fix ideas, LDA is a Bayesian factor model for discrete data. In a model with K topics, each topic is a probability vector β_k over the V unique words in the textual corpus ($k = 1, \ldots, K$). Each article is modeled as a distribution over topics, with articles being independently but not identically distributed. We denote the distribution over topics for each article (document) by θ_d. θ_d^k represents the share of the k^{th} topic in document d. The data generating process that produces the list of words in document d consists of two steps. A document is a collection of N slots, one for each word. First, each slot n is assigned a topic z_n by drawing from the distribution θ, where the subscript d is omitted for notational convenience. Next, every word is drawn from the distribution β_k, given the topic assignment z_n.

Given the distributions of β_k, for all $k = \{1, \ldots, K\}$, and a distribution θ_d, the probability that any given word in article d equals the v^{th} word in the vector of unique words is $p_{d,v} = \sum_k \theta_d^k \beta_k^v$, where β_k^v is the conditional probability that the v^{th} word is drawn from topic k. Let $x_{d,v}$ denote the number of times that word v appears in article d. Then, the likelihood of observing the entire set of articles is given by $\prod_d \prod_v p_{d,v}^{x_{d,v}}$.

LDA assumes Dirichlet priors of the two probability distributions for topics and topic shares. To each β_k, a symmetric Dirichlet prior distribution with V dimensions and hyperparameter α is assigned. To each θ_d, a symmetric Dirichlet prior with K dimensions and hyperparameter η is assigned. The hyperparameters measure the concentration of the realizations. A high value indicates that the distributions are relatively flatter, with a relatively even distribution of the probability mass.

The inference problem in LDA is to approximate the posterior distributions of β_k for every topic k and of θ_d for every document d, given K, α, and η. In our case, LDA will deliver one posterior distribution β_k for each topic k, and one posterior distribution θ_d for each document in our set of 33,735 articles (i.e., a matrix 33,735 by K of posterior probabilities), which will be the topic shares. For the estimation of topics, β_k, and article-topic distributions, θ_d, one can rely on the Gibbs sampling algorithm. The algorithm begins by randomly assigning topics to words and then updating topic assignments by repeatedly sampling from the appropriate posterior distribution. We relegate the technical details to the Appendix A. In line with Heinrich (2009), we set $\alpha = 1/K$ and $\eta = 1/10$. We rely on the C_V coherence measure by Röder et al. (2015) to select the optimal number of topics and select a model with 25 topics.

3.4 Estimated Topics: Interpretation

Within the corpus of climate change articles, our LDA model classifies the unique words in 25 different topics. To interpret them, we create the heat map reported in Figure 1. For every topic, we order first the most frequent word, and then words follow in decreasing order of frequency. We use darker (brighter) colors for words with higher (lower) relative frequencies.

[Figure 1 about here.]

We can see that two topics relate to natural disasters and global warming. Topic 24 relates to natural disasters (droughts, flooding, wild fires, damages) and Topic 17 relates to news about the effects of fossil-fuel emissions on global warming, including the results of scientific research.

Topic 18 collects news related to international summits, where the political leaders of many countries meet to discuss issues related to climate change, in an attempt to reduce global emissions. Examples include the United Nations Copenhagen Conference of 2009, where representatives from 115 different countries met, as well as news that relate to discussions about the Kyoto Protocol of 1997, an international treaty with 192 signatories, where nations agreed to reduce greenhouse emissions. Topic 14 also reflects news about the implementation of the Kyoto Protocol, with a particular focus on the decisions taken at the level of the European Commission.

A few topics are related to policy discussions about climate change taking place in different countries: Topics 2 and 6 relate to Germany, topic 3 to Canada, topic 5 to Australia, topic 15 to a mix of countries including Africa, Indonesia and Brazil, topic 19 to Asia, topic 21 to the UK, topic 22 to Russia and Norway, and topics 4 and 7 focus on the US. Topic 4 primarily focuses on U.S. energy policy and its connections with the climate debate at the State level, whereas topic 7 is closely related to the debate on U.S. climate policy at the Federal level.

Regarding the rest of the topics, topic 1 is about scientific research documenting how marine life became endangered as a result of global warming. Topic 10 reflects news on renewable energies, with a focus on solar and wind technologies, as alternatives to more polluting energy sources like coal. Topic 25 is related to news about the oil market. Topic

19 is about political activism around climate change issues. Topics 8, 20 and 23 broadly reflect corporate news. The remaining topics, 9, 11, 12 and 13 do not seem to reflect a clear theme, or one that can be clearly associated with a specific aspect of climate news.

Given that in this paper, our research question is whether physical risks or government's intervention is reflected in U.S. stock prices, we opt to use the topics which satisfy the following criteria: (1) have a clear interpretation which ensures that they capture either of these two dimensions of climate risks, (2) represent market-wide measures of climate risks, and (3) are relevant to investors interested in U.S. equities.

Application of criteria (1)-(3), yields the following four topics for our analysis: U.S. climate policy (the union of topics 4 and 7), international summits (topic 18), natural disasters (topic 24) and global warming (topic 17). Therefore, we discard from our analysis the topics related to climate policy legislation in all countries other than the U.S., topics that relate to corporate news since they tend to carry company-level information, and the topics related to renewable energy that are not restricted to the U.S. market. Finally, we also discard the topics about maritime life research, oil, and political activism, as they are not directly related to the scope of this paper. To facilitate the visualization of the topics that we have selected for the asset pricing analysis (natural disasters, global warming, international summits, U.S. climate policy at a state and at a federal level), we report the respective word clouds in Figures 2a to 2e.

[Figure 2 about here.]

4 The four textual climate change risk factors

4.1 Construction, interpretation, and pattern

As we explained in Section 3.3, for any given news article, the estimated topic share for any given topic is the proportion of words contained in the article, which are estimated by LDA to be associated with the particular topic, relative to the total number of words contained in this article. For each of the four LDA topics that we focus on, we consider the time series of their estimated topic shares as the corresponding risk factors; in case more than one articles are released on day t, the risk factor value of the ith topic on day t

is the sum of the ith topic shares of the articles released on that day. This is because the ith risk factor's value is the intensity of news coverage of topic i which elicits information on climate risks for firms and investors.[13]

Typically, news about natural disasters and global warming factors would signal an adverse effect on the economy. Times when their news coverage is high, are times when these specific topics of climate change are particularly concerning. This assumption is based on the insight that news raises to the media's attention whenever there is a source for concern (see Engle et al. (2020)). Similarly, news about international summits also signal an adverse effect to the economy. Typically, these meetings discuss the introduction of a global tax on pollutants, which is "bad news" for the economy. While at this stage any claim about the content of the news is just a conjecture, we will formally validate such claims in Section 7, when discussing the three corresponding narrative factors, which are based on marking the content of each relevant article.

On the other hand, it is not clear in advance how one should interpret the economic effects of news associated with U.S. climate policy. High news coverage may signal high or low transition risks, depending on whether the political power is relatively more tilted towards Democrat or Republican views. In our sample, with the exception of the first term of the Obama administration, the U.S. political debate on climate change has hardly ever signaled high transition risks. Notably, in the period covered by our analysis, there were two climate-change skeptics as presidents of the USA, George W. Bush and Donald Trump. Moreover, the second term of the Obama administration has been characterized by the failure to pass any significant legislation through Congress, since the president lacked the required majority in the House throughout his second mandate and also in the Senate after 2014. Following the elections of November 2012, it became evident that any effort to tackle climate change was unlikely to be effective, and that many of the ambitions of the Obama administration would be scaled down.

Figures 3a, 3b, 3c, and 3d show the time series evolution of the four respective risk

[13]For any given day and topic, the intensity of topic's news coverage is determined by count of climate related articles weighted by the respective topic share. An increase in news coverage can reflect either an increase in the number of articles published on climate, and/or an increase in the media's attention to a particular topic, for a given number of articles published. Both factors contribute to news coverage capture media's attention to a particular climate topic. Therefore, the factor time series does not need to be standardised by dividing the factor value by the total number of daily published climate articles.

factors; we depict the monthly average over the daily values for each month. A common pattern arises. The factors reach their highest values in 2007 and they decrease thereafter. These two features are not an artifact of LDA. On the contrary, they are consistent with the patterns in Reuters news data. The pronounced increase of media's attention on 2007 can be explained by an increased coverage of important climate-related events in 2007, as we describe in section 4.2. It can also be explained by the award of the Nobel Peace Price to Al Gore and the Intergovernmental Panel on Climate Change (IPCC) in that year for *"their efforts to build up and disseminate greater knowledge about man-made climate change, and to lay the foundations for the measures that are needed to counteract such change"*. The subsequent decrease in media's attention demonstrated by our factors is also consistent with the data on Reuters news releases. Figure 4 depicts the time series of the total count of articles featuring the words "climate change" and "global warming". We can see that total word counts are elevated around 2007-2010 and then they decrease in line with the pattern depicted by our textual factors.[14]

[Figure 3 about here.]

[Figure 4 about here.]

4.2 Factors: What news releases do they relate to?

We delve into the content of news releases that make these factors vary over time. Figure 3a shows the time series of the natural disasters textual factor. This reflects news on the occurrence of catastrophic natural events, including the record highs of rainfall and drought in Asia in November 2000, the extremely cold winter in Europe in January 2006, Hurricane Dean in August 2007, flooding in Eastern India in August 2008, wildfires in Australia in February 2009, Cyclone Pam in March 2015, extreme pollution in New Delhi in November 2015, and wildfires in California in November 2018. The factor also reflects the content of scientific research and government reports that emphasize the role of climate change for the occurrence of natural disasters. Examples include the report by the Asia Development Bank in February 2012, which warned about the risk of mass

[14] A one-to-one correspondence between the patterns of the time series of the four textual factors and that of total climate-related word counts is not expected since the latter spreads over additional topics, too. Yet, the patterns are similar.

migration due to the increased occurrence of natural disasters in the region, and the third United Nations (U.N.) conference on Disaster Risk Reduction in March 2015.

Two remarks are in order regarding the natural disasters factor. First, the time series of natural disasters reflects global news, and not just U.S. news. As a result, this factor does not reflect risks associated with a direct negative impact of natural disasters on U.S. production. Its correlation with the Fernald (2014) measure of shocks to the U.S. total factor productivity adjusted for capacity utilization is only -0.10 at a quarterly frequency. However, it is still relevant for a U.S. investor. In the spirit of Engle et al. (2020) climate textual factor, this risk factor captures investors' concerns that the occurrence of natural disasters around the globe may signal a gradual worsening in the climate. This in turn implies that similar events may become more frequent and more disruptive, also in the U.S. Second, this factor is not intended to be a time series of natural disasters. Instead, it reflects news coverage of physical risks whenever these are cited along with the words "climate change" and "global warming". Hence, it captures news coverage of natural disasters whenever an explicit connection with climate change is made in the article. Natural disasters without such an explicit connection would not feature in the time series of the textual factor, even if they have been extensively covered in the press, but in a different context.

Figure 3b plots the time series of the global warming factor. This reflects mostly news on the rise in average temperatures that is explicitly linked to rising emissions. This news appears in multiple sources, including reports drafted by governmental and non-governmental organizations, both at a national and international level, publication of scientific studies in academic journals, and articles appearing in non-scientific magazines. This may explain the heterogeneity of this type of news which causes articles to have smaller weights (topic shares) on the global warming topic, relative to the natural disasters topic. As a result, the global warming factor can be related less often to a significant event, relative to natural disasters. Examples where a strong association can be established, include the publication of reports by the IPCC (February 2007, April 2007, November 2007), the U.N. Panel on Climate Change (December 2009), and the World Meteorological Organization (November 2015). All these documents warned about the impacts of global warming and stressed the need to reduce greenhouse gas emissions.

Figure 3c plots the time series of the international summits factor. This reflects the occurrence of international events, where governments' representatives from around the world meet to negotiate a coordinated intervention to tackle climate change. It also captures how legislation at a country level responds to these events. Indicative examples where our factor spikes to reflect the increased intensity of news on international summits include Hague talks (November 2000) and Bonn meetings (July 2001) which led to the ratification of the Kyoto protocol of 1997 (February 2005), the G8+5 meeting (February 2007), the Bali, U.N. Poznan and Bonn meetings (December 2007, December 2008, June 2009, respectively), the Copenhagen Summit (December 2009), and the Doha U.N. Climate Change Conference (November 2012). They also include legislative amendments, such as the coordination of U.S. and European exchanges on emission trading schemes (May 2006). After November 2012, the international summits textual factor stays at a relatively low level. Perhaps surprisingly, there is no pronounced movement in December 2017, when the U.S. announced their withdrawal from the Paris agreements. This is because the news of President Trump's intention to withdraw from the Paris agreement is not really news at that time; this decision was clearly communicated by the President many months in advance, and it appears extensively in numerous articles that precede December 2017.

Figure 3d plots the time series of the U.S. climate policy factor. The series reflects news releases on climate-related presidential announcements, the implications of elections in the House of Representatives and the Senate for the U.S. climate policy, the discussion and introduction of environmental bills, the political consequences of natural disasters, and the appointment to key positions of people with well declared views on environmental issues. Examples include the bills on capping greenhouse gas emissions for the first time and promoting the use of clean energy resources (June 2007, September 2009), the Lieberman-Warner Climate Security Act (June 2008), the bills introduced to stop the regulation of emissions and to approve the keystone XL pipeline (March 2011 and November 2014, respectively), the political aftermath of the BP oil spill in the Gulf of Mexico (April 2010), the appointment of Scott Pruitt by Donald Trump to head the Environment Protection Agency (December 2016), as well as news on the climate policy debate that followed the Democratic and Republican parties taking control of the House of Representatives (November 2006 and November 2010, respectively).

Appendix B provides a detailed description of the news releases associated with some of the pronounced increases in the value of each one of our textual factors, including the above-mentioned ones.

4.3 Correlation analysis

We examine the pairwise correlations between the daily four climate change textual factors, as well as their pairwise correlations with a set of standard equity factors, market volatility, macroeconomic and stocks' transaction costs variables. The equity factors are the market factor, the Fama and French (1993) value (HML), and size (SMB) factors, the (Carhart (1997)) momentum (UMD) factor, and the Fama and French (1993) operating profitability (RMW) and investment (CMA) factors. The market volatility variable is the CBOE Volatility index (VIX), and the macroeconomic variables are the Economic Policy Uncertainty Index (EPU, Baker et al. (2016) and the NBER recessions indicator which marks the NBER recession dates (a dummy variable which takes a value of one for recessions and zero for expansions; recession and expansion periods are detected by NBER). To proxy transaction costs, we use two variables. The cross-sectional average of stocks' bid-ask spreads and the cross-sectional standard deviation of the Hiraki and Skiadopoulos (2023) synthetic-stock difference (SSD) measure; SSD measures the effect of transaction costs to the expected returns of the U.S. common stocks and its cross-sectional standard deviation $stdevSSD$ is documented to be correlated with standard proxies of transaction costs. In Hiraki and Skiadopoulos (2023), transaction costs refer to typical trading costs (e.g., commissions, exchange fees, bid-ask spreads and market impact) that apply to buying and selling assets, as well as to short-selling costs. Hence, $stdevSSD$ encompasses various types of transaction costs, including bid-ask spreads.

Table 1 reports the results. We can see that the pairwise correlations between the climate textual factors are small and not greater than 0.31. In addition, the correlations of the climate textual factors with the rest of the factors and variables are also small.

[Table 1 about here.]

The low pairwise correlations between the four textual factors is a desirable outcome since it renders credibility to our textual analysis. It verifies that LDA has successfully dissected the multidimensional aspects of climate change risks. The low correlations imply that these time series are distinct, capturing different types of climate risks. This comes as no surprise. The different topics elicit information on different sources of risks which also refer to different time horizons when it comes to their realization. News about global warming and the occurrence of natural disasters typically signal a deterioration in the health of the planet. Given that the health of the planet changes slowly over time, this type of news is informative about its trend, and hence mostly reflects physical risks which will materialize in the long-term. Similarly, articles about international summits are also informative about transition risks which may take longer to be realized. This is because it takes longer for a wide set of countries to negotiate a common policy. The objective of many international summits is to reveal and understand the political positions of individual members states. This is a prerequisite to set up strategies that would eventually promote political convergence in future summits. Moreover, even when international agreements are reached, it takes time for them to filter through the domestic political debate, and eventually become law, if they ever do.

On the other hand, articles about U.S. climate policy are informative about transition risks which may be realized in the very short-term. These articles include news on the political debate on climate change, appointments in key positions in organisations like the Environment Protection Agency, and related laws passed in Congress. They represent imminent risks because they reflect political intentions and actions over the course of the government's administration, i.e., at most four years; political positions in the Congress may radically change with a new round of elections. These positions may well change whenever there is a change in the political composition of the Congress, even if the same president is re-elected; the change in the environmental policy of Barack Obama's government in its second term is an example.

The low correlations between each one of the climate factors and the set of the variables showcase that our climate factors contain information which is distinct from that contained in equity factors, market volatility, macroeconomic variables, and proxies of transaction costs. For instance, the correlation of the U.S. climate policy factor with VIX is only 0.13. This low correlation can be explained by the fact that our factors capture market-wide climate change risks which propagate to U.S. firms via their respective climate betas; an increase in the U.S. climate policy may signal bad news for some firms and good news for some other firms, thus decreasing and increasing their stock prices, respectively. On the other hand, an increase in VIX signals an increase in economic policy uncertainty (Baker et al. (2016). In Section 6.2, we provide further analysis which confirms that the U.S. climate policy factor is distinct from economic policy uncertainty.

5 Asset pricing tests

We investigate whether each climate factor is priced in the cross-section of U.S. stocks.

5.1 Portfolio sorts analysis: The design

To conduct our asset pricing test, we employ a standard portfolio sorts approach. Portfolio sorts constitute a non-parametric approach to testing the significance of asset pricing factors. They allow capturing any non-linear relations between expected returns and factors. We sort stocks into portfolios based on their sensitivity to each factor (climate beta). Then, we form a long-short spread portfolio consisting of going long in the portfolio that includes stocks with the highest climate beta, and going short in the portfolio that includes stocks with the smallest climate beta. We examine whether the spread portfolio yields a statistically significant abnormal performance. If it does, this would suggest that the climate risk proxied by the specific climate factor is priced.

To fix ideas, for every asset i, we estimate:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i F_t + \gamma_i' X_t + \epsilon_{i,t}, \tag{1}$$

where $r_{i,t}$ is the daily return on security i, $r_{f,t}$ is the risk-free return, F_t is the textual factor, X_t is a vector that includes standard controls that have been found to explain the cross-section of U.S. stock returns and $\epsilon_{i,t}$ is an i.i.d. error term with zero mean. At the end of every month, we estimate equation (1) recursively, by using a rolling window that consists of daily observations over the previous three months. The choice of the size for the rolling window is in line with the approach taken in asset pricing studies where the the sample size is relatively small, starting in late nineties/ early 2000, as it is our case (e.g., Chang et al. (2013)). We roll forward the starting date of the window by one month at each iteration. At the end of any given month, given the estimated betas across stocks, we rank stocks according to their estimated betas and group them in portfolios; we form decile and quintile portfolios, separately. Then, for each portfolio, we compute the portfolio's post-ranking value-weighted monthly returns. Next, we compute the long-short spread portfolio's monthly return. We repeat the process until we exhaust our sample. This yields a time series of 225 spread portfolio monthly returns. Finally, we estimate its alpha, and we assess its statistical significance.

To estimate the spread portfolio's alpha, we use the same asset pricing model (i.e., the same set of factors X_t) as the one we employed in equation (1) to estimate the stocks' betas. We use five alternative model specifications, regarding the choice of vector X_t in equation (1): the market model, which only includes the market portfolio return (market factor); the Fama-French three-factor model (FF3, Fama and French (1993)), which controls for the market factor, as well as the size and book-to-market factors; the Fama-French-Carhart (FFC, Carhart (1997)) four-factor model, which controls for the same factors as FF3, and also includes Carhart's momentum factor (UMD); the Fama-French five-factor model (FF5, Fama and French (2015)), which controls for the same factors as FF3, as well as for the profitability and investment factors; a specification that includes the momentum factor (UMD) in addition to the factors included in FF5.

Two remarks are in order at this point. First, we use the levels rather than the innovations of each climate change risk factor to conduct our asset pricing analysis. From an asset pricing point of view, both approaches (levels versus innovations) are acceptable. From a theoretical perspective, the latter approach can be justified within the setting of an Intertemporal Capital Asset Pricing model (ICAPM, Merton (1973)), where the state variables are modelled as innovations of the raw variables. We have adopted the former approach to avoid making assumptions on the validity of ICAPM; Maio and Santa-Clara (2012) have shown that most of the multifactor models in the asset pricing literature are not consistent with an ICAPM setting. The use of levels in our climate risk factors does not invalidate Pastor et al. (2021, 2022) who use instead climate shocks as a risk factor because their choice is dictated by a different objective than ours; their choice allows them to theoretically and empirically explain why green stocks outperform brown stocks in periods where climate change concerns increase *unexpectedly*. In the absence of this choice, their model can only explain previous evidence that brown stocks outperform green stocks.

More generally, our approach focuses on the level rather than the changes of climate change risks as a driver of equity risk premia.[15] Take a very risky stock, which is as much risky today as it was last month (i.e., the coverage in the press did not change, yet it remains elevated). An investor would still pay a premium to hedge it, even if the riskiness has not changed. Our approach is in line with Kölbel et al. (2022) and Sautner et al. (2022b) who also use the levels of their climate change risk factors to examine whether these affect the term structure of credit swaps and whether they are priced in the U.S. equities, respectively.[16]

Second, we identify topics by using the full sample period rather than by applying LDA on a rolling estimation fashion. This is consistent with the LDA assumption that topics are fixed in advance and time-invariant. From an implementation perspective, respecting this assumption ensures that topic shares will be estimated accurately. The bigger the sample size, the more accurate is the estimation of the topic share for each article released at *any* point over 2000-2018. Moreover, machine learning methods like LDA require extremely large data samples, thus rendering rolling window estimations

[15] In general, the choice (levels versus innovations of textual factors) depends on the research question/objective and the type of assumptions one wishes to adopt. For instance, Engle et al. (2020) and Ardia et al. (2022) use the innovations of their climate textual factors because their objective is the the construction of equity portfolios to hedge the *innovations* in news, and the examination of whether green stocks outperform brown stocks when concerns about climate change *unexpectedly*, respectively. On the other hand, Li et al. (2020), Berkman et al. (2021) and Sautner et al. (2022a) use the levels of their climate factors to examine whether these are related to firm's valuation. Similarly, Jung et al. (2021) use a non-textual climate change risk factor (the return of a 'stranded asset' portfolio), without extracting its innovations, to estimate climate betas for the purposes of constructing a systemic climate risk measure.

[16] As a robustness test, we have examined whether the results of our asset pricing tests prevail, once we use innovations of our climate change risk factors. In line with Engle et al. (2020), Chini and Rubin (2022) and Pastor et al. (2022), we estimate the innovations of our textual factors as the residuals from an AR(1) model fitted to the daily raw textual series. At the end of each month, we estimate the AR(1) model recursively by using the daily observations of each textual factor over the last three months. We obtain the innovations and then we estimate the climate beta with respect to the innovations of the textual factor We roll forward the starting date of the window by one month at each iteration. The unreported results based on the innovations of the climate textual factors are similar to the ones we report in the main body of the paper for the raw textual factors, i.e. the natural disasters, global warming and international summits factors are not priced, whereas the U.S. climate policy factor is priced.

practically infeasible.

In addition, from a conceptual perspective, the four identified climate change risk topics are expected to be known to investors from the very beginning of our sample. An investor reading an article in January 2000, when our sample commences, would be able to tell whether that article referred to natural disasters, global warming, international summits, or U.S. climate policy. Admittedly, such an identification would not be possible in 1900, when media's attention to climate change risks was only confined to natural disasters. However, standing in 2000, it is legitimate to assume that investors could identify climate change topics when reading the news. Furthermore, the four topics prevail over the *entire* sample period, i.e. it is not that some of them ceased to exist at some point over our sample or they appeared for the very first time sometime within our sample.[17] The idea that topics are fixed in advance is also pervasive in Engle et al. (2020) and Ardia et al. (2022).

5.2 First results and discussion

Table 2 reports the estimated alphas (unit is % per month) and their t-statistics within parentheses. We report results for the FF3, FFC and FF5 models for the case of quintile portfolios (Panels A, B, C, respectively). Panel D reports the percentage of significant alphas, once we collectively consider all five models and decile and quintile portfolio partitions.

[Table 2 about here.]

We can see that the alphas of the long-short portfolios formed on the natural disasters and global warming factor are statistically insignificant in all cases. In the case of international summits, we find that alphas are negative, yet statistically significant only for

[17]Natural disasters have been taking place since thousands of years ago. The notion of global warming had first appeared in 1895 when the Nobel Laureate Svante Arrhenius first talked about the Greenhouse effect. In 1988, the greenhouse effect theory was named and the Intergovernmental Panel on Climate Change (IPCC) was founded by the United Nations Environmental Programme and the World Meteorological Organization. Similarly, the first major conference on the environment took place in Stockholm, Sweden in 1972, and the first international summit on climate took place in Rio de Janeiro, Brazil in 1992. Finally, climate change emerged as a political issue in the 1970s, where activist and formal efforts were taken to ensure environmental crises were addressed on a global scale (for a review, see Haibach and Schneider (2013)).

20% of the cases. Therefore, we cannot reject the null hypothesis that the risks elicited by these factors are not priced. On the other hand, the alpha of the long-short portfolio formed on the U.S. climate policy factor is positive and statistically significant, in all but the FF3 and FFC specifications that rely on quintile sorting; alphas are stastistically significant in 70% of the cases. In the case where we consider decile (quintile) portfolios, the spread's portfolio alpha ranges between 0.46% and 0.96% (0.30% to 0.59%) per month across models to estimate climate betas and alphas. These results suggest that financial investors price the imminent risks from government intervention, rather the direct risks from climate change itself. We provide a hedging explanation to the documented climate policy-related premium in Section 5.3.

Our findings showcase the importance of dissecting textual heterogeneity in exploring whether climate risk is priced. The advantage is twofold. First, considering an aggregate climate textual factor could mask important information for pricing purposes. The different risks may represent positive and negative shocks to the economy which may offset each other and they may show no pricing effects if not dissected; for instance, news about the occurrence of natural disasters and news about the reluctance of policymakers to tax polluting businesses are negative and positive shocks, respectively. We show that this is indeed the case, by repeating the portfolio sorts analysis using an aggregate textual factor constructed by simply counting the articles featuring the words "climate change" or "global warming" on any day (see also Donadelli et al. (2020), Gavriilidis (2021), Basaglia et al. (2022), and Meinerding et al. (2022), for a similar counting words-based construction of climate change risk factors). Unreported results show that the aggregate textual factor is not priced, thus hiding the valuable information contained in news related to U.S. climate policy for the purpose of pricing the cross-section of U.S. equities. This confirms the necessity to decompose climate risk in its various aspects, and highlights the benefits of LDA as a textual analysis technique to address our research question.

Second, the fact that we decompose climate risk in its different aspects (physical and transition) allows us to reconcile some seemingly different findings reported in the literature. Barnett (2019), Bolton and Kacperczyk (2021), Ramelli et al. (2021) Bolton and Kacperczyk (2022), and Hsu et al. (2022) find that transition risks related to carbon emissions are priced. These results are consistent with our finding that the U.S. stock market reacts to the news on the U.S. political debate on climate change, which loads very heavily on topics related to energy production and emissions. On the other hand, Manela and Moreira (2017) find that natural disasters do not account for the variation in the market risk premium and Hong et al. (2019) find that increasing risks of droughts caused by global warming are not efficiently discounted by prices of food shares. These results are consistent with our findings that stock market prices only reflect the effects of government intervention, and not the direct effects of climate change itself.

5.3 An explanation: Hedging climate policy risks

The statistically significant positive risk premium of the U.S. climate policy factor can be explained through the lens of an intertemporal hedging motive. To establish our argument, we conjecture that news coverage of the U.S. political debate on climate policy has typically reassured investors that transition risks would not materialize. If this is the case, an increase in this factor signals a fall in transition risks and thus good news to the economy. Conversely, a decrease in this factor translates to bad news, and hence it deteriorates the investors' opportunity set. To hedge against such an unfavorable shock, investors would buy (short sell) stocks with negative (positive) climate betas, thus increasing (decreasing) their prices and reducing (increasing) their return. As a result, the long-short portfolio (i.e., high climate beta stocks minus low climate beta stocks) would yield a positive alpha, as we find.

To validate our hedging explanation for the existence of a positive risk premium for the U.S. climate policy factor, we need to ensure that the conjectured interpretation of fluctuations in the textual factor holds. To this end, as a first step, we conduct the asset pricing tests on the textual factor by carrying out a subsample analysis. We take November 6$^{\text{th}}$ 2012 as a splitting point. This splitting point marks the beginning of the second term of the Obama administration. As we discussed in the Introduction and in Section 4, news over the the post-November 2012 period signal inability, or reluctance, to tackle climate change. Hence, an increase in this factor captures a reduction in transition risks, and can therefore be interpreted as "good news" for the economy. Therefore, our conjecture that a decrease in the U.S. climate policy textual factor signals "bad news" for the economy is expected to hold. As a result, the textual factor should carry a positive risk premium over this period, should the hedging argument holds.

We test whether the U.S. climate policy factor is priced by repeating the portfolio sorts analysis over the sub-periods January 1st 2000 – November 5th 2012 and November 6th 2012 – December 31st 2018. Table 3 reports the results. We can see that the alphas of the spread portfolio sorted on the U.S. climate policy factor are positive and statistically significant across all models and portfolio schemes in the post-2012 period, including those that showed no significance over the full sample in Table 2. Notably, in most of the cases, $t-$ statistics are close and they even exceed the threshold of three suggested by Harvey (2017) to address data mining concerns (see also Hou et al. (2020)). In contrast, alphas are significant in only 10% of the pre-2012 cases. These findings indicate that the evidence on U.S. climate policy being priced over 2000-2018, reported in Table 2, is driven by the period that follows the second mandate of President Obama. Interestingly, the international summits factor is priced in 40% of the cases in the pre-2012 period, yet any significance vanishes in the post-2012 period. This finding is consistent with the fact that the U.S. withdrew from agreements associated with international summits over that period, and hence, this factor posed no threat to hedge against it (e.g., on 1st June 2017, President Trump announced his intention to withdraw U.S. from the Paris Climate Agreement).

Our findings imply that investors have started taking climate risk into account only recently. Further breakdowns of the sample over the period before 2012, by excluding for instance the term of Obama's first mandate, also reveal a lack of significance. These results are in line with the findings in Goldsmith-Pinkham et al. (2021), Krueger et al. (2020), Painter (2020) and Bolton and Kacperczyk (2021), who also conclude that the pricing of climate risk is a recent phenomenon.

[Table 3 about here.]

5.4 Hedging portfolio: Characteristics

To further explore the economics behind the evidence on U.S. climate policy being priced in the U.S. stock market, we report characteristics of the quintile portfolios constructed by sorting stocks on the climate beta with respect to this factor over November 6th 2012 –

December 31st 2018 by using the FF3, FFC, and FF5 model specifications. Table 4 reports the descriptive statistics associated with the differences in the portfolios climate policy textual betas. Entries report the average at a portfolio level return, climate beta with respect to the U.S. textual climate factor, the total ESG score, the environmental pillar indicator of the Refinitiv 'E' score, the share of brown firms in the portfolio (polluters), the direct carbon dioxide (CO_2) emissions intensity (i.e. Scope 1 plus Scope 2 CO_2 equivalent emissions to revenues USD in million) and the indirect (Scope 3) emissions intensity, the size (log of average market capitalization), institutional ownership as a percent of total outstanding stocks (Inst Own.), return on assets (ROA), gross profitability per total assets (GProf), R&D expenses per sales, and the average number (N) of firms for each portfolio. We label firms as brown or green according to the Scope 1 emissions classification of Bolton and Kacperczyk (2021); brown (green) firms are the top (bottom) 10 most (least) polluting industries according to scope 1 emissions.

Regarding the comparison of the characteristics of the firms that are most and least exposed to climate risks, i.e. the firms in portfolios 5 and 1, respectively, we notice that these two groups of firms share some similarities. Both portfolios comprise firms with low total ESG and environmental score. In addition, the share of firms in the top-10 most polluting businesses is just as prevalent in portfolio 5 as it is in portfolio 1. These findings may seem surprising; a common prior is that brown (green) firms would populate portfolio 5 (1). Engle et al. (2020), Alekseev et al. (2022) and Ardia et al. (2022) also report similar results to ours, i.e. the way to hedge climate change news does not involve going long in green stocks and short in brown stocks. From a theoretical perspective, Pastor et al. (2021) and Baker et al. (2022) show that the climate hedging portfolio may also contain brown firms in the case where negative climate shocks stem from positive shocks to their outputs; in this case, the output shock will yield a positive unexpected return for the stocks of these firms, thus rendering brown stocks climate hedges. Cohen et al. (2020) offer an innovation-based explanation to these results by noting that firms operating in the industries with higher emissions are also among the biggest innovators of green patents. Forward-looking investors may price the expected behaviour of companies with respect to sustainability by looking beyond the current status of their technology as being reflected in their current ESG ratings.

On the other hand, firms in the 5th quintile emit a much higher level of CO_2 than firms in the 1st quintile. Also, firms in quintiles 1 and 2 emit much less than firms in quintiles 4 and 5. These patterns are not in contrast with the fraction of polluters' pattern; the share of firms operating in polluting industries is only a relatively small fraction of the overall portfolio share (about one fourth). They do not invalidate the patterns in the ESG scores, either. There is not a one-to-one mapping between emissions and ESG/'E' scores; emissions are only one of the multiple inputs used by Refinitiv to compute its ESG scores (Refinitiv (2020), white paper). The pattern in emissions suggests that emissions may indeed play a role in the markets' assessment of firms' exposure to climate risks, though they do not offer an all-encompassing explanation. Taking stock of the results in Table 4, it may well be that, as theory suggest, hedge portfolios should not only include green firms. And even when green firms are part of an optimal portfolio, the definition of what makes a firm green may be a multifaceted object, which does not seem to conform to what is captured by the ESG indicators. On average, investors tend to consider high emissions firms to be relatively more exposed to climate risks. However, some high emission businesses also enter the hedging portfolio, in line with previous results found in the literature.

Regarding the other characteristics, firms in portfolios 1 and 5 tend are small, they are characterized by low institutional ownership and they exhibit low returns on assets, low profitability, and high R&D expenses. These characteristics are not particularly useful to explain why financial investors resort to some stocks, and not to others, to hedge climate risks, other than that it is well documented that small firms have low ESG scores because of the lack of resources to promote their progress on ESG issues (Drempetic et al. (2020)). This may also explain the documented low institutional ownership they face.

[Table 4 about here.]

A final remark is in order at this point. Admittedly, the post-2012 period may not contain only good news for the economy. If this is the case, increases in the value of the factor could also signal bad news for the economy. This would invalidate the hedging argument as an explanation of the positive risk premium of the textual factor. We will explore this further in Section 6.

5.5 Fama-MacBeth regressions

The portfolio sorts analysis provides evidence that the U.S. climate policy is priced in the cross-section of individual U.S. equities. In addition, it is the 2012-2018 period that drives this evidence. We perform a further robustness test by conducting Fama-MacBeth (FM, Fama and MacBeth (1973)) regressions over the 2012-2018 period. FM regressions have the advantage over the portfolio sorts analysis that they can account for the effects of multiple regressors. On the other hand, they can only account for linear relations.

We perform FM regressions by examining five alternative specifications: the first four use the four respective textual factors separately as a regressor, and the last uses all four textual climate factors simultaneously. In each specification, we use the Carhart (1997) set of control variables augmented with a proxy for economic uncertainty in line with Bali et al. (2017); we proxy the latter using the Baker et al. (2016) economic policy uncertainty (EPU) index. As a result, the expected return-beta representation equation to be estimated is

$$\begin{aligned} E(r_i) - r_f = \lambda_0 + \lambda_{MKT}\beta^i_{MKT} + \lambda_{HML}\beta^i_{HML} + \lambda_{SMB}\beta^i_{SMB} + \lambda_{UMD}\beta^i_{UMD} \\ + \lambda_{EPU}\beta^i_{EPU} + \lambda_{ND}\beta^i_{ND} + \lambda_{GW}\beta^i_{GW} + \lambda_{IS}\beta^i_{IS} + \lambda_{CP}\beta^i_{CP} \end{aligned} \tag{2}$$

To minimize the effects of errors-in-variables, we use portfolios as test assets. We opt for a wide set of test assets using two separate sets of 55 and 74 portfolios. Both sets of test assets include the 25 Fama-French portfolios sorted on size and book-to-market. They differ in that the first also includes the 30 Fama-French industry portfolios, and the second includes the 49 Fama-French industry portfolios. The inclusion of industry portfolios serves two purposes. First, Lewellen et al. (2010) argue that asset pricing tests may yield misleading results in the case one employs only size and book-to-market portfolios as test assets, due to their strong structure of returns; they propose the inclusion of industry portfolios as a solution. Second, grouping stocks in industry sectors is a natural choice because the effect of climate risks may differ across different industries (e.g., Graff Zivin and Neidell (2014)). In the first-pass regressions, for each portfolio, we estimate climate betas using a rolling window of the daily observations over the past three months. We repeat the procedure by rolling the beta estimation window by one month, just as we did in the asset pricing tests where we employed the portfolio-sort approach. In the second pass regressions, at each time step, we obtain the price of risk of each factor by running cross-sectional regressions of the portfolio returns over the next month on the estimated betas of the factors obtained from the first-pass regressions.

Table 5 reports the price of risk (averaged over time) and its t-statistic for each factor. We can see that the U.S. climate policy factor is priced in most of the specifications for the set of control variables in the 2012-2018 period and the price of risk is positive. This holds irrespectively of whether one uses the factor in a stand-alone fashion in the FM regressions (column (iv)), or jointly with the other climate textual factors (column (v)). It also holds regardless of whether one employs the 55 or 74 test portfolios. The other three climate textual factors are insignificant when considered in a stand-alone fashion or simultaneously (columns (i)-(iii) and column (v)). Therefore, the FM regressions confirm the results from the portfolio sorts analysis, i.e., the climate policy factor is priced whereas natural disasters, global warming and international summits are not.[18]

[Table 5 about here.]

6 A narrative factor for U.S. climate-policy news

6.1 Construction

In this section, we check whether our hedging argument explanation holds, by accounting for the *content* of the news and creating a U.S. climate policy factor whose increase (decrease) signals an increase (decrease) in transition risks by construction. Then, according to our hedging explanation, the factor should command a negative risk premium; to hedge this risk, investors would buy (short-sell) the positive (negative) climate beta stocks.

To construct a factor that accounts for the content of every article related to the U.S. climate-policy debate, we conduct a narrative analysis, in the spirit of Romer and Romer (2010). First, we select articles with a topic share on the domestic policy topic

[18]The market and EPU factors are priced post-2012 whereas the other equity factors used as control variables are not priced. This is in line with previous empirical evidence on these controls not being priced, when relatively short periods are examined (Chang et al. (2013)).

greater than 40%; this yields 3,500 articles. We read each one of these 3,500 articles covering the topic of U.S. policy news and mark it with a 1 if it signals an increase in transition risks, with a -1 if it signals a fall, and with a zero if its content is mixed. Then, we create a time series capturing the transition risks elicited by the U.S. political debate by summing the marks given to the articles over each day. Note that the choice of the threshold value of 40% on the topic share ensures that the articles to be analyzed are substantially correlated with the U.S. climate policy, thus rendering meaningful the subsequent narrative analysis.

Figure 5 shows the time series of climate change news based on the narrative analysis. It reports the monthly averages of the markings assigned at a daily frequency. Note that values close to zero do not necessarily imply that there were no news in a given month. Rather, they could indicate that daily news signalling an increase and a decrease of transition risk cancel out on average over a month. We identify four main periods based on the patterns of our time series. The first period spans January 2000 – November 2006. Over this period, our narrative variable hovers around zero, revealing either a lack of interest from the government administration in tackling issues related to climate change, and/or a mix of positive and negative news for the economy which were cancelling out. This period corresponds to the administration of George W. Bush, until the Republicans lost the majority in the House of Representatives in November 2006. Over this period, the Republican party controlled both the House and the Senate, so President Bush was free to lead his political agenda on climate change.

[Figure 5 about here.]

The second period spans November 2006 – November 2010, over which our narrative variable often takes positive values, signalling higher transition risks. This is a period where the Democratic party controls the House of Representative, and it is characterized by the administration of George W. Bush until November 2008 and that of Barack Obama afterwards. The third period spans November 2012 to November 2016, over which the time series of transition risks hovers again around zero, in a way that closely resembles the period of Bush' administration. This period is instead characterized by Obama's loss of control over Congress. In November 2012, the Democratic Party lost the majority in the House of Representatives, and in November 2014 it also lost the majority in the Senate. Over this period of time, the news reveals the inability of President Obama to tackle climate change which is reflected in the observed pattern of our variable. Finally, the fourth period starting in November 2016 covers the Trump's administration, which was clearly characterized by a very pronounced fall in transition risks. Overall, the pattern of the time series in Figure 5 verifies our conjecture that after November 2012, the news coverage of U.S. climate policy tends to reflect a fall in transition risks, which becomes most pronounced after November 2016. It should also be noted that while both presidential and congressional elections help identifying four main periods in Figure 5, political events at the federal level do not exhaust the variation in this time series. Indeed, the climate policy factor also captures news about the climate policy debate at the state level, which is important, given that national states have some autonomy to legislate in matters related to climate-change policy, e.g. energy regulations and standards. The factor also reflects important decisions taken by federal judges in matters that have important implications for energy policy, such as the construction of the Keystone XL pipeline.

6.2 Asset pricing results

Next, we explore whether the U.S. climate policy narrative factor is priced. Given that an increase in the factor signals an increase in transition risks by construction, it should command a negative risk premium, should our hedging perspective explanation holds. Table 6 reports the alphas of spread portfolios constructed from portfolio sorts with respect to the narrative measure of climate risks. We report results for quintile portfolios for FF3, FFC, and FF5 model, as well as the percentage of significant alphas over the five model specifications and decile and quintile portfolios, over the full period and over 2000-2012 and 2012-2018 subsamples. We can see that the results are consistent with those reported in Section 5 (Tables 2 and 3). The narrative factor is priced over the 2000-2018 period in 50% of the cases. However, it is priced in the post-2012 period in 90% of the cases, whereas it is priced in the pre-2012 period in only 10% of the cases. Moreover, alphas are negative. The results confirm the hedging argument as an explanation for the reported positive (negative) risk premium of the textual (narrative)

U.S. climate policy factor. Stocks which are positively (negatively) correlated with the textual (narrative) factor are riskier because a decrease (increase) in the factor signals an increase in transition risks. To hedge the risk of the textual (narrative) factor, investors buy stocks with negative (positive) climate betas, thus increasing their prices and lowering their returns. As a result, the long-short spread portfolio formed with respect to the textual (narrative) factor will yield a positive (negative) alpha, just as we find. The analysis based on the narrative approach corroborates the conclusion that the transition risks elicited by the U.S. political debate on climate change have only started to be priced in the most recent years, in line with the evidence from the analysis on the textual factor.

[Table 6 about here.]

Table 7 reports the portfolio characteristics of the quintile portfolios sorted on the U.S. climate policy narrative factor November 6$^{\text{th}}$ 2012 – December 31$^{\text{st}}$ 2018. We can see that the patterns of the association of portfolio climate policy betas with firms' characteristics are similar with these obtained when portfolios have been sorted on the U.S. climate policy textual factor (Table 4). In sum, on average, investors tend to consider high emissions firms to be relatively more exposed to climate risks. However, some high emission businesses also enter the hedging portfolio, in line with previous results found in the literature as we have discussed in Section 5.4.

[Table 7 about here.]

A final remark is in order. One may argue that our textual and narrative policy factors may conflate climate risks with economic policy uncertainty (EPU) and/or political risks. We document that this is not the case by conducting bivariate conditional portfolio sorts. We control for EPU and political risks, separately, by following the approach of Bali et al. (2017). Every month, first, we sort stocks in two portfolios based on a measure of the risk factor to control for (control factor). Then, within each portfolio, we sort stocks in quintile portfolios by their climate betas computed with respect to the given climate policy factor (textual or narrative). Next, for each climate quintile, we compute post-ranking value-weighted portfolio returns and then, we average portfolio returns across the two portfolios formed on the control factor. Repeating this process over our sample, yields five time series for the respective five climate portfolios. By construction, they have all controlled for the control factor since they all correspond to an average value of the control factor. Then, at any point in time, we compute the spread portfolio return (portfolio five minus portfolio one returns). Finally, we estimate the alpha of the spread portfolio. We measure EPU and firm-level political risks by using the textual EPU measure by Baker et al. (2016) and the firm-level political risk measure by Hassan et al. (2019) (PRisk), respectively. The former is a daily aggregate measure of EPU whereas the latter is a quarterly firm-level factor. Hence, in the bivariate sorts, we sort stock with respect to EPU betas and the actual values of the PRisk factors, separately, to control for the two respective factors. We estimate EPU betas on a monthly basis by using the daily observations over the past three months. We set the same value of PRisk in all months for any given quarter.

Table 8 presents the alphas of the spread climate portfolios for each one of the two controls (EPU and PRisk) sorting stocks on the textual and narrative climate factors, separately; alternative specifications are used to estimate alphas. We can see that alphas are significant for both the textual and narrative factors in 90% and 80% of the cases, once we control for EPU and PRisk, respectively. This confirms that our policy factors genuinely reflect climate risks and they do not confound the effects stemming from other sources of uncertainty generated by government intervention, like economic policy uncertainty or political risks more broadly.

[Table 8 about here.]

7 Narrative factors for physical risks and international summits

In Section 4, we have conjectured that an increase in the news coverage for the topics of global warming, natural disasters and international summits are likely to signal adverse effects to the economy. Hence, we have interpreted an increase in news coverage for each of these topics as signaling an increase in either physical or transition risk. We now check the validity of this interpretation, by also providing narrative factors for these three topics; we construct them in the same way as we did for the U.S. climate policy factor. By construction, an increase (decrease) in the narrative factor signals an increase (decrease) in risk. In total, we have marked 1,129 articles on natural disasters, 1,424 articles on global warming, and 2,142 articles on international summits; selected articles falling in each topic have a topic share of 40% or more on the respective topic.

Figure 6 shows the time series of the three narrative factors over January 2000-December 2018. We can see that the pattern of the three factors validates our conjecture that articles on these topics tend to reflect an increase in risk. Careful inspection of every single article for the natural disasters and global warming narrative factors reveals that most of the articles report concerns related to the occurrence of catastrophic meteorologic events or increasing temperatures in connection with climate change. Occasionally, some articles defy the connection between natural disasters or global warming and climate change, but only very rarely. Similarly, in the case of the international summit factor, most articles discuss the political intentions of imposing carbon taxes. Occasionally, some articles report on the failure of international summits to reach agreements, for the benefit of polluting businesses, but only in a minority of cases. Comparison of the pattern of the narrative factors (Figure 6) with that of the textual factors (Figure 3) reveals similar spikes of media's attention in connection with the same major events.

[Figure 6 about here.]

Next, we examine whether these three narrative factors are not priced, as it was the case with the corresponding textual factors. A similar portfolio sort analysis carried out on these narrative factors confirms the results obtained with the respective textual factors. Table 9 reports the alphas of the spread portfolios formed from quintile portfolios over January 1st 2000 – December 31st 2018. We can see that alphas tend are insignificant across all cases for each narrative factor. Therefore, the analysis based on the narrative factors confirms that natural disasters, global warming and international summits are not priced in the cross-section of U.S. equities.

[Table 9 about here.]

8 Conclusions

Using textual analysis within a two-step validation approach, we have constructed novel daily proxies for market-wide physical and transition risks. We found that only the risks stemming from the U.S. climate-policy debate is priced and that this pricing is a recent phenomenon. Our results also suggest that investors hedge against the realization of imminent transition risks.

Our findings reveal that it is the risks generated by government intervention rather than the direct risks from climate change that are priced in the stock market. There is a number of possible explanations for this finding. One possibility, is limited attention from financial investors. Under this view, the U.S. political arena serves as a "wake up" call. A second possibility, is that investors lack information on the exposure of businesses to all sources of climate risk. This view seems to be shared by several institutions and financial regulators and it is inspiring new regulation on the disclosure of climate risks (EU Platform on Sustainable Finance (2021), SEC (2022)). A third possibility is that financial investors are myopic, in that they are only focused on risks that have immediate financial effects. All three explanations imply mispricing of climate risks, and they are in line with the view expressed by a number of policy makers (see, for instance, Lagarde (2021)). According to this view, policy intervention is required to address the market failure underlying the mispricing.

Finally, a very different potential explanation for our results is that climate change per se does not pose a material financial risk, and hence it is not expected to be priced. In contrast, any government intervention is expected to be priced, yet it can threaten financial stability by stranding assets and hurting firms' profitability (Cochrane (2021a) and Cochrane (2021b)). Disentangling between these different views is beyond the scope of this study, but is arguably one of the most pressing question for climate research to address in the near future.

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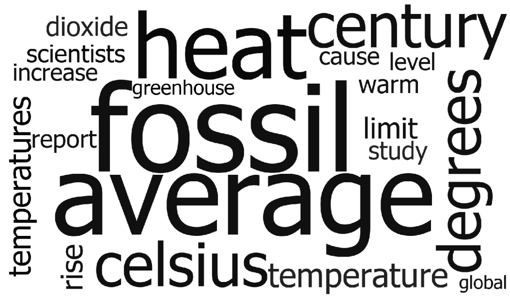
1	marine	research	earth	bear	ocean	university	fish	coral	reef	species	melt	polar	ice	sea	scientists	study	years	time	temperatures	north
2	germany	leave	social	centre	coalition	chancellor	parliament	spd	euro	angela	merkel	want	democrats	german	green	economy	vote	europe	party	berlin
3	canada	canadian	leader	conservative	pipeline	province	ottawa	liberal	seat	conservatives	alberta	sand	liberals	trudeau	harper	federal	win	prime	opposition	election
4	use	legislation	standards	efficiency	california	ethanol	nuclear	vehicles	electric	fuel	cost	reduce	cars	build	plant	energy	power	industry	tax	plan
5	policy	australian	poll	labor	rudd	australia	opposition	support	scheme	prime	renewable	election	green	government	tax	target	percent	price	party	cut
6	hold	continue	events	news	conference	political	september	august	frankfurt	gmt	october	november	diary	general	visit	berlin	economic	german	july	march
7	campaign	house	clinton	republican	senator	congress	democratic	white	administration	department	senate	presidential	republicans	barack	obama	trump	democrats	federal	president	court
8	bond	service	rat	term	information	insurance	available	debt	revenue	provide	fiscal	site	fitch	risk	credit	budget	city	financial	increase	report
9	ban	equities	france	result	car	accord	paris	french	half	carmakers	diesel	strategy	donald	hollande	cars	agreement	electric	tuesday	vehicles	commission
10	solar	source	wind	technology	coal	capacity	electricity	produce	mine	generation	plant	renewable	fire	cost	power	build	project	energy	years	million
11	data	dutch	national	tonnes	zealand	pledge	shell	intensity	country	set	china	beijing	target	chinese	reduce	growth	emissions	greenhouse	carbon	cut
12	take	work	move	go	live	old	francis	life	like	word	gore	know	young	film	think	pope	women	time	win	want
13	washington	iran	war	military	iraq	bush	foreign	leaders	president	security	deal	talk	russia	summit	prime	britain	unite	europe	union	trump
14	cap	permit	commission	environment	dioxide	limit	set	kyoto	scheme	cut	union	target	reduce	emissions	european	level	trade	greenhouse	carbon	europe
15	africa	agriculture	deforestation	food	land	protect	crop	grow	development	need	tree	farm	farmers	indonesia	brazil	amazon	forest	areas	help	environment
16	announce	anniversary	june	london	wednesday	april	elections	friday	monday	sunday	date	january	saturday	link	tentative	award	festival	annual	tuesday	day
17	fossil	average	heat	century	celsius	degrees	temperature	temperatures	rise	limit	dioxide	warm	study	scientists	report	cause	increase	level	greenhouse	global
18	japan	rich	agree	pact	copenhagen	protocol	develop	talk	deal	nations	kyoto	agreement	countries	summit	leaders	unite	tell	cut	warm	level
19	activists	asia	india	police	pacific	protest	protesters	chinese	south	beijing	foreign	china	security	trade	visit	group	include	summit	issue	leaders
20	investment	invest	capture	ccs	euros	finance	fund	help	project	credit	billion	investors	market	bank	develop	green	carbon	million	scheme	price
21	british	brown	public	labour	spend	pound	case	exxon	britain	court	budget	norway	rule	finance	tax	financial	right	general	group	government
22	open	russian	transport	natural	coast	region	exploration	spill	ship	route	drill	port	hydrogen	lng	arctic	russia	north	norway	sea	oil
23	firm	business	chief	executive	corp	epa	rule	investors	group	environmental	company	include	industry	risk	issue	fund	oil	report	fuel	gas
24	hit	warn	weather	disaster	storm	damage	drought	kill	home	local	rain	flood	city	south	people	areas	high	fire	country	cause
25	expect	share	supply	demand	stock	production	barrel	crisis	fall	economy	price	high	growth	market	financial	bank	oil	increase	rise	economic

Figure 1. Topics and Terms Within Topics Ranked by Probability. Entries are delivered by the Latent Dirichlet Allocation (LDA) method.

(a) Natural disasters



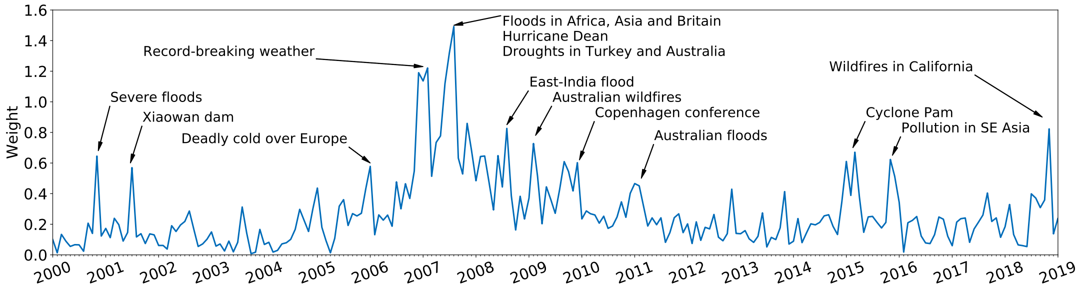
(b) Global warming

(c) International summits

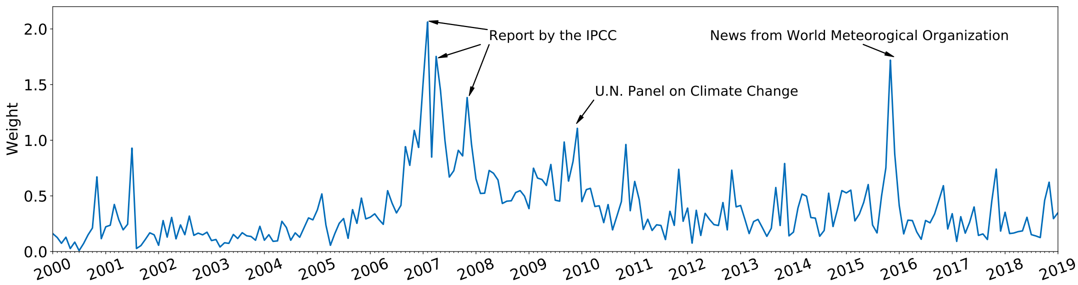
(d) State-level climate policy

(e) Federal-level climate policy

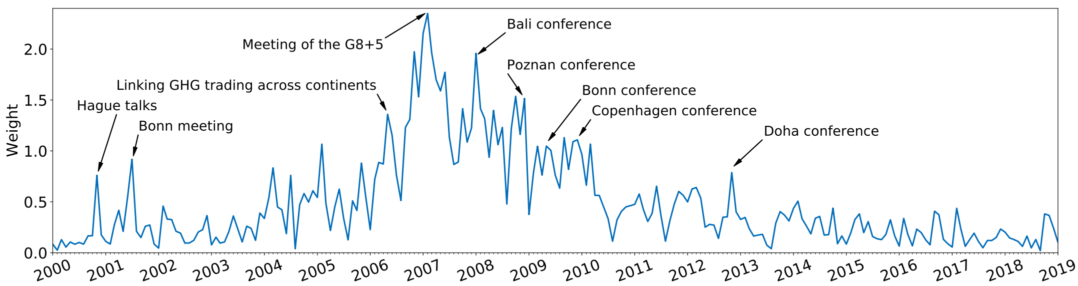
Figure 2. Word clouds for the various topics. Word clouds are delivered by the Latent Dirichlet Allocation (LDA) method. Words in bigger fonts occur more frequently in the word cloud.



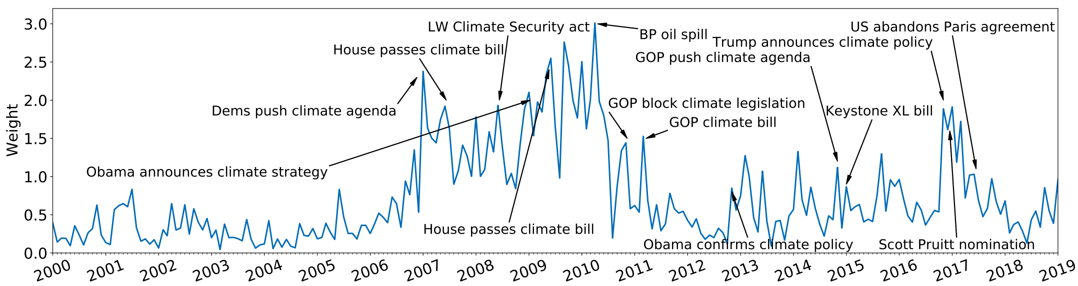
(a) Natural disasters textual factor.



(b) Global warming textual factor.



(c) International summits textual factor.



(d) U.S. climate policy textual factor.

Figure 3. Climate textual factors over January 1st 2000 – December 31st 2018 and their association with news releases. The vertical axis measures the topic shares for each factor, i.e. the percentage of words in each article associated with a given factor. To obtain the daily topic share associated with a given factor, we add up the topic shares of all articles published on that day. To enhance readability, monthly average of the daily topic shares are reported.

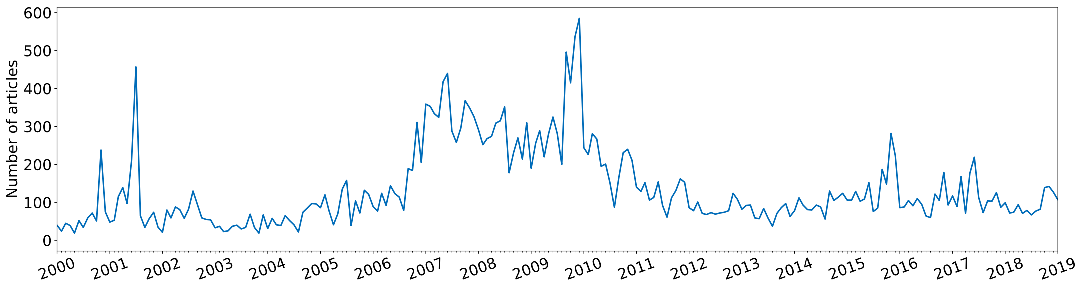


Figure 4. Total Counts of Reuters Climate Change Articles. The figure reports the monthly averages of the total number of published Reuters articles featuring the words "climate change" or "global warming" over January 1st 2000 – December 31st 2018.

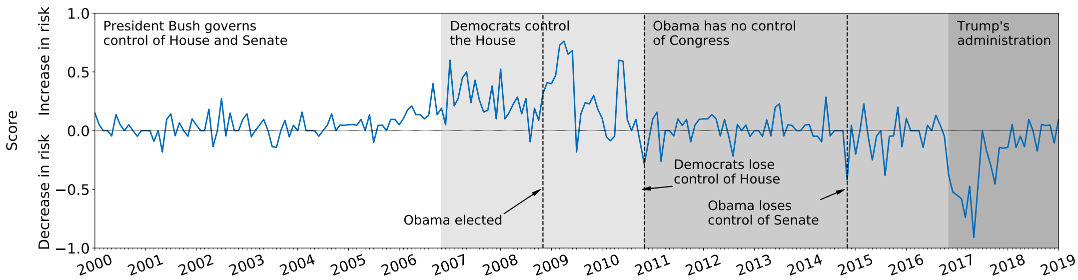
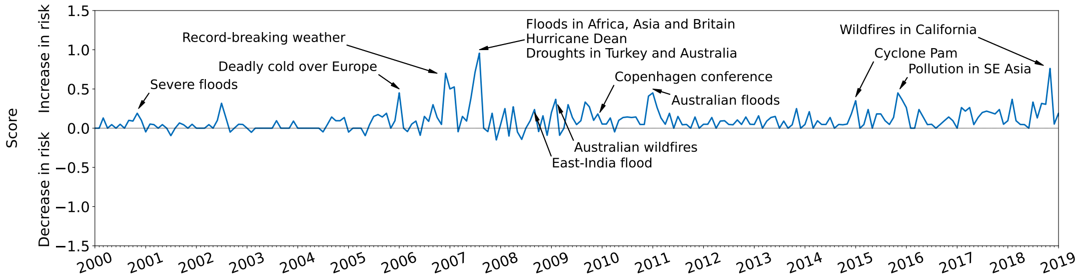
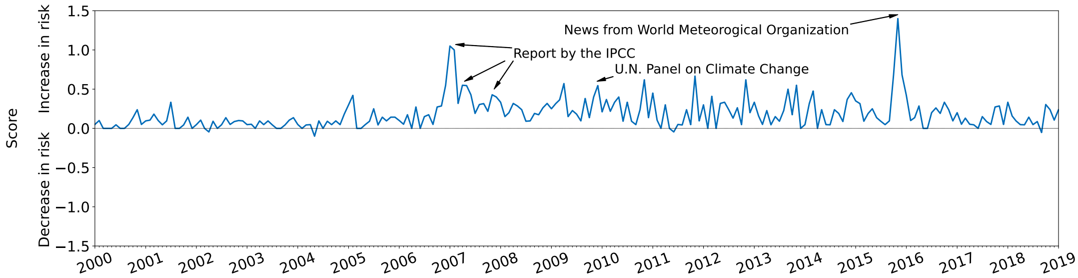


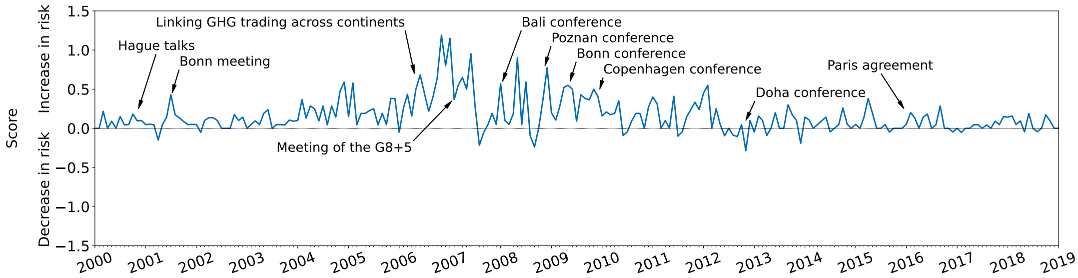
Figure 5. A Narrative Measure of U.S. Climate Policy Risks. The figure reports the monthly averages of the markings assigned at a daily frequency to each one of the 3,500 articles related to U.S. climate policy topic with a topic share greater than 40%. An increase (decrease) in the factor signifies an increase (decrease) in transition risks by construction.



(a) Natural disasters narrative factor.



(b) Global warming narrative factor.



(c) International summits narrative factor.

Figure 6. Other climate narrative factors over January 1st 2000 – December 31st 2018 and their association with news releases. The figure reports the monthly averages of the markings assigned at a daily frequency to each one of the 1,129, 1,424, and 2,142 articles related to the natural disasters, global warming, and international summits topics, respectively, with a factor loading greater than 40%. An increase (decrease) in the factor signifies an increase (decrease) in risks by construction.

Table 1. Pairwise correlations between climate change risk textual factors and other variables

	U.S. Policy	Int. Summits	Global Warming	Natural Disasters	mktrf	HML	SMB	RMW	CMA	UMD	VIX	EPU	NBER	aveBA	stdevSSD
U.S. Policy	1.00	0.30	0.27	0.18	−0.02	−0.02	0.01	0.02	−0.02	0.00	0.13	0.11	0.18	−0.09	0.00
Int. Summits		1.00	0.31	0.24	−0.01	0.01	0.00	0.02	−0.01	0.00	0.07	0.00	0.18	−0.07	−0.10
Global Warming			1.00	0.34	−0.01	−0.01	−0.01	0.02	−0.01	0.01	0.00	−0.03	0.06	−0.11	−0.03
Natural Disasters				1.00	−0.02	−0.03	−0.02	0.02	−0.01	0.04	0.00	−0.05	0.07	−0.09	−0.06
mktrf					1.00	0.06	0.11	−0.44	−0.28	−0.30	−0.13	0.02	−0.02	−0.05	−0.03
HML						1.00	−0.18	0.06	0.45	−0.33	−0.04	0.00	−0.01	0.03	0.01
SMB							1.00	−0.35	−0.05	0.13	−0.02	−0.02	0.01	0.02	0.02
RMW								1.00	0.26	0.17	0.08	0.01	0.02	0.06	−0.02
CMA									1.00	0.11	0.03	−0.02	−0.01	0.07	−0.01
UMD										1.00	0.00	−0.03	−0.03	0.00	−0.05
VIX											1.00	0.44	0.51	0.58	0.18
EPU												1.00	0.24	0.17	0.06
NBER													1.00	0.34	0.06
aveBA														1.00	0.11
stddevSSD															1.00

Notes: Entries report the pairwise Pearson correlations between the textual climate change risks factors and a set of of variables over January 1st 2000 – December 31st 2018. The set of variables comprises the market factor, the Fama and French (1993) value (HML) and size (SMB) factors, the Carhart (1997) momentum (UMD) factor, the Fama and French (1993) operating profitability (RMW) and investment (CMA) factors, S&P 500 option-based volatility index VIX, the Baker et al. (2016) Economic Policy Uncertainty Index (EPU), the NBER recessions indicator which marks the NBER recession dates (a dummy variable which takes a value of one for recessions and zero for expansions), the cross-sectional average of stocks' bid-ask spreads (aveBA), and the cross-sectional standard deviation of the Hiraki and Skiadopoulos (2023) synthetic-stock difference (SSD) measure (stdevSSD). All time series are daily.

Table 2. Portfolio sorts analysis: Climate textual factors, January 1st 2000 – December 31st 2018

U.S. Climate	International Summits	Global Warming	Natural Disasters
Panel A: Fama-French three-factor model			
0.30	−0.25	0.09	0.01
(1.24)	(−1.21)	(0.55)	(0.04)
Panel B: Fama-French-Carhart model			
0.09	−0.14	0.27*	0.06
(0.46)	(−0.71)	(1.92)	(0.38)
Panel C: Fama-French five-factor model			
0.54***	−0.18	0.13	0.04
(2.63)	(−0.96)	(0.67)	(0.19)
Panel D: Percentage of significant alphas across models and portfolio partitions			
70.0%	20.0%	0.0%	0.0%

Notes: Entries report the alpha of the spread portfolio, estimated from monthly post-ranking returns, over January 1st 2000 – December 31st 2018; the unit is % per month. At the end of each month t, we sort stocks in ascending order in portfolios, based on the magnitude of their estimated climate betas with respect to a given climate textual factor (global warming, natural disasters, international summits and U.S. climate policy textual factors). Then, we compute the post-ranking value-weighted portfolio monthly return over the period t to $t+1$. The resulting spread's portfolio return at $t+1$ is computed as the difference between the return of portfolio 10 (high climate beta) minus the return of portfolio 1 (low climate beta). A rolling window of daily observations over the past three months is used to estimate climate betas, and the window is rolled forward by one-month at each estimation step. The climate betas of stocks and the alpha of the spread portfolio are estimated by the same set of control variables X_t in equation (1). We use two alternative portfolio partition schemes (decile and quintile portfolios) and five alternative model specifications. The market model includes only the market factor. FF3 denotes the Fama-French (Fama and French (1993)) three-factor model which includes the market, size and book to market factors. FFC is the four-factor Fama-French-Carhart (Carhart (1997)) model that adds a momentum factor to the controls in FF3. FF5 is the Fama-French five-factor model (Fama and French (2015)) that includes investment and profitability factors, in addition to the controls in FF3. FF5+ UMD is a model that includes the momentum factor in addition to the controls in FF5. Panels A, B, and C report results for quintile portfolios for the FF3, FFC, and FF5 models, respectively. Panel D reports the percentage of significant alphas (at either 1%, 5%, or 10% level of significance), once we collectively consider all five models and decile and quintile portfolio partitions. Newey and West (1987) t-statistics with six lags are reported in parentheses. One, two, and three stars indicate 10%, 5% and 1% significance, respectively.

Table 3. Portfolio sorts analysis: Climate policy Factor, Pre- and Post-Obama's second election

	U.S. Climate		International Summits		Global Warming		Natural Disasters	
	Pre-2012	Post-2012	Pre-2012	Post-2012	Pre-2012	Post-2012	Pre-2012	Post-2012
Panel A: Fama-French three-factor model								
	0.06	0.70***	−0.52*	0.12	−0.03	0.16	0.01	0.21
	(0.17)	(3.11)	(−1.94)	(0.38)	(−0.13)	(0.60)	(0.04)	(0.64)
Panel B: Fama-French-Carhart model								
	−0.11	0.46**	−0.31	−0.10	0.10	0.28	0.13	−0.02
	(−0.43)	(2.52)	(−1.23)	(−0.40)	(0.59)	(1.23)	(0.69)	(−0.06)
Panel C: Fama-French five-factor model								
	0.45*	0.59**	−0.48**	0.31	0.24	0.05	0.10	0.03
	(1.73)	(2.15)	(−2.05)	(1.09)	(1.00)	(0.20)	(0.37)	(0.10)
Panel D: Percentage of significant alphas across models and portfolio partitions								
	10.0%	100.0%	40.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Notes: Entries report the alpha of the spread portfolio, estimated from monthly post-ranking returns, over the sub-periods January 1st 2000 – November 5th 2012 and November 6th 2012 – December 31st 2018; the unit is % per month. At the end of each month t, we sort stocks in ascending order in portfolios, based on the magnitude of their estimated climate betas with respect to a given climate textual factor (global warming, natural disasters, international summits and U.S. climate policy textual factors). Then, we compute the post-ranking value-weighted portfolio monthly return over the period t to $t+1$. The resulting spread portfolio return at $t+1$ is computed as the difference between the return of portfolio 10 (high climate beta) minus the return of portfolio 1 (low climate beta). A rolling window of daily observations over the past three months is used to estimate climate betas, and the window is rolled forward by one-month at each estimation step. The climate betas of stocks and the alpha of the spread portfolio are estimated by the same set of control variables X_t in equation (1). We use two alternative portfolio partition schemes (decile and quintile portfolios) and five alternative model specifications. The market model includes only the market factor. FF3 denotes the Fama-French (Fama and French (1993)) three-factor model which includes the market, size and book to market factors. FFC is the four-factor Fama-French-Carhart (Carhart (1997)) model that adds a momentum factor to the controls in FF3. FF5 is the Fama-French five-factor model (Fama and French (2015)) that includes investment and profitability factors, in addition to the controls in FF3. FF5+ UMD is a model that includes the momentum factor in addition to the controls in FF5. Panels A, B, and C report results for quintile portfolios for the FF3, FFC, and FF5 models, respectively. Panel D reports the percentage of significant alphas (at either 1%, 5%, or 10% level of significance), once we collectively consider all five models and decile and quintile portfolio partitions. Newey and West (1987) t-statistics with six lags are reported within parentheses. One, two, and three stars indicate 10%, 5% and 1% significance, respectively.

Table 4. U.S. climate policy textual factor: Portfolio characteristics

	1 (L)	2	3	4	5 (H)
Panel A: Fama-French three-factor model					
Return	0.60	0.97***	0.87***	0.97***	1.23***
	(1.27)	(2.72)	(2.85)	(3.05)	(2.92)
Climate β	−0.48	−0.16	0.00	0.16	0.48
ESG score	35.36	40.63	41.51	40.19	34.86
E score	24.14	31.15	33.00	31.53	24.87
Share of polluters	0.25	0.18	0.15	0.17	0.24
Direct emissions intensity	447.55	426.91	505.00	463.95	536.91
Scope 3 emissions intensity	493.84	488.21	542.68	518.99	644.06
log(size)	6.39	6.91	7.01	6.91	6.43
Inst own	0.52	0.64	0.65	0.64	0.53
ROA	−0.09	0.05	0.07	0.05	−0.07
GProf	0.23	0.26	0.25	0.25	0.22
R&D	8.05	4.48	1.66	4.23	7.75
N	747	750	751	751	746
Panel B: Fama-French-Carhart model					
Return	0.80*	1.03***	0.87***	0.89**	1.07***
	(1.84)	(2.88)	(2.84)	(2.60)	(2.66)
Climate β	−0.48	−0.16	0.00	0.15	0.47
ESG score	35.12	40.37	41.66	40.29	34.86
E score	23.50	31.01	33.21	31.60	24.83
Share of polluters	0.25	0.18	0.15	0.17	0.24
Direct emissions intensity	449.64	404.11	512.33	515.91	491.75
Scope 3 emissions intensity	496.20	445.73	552.30	584.33	597.31
log(size)	6.36	6.91	7.02	6.91	6.43
Inst own	0.52	0.64	0.65	0.64	0.53
ROA	−0.09	0.05	0.07	0.06	−0.06
GProf	0.23	0.26	0.25	0.26	0.23
R&D	8.01	2.32	3.79	2.04	10.00
N	747	751	751	750	747
Panel C: Fama-French five-factor model					
Return	0.71	1.01***	0.86***	0.95***	1.10***
	(1.40)	(2.76)	(2.79)	(3.09)	(2.93)
Climate β	−0.48	−0.16	0.00	0.16	0.48
ESG score	35.15	40.51	41.37	40.37	35.15
E score	23.80	31.01	32.76	31.74	25.62
Share of polluters	0.25	0.18	0.15	0.17	0.25
Direct emissions intensity	434.74	377.88	531.71	485.00	552.43
Scope 3 emissions intensity	478.33	443.69	548.81	581.70	641.59
log(size)	6.38	6.92	7.01	6.91	6.43
Inst own	0.52	0.64	0.65	0.64	0.53
ROA	−0.09	0.05	0.07	0.05	−0.06
GProf	0.23	0.26	0.25	0.26	0.23
R&D	8.00	2.84	1.76	3.88	9.69
N	747	748	752	752	747

Notes: Entries report characteristics of the quintile portfolios constructed by sorting stocks on the climate beta estimated with respect to the U.S. climate policy textual factor over November 6^{th} 2012 – December 31^{st} 2018 by using the FF3, FFC, and FF5 models, separately. Entries report the average at a portfolio level return, climate beta with respect to the U.S. textual climate factor, the total ESG score, the environmental pillar indicator of the Refinitiv 'E' score, the share of brown firms in the portfolio (polluters), the direct carbon dioxide (CO_2) emissions intensity (Scope 1 plus Scope 2 CO_2 equivalent emissions to revenues USD in million, the indirect (Scope 3) emissions intensity, the size (log of average market capitalization), institutional ownership as a percent of total outstanding stocks (Inst Own.), return on assets (ROA), gross profitability per total assets (GProf), R&D expenses per sales, and the average number (N) of firms for each portfolio. We label firms as brown or green according to the Scope 1 emissions classification of Bolton and Kacperczyk (2021); brown (green) firms are the top (bottom) 10 most (least) polluting industries according to scope 1 emissions. One, two, and three asterisks indicate significance at a 10%, 5% and 1% level, respectively.

Table 5. Fama and MacBeth (1973) regressions

	55FF					74FF				
	(i)	(ii)	(iii)	(iv)	(v)	(i)	(ii)	(iii)	(iv)	(v)
Panel A: 2000-2012										
mktrf	−0.01***	−0.01***	−0.01***	−0.01***	−0.01***	−0.01**	−0.01**	−0.01***	−0.01***	−0.01***
	(−3.01)	(−3.03)	(−3.22)	(−2.85)	(−3.25)	(−2.47)	(−2.63)	(−2.99)	(−2.61)	(−3.13)
hml	0.00	0.00	0.00	0.00	0.00	0.00*	0.00**	0.00**	0.00*	0.00*
	(1.41)	(1.45)	(1.52)	(1.11)	(1.17)	(1.82)	(2.01)	(1.95)	(1.75)	(1.65)
smb	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.49)	(0.68)	(0.40)	(0.50)	(0.57)	(0.39)	(0.54)	(0.39)	(0.36)	(0.45)
umd	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(−0.66)	(−0.31)	(−0.41)	(−0.63)	(−0.38)	(−0.80)	(−0.65)	(−0.67)	(−0.82)	(−0.45)
epu	−0.37	−0.42	−0.49	−0.40	−0.29	0.13	0.05	−0.01	−0.03	−0.12
	(−0.87)	(−0.95)	(−1.13)	(−0.86)	(−0.69)	(0.32)	(0.13)	(−0.01)	(−0.08)	(−0.31)
Natural Disasters	−0.04				−0.15	0.05				−0.07
	(−0.11)				(−0.35)	(0.25)				(−0.27)
Global Warming		0.12			0.23		0.47			0.39
		(0.20)			(0.48)		(1.15)			(1.12)
International Summits			0.22		−0.10			−0.04		−0.32
			(0.32)		(−0.15)			(−0.05)		(−0.43)
U.S. Climate Policy				0.92*	0.02				0.60	0.10
				(1.27)	(0.27)				(0.86)	(0.15)
Panel B: 2012-2018										
mktrf	−0.01**	−0.01***	−0.01***	−0.01**	−0.01***	−0.01**	−0.01**	−0.01*	−0.01*	−0.01**
	(−2.28)	(−2.58)	(−2.15)	(−1.80)	(−2.18)	(−2.13)	(−2.07)	(−1.59)	(−1.50)	(−1.92)
HML	0.00*	0.00*	0.00*	0.00**	0.00*	0.00	0.00*	0.00	0.00*	0.00*
	(−1.78)	(−1.83)	(−1.57)	(−2.03)	(−1.40)	(−1.25)	(−1.34)	(−1.28)	(−1.64)	(−1.35)
SMB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(−0.32)	(−0.38)	(−0.25)	(−0.09)	(0.24)	(−0.64)	(−0.75)	(−0.85)	(−0.53)	(−0.14)
UMD	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(−0.09)	(0.22)	(−0.25)	(−0.14)	(0.09)	(0.41)	(0.55)	(0.43)	(0.49)	(0.54)
EPU	−1.21	−1.33**	−1.16**	−1.22**	−1.09	−0.53	−0.57	−0.55*	−0.70*	−0.60*
	(−1.65)	(−1.85)	(−1.79)	(−1.9)	(−1.81)	(−1.29)	(−1.23)	(−1.50)	(−1.65)	(−1.48)
Natural Disasters	−0.20				−0.94**	−0.28				−0.87*
	(−0.41)				(−2.08)	(−0.53)				(−1.46)
Global Warming		0.06			0.10		−0.17			−0.20
		(0.12)			(0.20)		(−0.35)			(−0.37)
International Summits			0.86***		0.43			0.13		0.10
			(3.35)		(1.25)			(0.45)		(0.35)
U.S. Climate Policy				2.30***	2.36***				2.32***	2.02***
				(2.74)	(2.98)				(3.11)	(2.71)

Notes: Entries report the prices of risks obtained from Fama and MacBeth (1973) regressions (FM) over the 2012-2018 period. We apply FM regressions to the 55 and 74 Fama-French industry portfolios, separately. In the first-pass regressions, for each security, we estimate climate betas using a rolling window of the daily observations over the past three months. We repeat the procedure by rolling the beta estimation window by one month, just as we did in the portfolio-sort approach to asset pricing tests. We estimate factor betas by using the Carhart (1997) model augmented by the Baker et al. (2016) economic policy uncertainty (EPU) index. In the second pass regressions, at each time step, we obtain the price of risk of each factor by running cross-sectional regressions of the stock returns over the next month on the estimated betas of the factors obtained from the first-pass regressions. Specifications (i), (ii), (iii), (iv) and (v), consider the four textual factors (natural disasters, global warming, international summits, U.S. climate policy) separately and jointly, respectively, while controlling for the Carhart (1997) factors. Newey and West (1987) t-statistics with six lags are reported within parentheses. One, two, and three stars indicate 10%, 5% and 1% significance, respectively.

Table 6. U.S. climate policy narrative factor: Portfolio-sorts analysis over subsamples

	2000-2018	2000-2012	2012-2018
Panel A: Fama-French three-factor model			
	-0.58^{***}	-0.20	-1.05^{***}
	(-2.64)	(-0.78)	(-3.67)
Panel B: Fama-French-Carhart model			
	-0.48^{**}	-0.24	-0.93^{***}
	(-2.30)	(-1.05)	(-2.86)
Panel C: Fama-French five-factor model			
	-0.39^{*}	-0.16	-0.69^{**}
	(-1.89)	(-0.62)	(-2.53)
Panel D: Percentage of significant alphas across models and portfolio partitions			
	50.0%	10.0%	90.0%

Notes: Entries report the alpha of the spread portfolio, estimated from monthly post-ranking returns, over January 2000 – December 2018, January 2000 – November 2012, and November 2012 – December 2018; the unit is % per month. At the end of each month t, we sort stocks in ascending order in decile portfolios, based on the magnitude of their estimated climate betas with respect to the narrative U.S. climate policy factor. Then, we compute the post-ranking value-weighted portfolio monthly return. The resulting spread portfolio return is computed as the difference between the return of the portfolio with the highest climate beta minus the return of the portfolio with the lowest climate beta. A rolling window of daily observations over the past three months is used to estimate climate betas, and the window is rolled forward by one-month at each estimation step. The climate betas of stocks and the alpha of the spread portfolio are estimated by the same set of control variables X_t in equation (1). We use two alternative portfolio partitions (decile and quintile portfolios) and five alternative specifications. The baseline model includes only the market factor. FF3 denotes the Fama-French (Fama and French (1993)) three-factor model which includes the market, size and book to market factors. FFC is the four-factor Fama-French-Carhart (Carhart (1997)) model that adds a momentum factor to the controls in FF3. FF5 is the Fama-French five-factor model (Fama and French (2015)) that includes investment and profitability factors, in addition to the controls in FF3. FF5+ UMD is a model that includes the momentum factor in addition to the controls in FF5. Panels A, B, and C report results for quintile portfolios for the FF3, FFC, and FF5 models, respectively. Panel D reports the percentage of significant alphas (at either 1%, 5%, or 10% level of significance), once we collectively consider all five models and decile and quintile portfolio partitions. Newey and West (1987) t-statistics with 6 lags are reported in parentheses. One, two, and three stars indicate 10%, 5% and 1% significance, respectively.

Table 7. U.S. climate policy narrative factor: Portfolio characteristics

	1 (L)	2	3	4	5 (H)
Panel A: Fama-French three-factor model					
Return	1.49***	0.79**	1.04***	0.93***	0.36
	(2.93)	(2.43)	(3.27)	(3.02)	(0.95)
Climate β	−0.67	−0.22	0.01	0.23	0.67
ESG score	35.07	40.05	41.71	40.45	35.28
E score	23.74	31.01	33.47	31.66	23.87
Share of polluters	0.25	0.18	0.16	0.17	0.24
Direct emissions intensity	422.78	379.06	451.48	568.30	549.12
Scope 3 emissions intensity	513.34	394.57	521.32	670.39	567.43
log(size)	6.44	6.91	7.01	6.90	6.40
Inst own	0.53	0.64	0.65	0.64	0.53
ROA	−0.08	0.05	0.07	0.05	−0.07
GProf	0.22	0.26	0.25	0.26	0.23
R&D	11.29	2.76	1.94	4.45	5.72
N	744	751	751	751	747
Panel B: Fama-French-Carhart model					
Return	1.34**	0.95***	0.91***	1.01***	0.42
	(2.57)	(2.83)	(2.95)	(3.25)	(1.10)
Climate β	−0.67	−0.22	0.01	0.22	0.66
ESG score	35.17	40.13	41.73	40.36	35.04
E score	23.79	31.12	33.39	31.69	23.42
Share of polluters	0.25	0.18	0.16	0.17	0.24
Direct emissions intensity	436.72	386.16	478.85	554.42	510.75
Scope 3 emissions intensity	489.60	429.84	536.54	657.68	552.54
log(size)	6.41	6.91	7.02	6.90	6.39
Inst own	0.53	0.64	0.65	0.64	0.52
ROA	−0.08	0.05	0.07	0.05	−0.07
GProf	0.23	0.26	0.25	0.26	0.23
R&D	11.27	2.98	1.49	2.35	8.07
N	745	751	751	751	745
Panel C: Fama-French five-factor model					
Return	1.17**	0.94***	0.98***	0.99***	0.40
	(2.33)	(2.83)	(3.13)	(3.18)	(1.03)
Climate β	−0.67	−0.22	0.00	0.23	0.67
ESG score	35.09	40.16	41.81	40.24	35.24
E score	23.78	31.18	33.61	31.33	23.81
Share of polluters	0.25	0.18	0.16	0.17	0.24
Direct emissions intensity	465.60	383.18	467.95	545.30	532.26
Scope 3 emissions intensity	532.44	424.77	535.59	630.84	562.14
log(size)	6.42	6.91	7.02	6.90	6.39
Inst own	0.53	0.64	0.65	0.64	0.52
ROA	−0.08	0.05	0.07	0.05	−0.07
GProf	0.22	0.26	0.25	0.26	0.23
R&D	11.12	2.83	2.15	2.09	7.97
N	746	752	752	750	747

Notes: Entries report characteristics of the quintile portfolios constructed by sorting stocks on the climate beta estimated with respect to the U.S. climate policy narrative factor over November 6^{th} 2012 – December 31^{st} 2018 by using the FF3, FFC, and FF5 models, separately.Entries report the average at a portfolio level return, climate beta with respect to the U.S. textual climate factor, the total ESG score, the environmental pillar indicator of the Refinitiv 'E' score, the share of brown firms in the portfolio (polluters), the total (Scope 1 plus Scope 2) carbon dioxide (CO_2) emissions intensity (Scope 1 plus Scope 2 CO_2 equivalent emissions to revenues USD in million, the Scope 3 emissions intensity, the size (log of average market capitalization), institutional ownership as a percent of total outstanding stocks (Inst Own.), return on assets (ROA), gross profitability per total assets (GProf), R&D expenses per sales, and the average number (N) of firms for each portfolio. We label firms as brown or green according to the Scope 1 emissions classification of Bolton and Kacperczyk (2021); brown (green) firms are the top (bottom) 10 most (least) polluting industries according to scope 1 emissions. One, two, and three asterisks indicate significance at a 10%, 5% and 1% level, respectively.

Table 8. Controlling for economic policy uncertainty and political risk

	EPU	PRisk
Panel A: Fama-French three-factor model		
Textual	0.63**	0.7***
	(2.54)	(2.84)
Narrative	−0.96***	−0.84***
	(−3.78)	(−2.75)
Panel B: Fama-French-Carhart model		
Textual	0.43***	0.42**
	(3.06)	(2.2)
Narrative	−0.89***	−0.65**
	(−2.68)	(−2.14)
Panel C: Fama-French five-factor model		
Textual	0.56**	0.46*
	(2.31)	(1.76)
Narrative	−0.53**	−0.46**
	(−2.45)	(−2.17)
Panel D: Percentage of significant alphas across models textual and narrative factors		
	90.0%	80.0%

Notes: Entries report the alpha of the spread portfolio, estimated from monthly post-ranking returns, November 2012 – December 2018; the unit is % per month. At the end of each month t, we perform a conditional bivariate portfolio sort. First, we sort stocks in two portfolios based on a measure of the risk factor to control for; the control factor is either the Baker et al. (2016) or the Hassan et al. (2019) PRisk measures. Then, within each portfolio, we sort stocks in quintile portfolios by their climate betas computed with respect to the given climate policy factor (textual or narrative). Then, we compute post-ranking value-weighted portfolio returns for each climate quintile. Then, for each climate quintile portfolio, we average portfolio returns across the two portfolios formed on the control factor. This yields a time series of five climate portfolio returns. By construction, they have all controlled for the control factor since they all correspond to an average value of the control factor. Then, at any point in time, the resulting spread portfolio return is computed as the difference between the return of the portfolio with the highest climate beta minus the return of the portfolio with the lowest climate beta. A rolling window of daily observations over the past three months is used to estimate climate betas, and the window is rolled forward by one-month at each estimation step. The climate betas of stocks and the alpha of the spread portfolio are estimated by the same set of control variables X_t in equation 1. We use five alternative specifications. The baseline model includes only the market factor. FF3 denotes the Fama-French (Fama and French (1993)) three-factor model which includes the market, size and book to market factors. FFC is the four-factor Fama-French-Carhart (Carhart (1997)) model that adds a momentum factor to the controls in FF3. FF5 is the Fama-French five-factor model (Fama and French (2015)) that includes investment and profitability factors, in addition to the controls in FF3. FF5+ UMD is a model that includes the momentum factor in addition to the controls in FF5. Panels A, B, and C report results for the FF3, FFC, and FF5 models, respectively. Panel D reports the percentage of significant alphas, once we collectively consider all five models and the textual and narrative U.S. climate policy factors.Newey and West (1987) t-statistics with 6 lags are reported in parentheses. One, two, and three stars indicate 10%, 5% and 1% significance, respectively.

Table 9. Portfolio sorts analysis: Other climate narrative factors, January 1st 2000 – December 31st 2018

	International Summits	Global Warming	Natural Disasters
Panel A: Fama-French three-factor model			
	−0.29*	0.32	0.20
	(−1.68)	(1.46)	(1.16)
Panel B: Fama-French-Carhart model			
	−0.13	0.27	0.25
	(−0.70)	(1.48)	(1.26)
Panel C: Fama-French five-factor model			
	−0.42*	−0.13	0.19
	(−1.97)	(−0.66)	(0.96)
Panel D: Percentage of significant alphas across models and portfolio partitions			
	0.0%	0.0%	0.0%

Notes: Entries report the alpha of the spread portfolio, estimated from monthly post-ranking returns, over January 2000 – December 2018; the unit is % per month. At the end of each month t, we sort stocks in ascending order in quintile portfolios, based on the magnitude of their estimated climate betas with respect to the narrative international summits, global warming and natural disasters factors, separately. Then, we compute the post-ranking value-weighted portfolio monthly return. The resulting spread portfolio return is computed as the difference between the return of the portfolio with the highest climate beta minus the return of the portfolio with the lowest climate beta. A rolling window of daily observations over the past three months is used to estimate climate betas, and the window is rolled forward by one-month at each estimation step. The climate betas of stocks and the alpha of the spread portfolio are estimated by the same set of control variables X_t in equation (1). We use two alternative portfolio partitions (decile and quintile portfolios) and five alternative specifications. The baseline model includes only the market factor. FF3 denotes the Fama-French (Fama and French (1993)) three-factor model which includes the market, size and book to market factors. FFC is the four-factor Fama-French-Carhart (Carhart (1997)) model that adds a momentum factor to the controls in FF3. FF5 is the Fama-French five-factor model (Fama and French (2015)) that includes investment and profitability factors, in addition to the controls in FF3. Panels A, B, and C report results for quintile portfolios for the FF3, FFC, and FF5 models, respectively. Panel D reports the percentage of significant alphas, once we collectively consider all five models and decile and quintile portfolio partitions. Newey and West (1987) t-statistics with 6 lags are reported in parentheses. One, two, and three stars indicate 10%, 5% and 1% significance, respectively.

A Latent Dirichlet Allocation for Topic Identification

To process the news articles, we follow standard procedures. We first remove punctuation marks, newlines and tabs, and convert letters to lower case. Then we remove stop words (such as *the*, *is*, *are*, and *this*) and lemmatize all words; the purpose of the latter is to reduce words to their respective word stems to limit the textual variability across documents. Finally, we trim the corpus such that tokens that occur less than 15 times and in more than 50% of the documents are removed in order to filter tokens that are either very rare or typical. This procedure returns a final dictionary with 6,158 tokens.

Sampling Algorithm Latent Dirichlet Allocation (LDA) is conceptually a relatively simple procedure, yet computationally infeasible to estimate exactly due to the large discrete state space. Several approximate inference algorithms exist where the introductory paper by Blei et al. (2003) used a variational Bayes approximation of the posterior distribution.[19] An alternative is collapsed Gibbs sampling, which in the context of LDA was first employed by Griffiths and Steyvers (2004). We will briefly summarize the main idea behind LDA-estimation via Gibbs sampling as it is easy to understand and provides an intuitive idea of how LDA works.

Gibbs sampling works by sampling all variables from their conditional distributions with respect to the current values of all other variables and the data. In the current setting, the data are the words and the quantity of interest is the topic allocation of each word. Denoting the topic allocation of word n in document d by $z_{d,n}$, the conditional distribution of $z_{d,n}$ given all other word-topic assignments $z_{-(d,n)}$ and the vector of words $\mathbf{w}$ in all documents is given by (Hansen et al., 2017)

$$P(z_{d,n} = k \mid z_{-(d,n)}, \mathbf{w}) \propto \frac{m^k_{v,-(d,n)} + \eta}{\sum_{v=1}^{V} (m^k_{v,-(d,n)} + \eta)} (m^d_{k,-n} + \alpha) \tag{A.1}$$

The collapsed Gibbs sampling for LDA works by repeating this procedure until convergence has been reached

[19] In Hoffman et al. (2010) an online variational Bayes algorithm is developed, which is well-suited for large document collections such as ours.

1. Randomly assign all words in all documents to a topic in $\{1, \ldots, K\}$

2. Form the counts m_k^d and m_v^k

3. Iterate through each word in each document and

   (a) Drop $w_{d,n}$ from the sample and form the counts $m_{k,-n}^d$ and $m_{v,-(d,n)}^k$

   (b) Assign a new topic for word $w_{d,n}$ by sampling from (A.1)

   (c) Form new counts m_k^d and m_v^k by adding the new assignment of $w_{d,n}$ to $m_{k,-n}^d$ and $m_{v,-(d,n)}^k$

   (d) Move on to the next word

The estimate of the $(K \times V)$ term distribution matrix (to be used to label topics) after a given iteration is

$$\hat{\beta}_k^v = \frac{m_v^k + \eta}{\sum_{v=1}^V m_v^k + \eta} \tag{A.2}$$

and the $(D \times K)$ topic distribution matrix (which yields the topic shares) is

$$\hat{\theta}_d^k = \frac{m_k^d + \alpha}{\sum_{k=1}^K m_k^d + \alpha} \tag{A.3}$$

Table A.1 provides an overview of the introduced variables in this section.

Symbol	Description
N_d	Number of words in document d
D	Total number of documents
d	Indexes a document
V	Total number of unique tokens (i.e., vocabulary)
v	Indexes a unique token
K	Number of total topics
k	Indexes a topic
$w_{d,n}$	Word n in document d
$z_{d,n}$	Topic allocation of word n in document d
$v_{d,n}$	Topic index of word n in document d
β_k	Term distribution for topic k (positive V-vector)
η	Dirichlet hyperparameter associated with term distributions
θ_d	Topic distribution for document d (positive K-vector)
α	Dirichlet hyperparameter associated with topic distributions
m_k^d	Count of words in document d allocated to topic k
m_v^k	Count of times token v is allocated to topic k
$m_{k,-n}^d$	Excluding token n, count of words in document d allocated to topic k
$m_{v,-(d,n)}^k$	Excluding token n in document d, count of times token v is assigned topic k

Table A.1. Notation of LDA.

B Textual time series: A chronology of climate-related releases

In this Appendix, we provide a chronology of climate related news releases reflected by the spikes in each one of our textual factors.

B.1 Natural Disasters

November 2000: Rainfall in Southeast Asia and the time duration of drought across Central Asia, reached record-highs over the previous 100 years. At the same time, large parts of Europe also experienced severe floods, and Britain in particular suffered the worst flood in 50 years.

July 2001: Chinese authorities plan a 300-metre-high Xiaowan dam, to help relieve the heavy annual flooding in the Mekong river delta, which has become more frequent and intense over the years.

January 2006: Extreme cold winter snap that affected all of Europe, from Moscow to Paris and caused hundreds of deaths.

Early 2007: A series of record-breaking weather events, ranging from flooding in Asia to heatwaves in Europe and snowfall in South Africa.

August 2007: Hurricane Dean, a category-5 hurricane with a power comparable to Katrina, battered the Caribbean. At the same time, Sahel Africa and South Asia were devastated by floods, Britain suffered the worst flood in 60 years, and Turkey and Australia a pronounced drought.

August 2008: Eastern India suffered its worst flood in 50 years, destroying 250,000 houses and affecting about two million people. In that same month, the melting of arctic ice due to record-high temperature caused floods also in Canada, whereas Cyprus suffered its worst ever drought.

February 2009: Wildfires in Australia, causing hundreds of deaths, and on the heavy rains and floods that followed one week after the fire was put under control.

December 2009: In parallel with the Copenhagen conference on climate change, news report on the increased incidence of natural disasters around the globe, calling for urgent international cooperation.

January 2011: Floods in Australia extensively covered by media.

February 2012: News mostly reported on cyclone Yasi in Australia, and on a report by the Asia Development Bank, which warned about the risk of mass migration linked to the increased occurrence of natural disasters in the region.

March 2015: Cyclone Pam, the second most intense tropical cyclone of the South Pacific Ocean in terms of sustained wind, inflicted one of the worst natural disasters to the Pacific island of Vanuatu, over its history. At the same time, Chile and Zimbabwe suffered heavy floods. In March 2015, news also report extensively on the third United Nations (U.N.) conference on Disaster Risk Reduction; U.N. member States met to set a common policy framework to deal with the catastrophic consequences of natural disasters.

November 2015: Wildfires raged over Southern Australia, while Beijing and New Delhi were covered by a choking cloud of pollution, forcing inhabitants of the Chinese capital to stay indoors.

November 2018: Wildfires raged in South California, destroying about 2,000 homes and led more than 500,000 civilians to evacuate their homes, while Hurricane Paloma battered the British Caribbean.

B.2 Global Warming

February 2007: Publication of the IPCC report, a U.N. organization that groups 2,500 researchers from more than 130 nations. For the first time, the report attributed climate change to human actions with a probability of 90%. This was a substantial upward revision with respect to previous publications, which also implied potentially catastrophic scenarios for the end of the century.

April 2007: IPCC outlined the likely impacts of warming and noticed that rising temperatures could lead to more hunger, water shortage, more extinctions of animals and plants, crop yields could drop by 50% by 2020 in some countries, and projected a steadily shrinking of the arctic sea ice in summers. It also stated that by the 2080s, millions of people will be threatened by floods because of rising sea levels, especially around river deltas in Asia and Africa and on small islands.

November 2007: IPCC agreed to a set of guidelines for policymakers to cope with the rising risks of climate change, urging for prompt actions to reduce drastically greenhouse gas emissions.

December 2009: News reflected the coordinated attempt of the British Meteorological Office and the U.N. Panel on Climate Change to reiterate the validity of scientific evidence on human's actions causing climate change. This followed accusations by climate change sceptics who seized leaked emails from the University of East Anglia and accused climate experts of colluding to manipulate data.

November 2015: A number of articles discussed the World Meteorological Organization announcement that 2015 was the hottest year ever, and that temperatures in 2015 were likely to reach the milestone of 1 degree Celsius above the pre-industrial era.

B.3 International Summits

November 2000: The Hague meeting on climate change. The meeting took place to ratify (i.e., make it legally binding) the Kyoto protocol of 1997, in which countries expressed their joint intention to reduce greenhouse gases by an average of 5% by 2008-2012. In Hague, countries discussed the concept of "emission trading", which would allow companies to buy and sell the right to pollute. The countries failed to ratify the Kyoto agreement, yet they took a first step in that direction.

July 2001: Bonn meeting. This continued the negotiations started in Hague, yet no ratification of the Kyoto protocol was achieved either.

February 2005: Ratification of Kyoto protocol. U.S. did not agree, as President Bush decided to refrain. Even though U.S. did not ratify the Kyoto protocol at the federal level, a number of States on the east and west coasts began to set up regional climate pacts that would require power companies to trade emissions of heat-trapping gases, moving de facto U.S. climate change policy more in line with the aim of the international treaties.

May 2006: First transaction in the Chicago Climate Exchange linking greenhouse gas emission trading systems in Europe and North America.

February 2007: The Global Legislators Organisation held a meeting of the G8+5 (the five leading emerging economies: Brazil, China, India, Mexico, and South Africa) Climate Change Dialogue, where a non-binding agreement was reached to cooperate on tackling global warming. The group accepted that there should be a global rule on emission caps and on trading carbon emissions schemes, applying to both industrialized nations and developing countries. The group hoped this policy to be in place by 2009, to supersede the Kyoto Protocol.

December 2007: Delegates from more than 180 nations met in Bali to start negotiations on a new climate change treaty to succeed the Kyoto Protocol.

December 2008: U.N. Climate change Conference in Poznan, continuing previous negotiations, in preparation for the Copenhagen Summit of December 2009.

June 2009: U.N. Climate change Conference in Bonn, continuing previous negotiations, in preparation for the Copenhagen Summit of December 2009.

December 2009: Copenhagen Summit. The Copenhagen accord declared that climate change is one of the greatest challenges nowadays, and that actions should be taken to ensure that temperature would not increase beyond 2 degrees Celsius. However, the document was not legally binding and did not contain any legally binding commitments for reducing CO_2-emissions, only an intention to reduce carbon emissions further.

November 2012: U.N. climate change conference in Doha.

B.4 U.S. climate policy

November 2006: The Democratic party takes control of the House of Representatives, and puts pressure on capping carbon emissions, despite the opposition of President Bush.

January 2007: Press coverage reflects the climate related content in the Bush's State of the Union Address. Bush called for doubling the capacity of the strategic petroleum reserve and for an increase in transportation fuel standards, but did not advocate limits on the emission of greenhouse gases.

June 2007: An environmental funding bill is passed in the House of Representatives, specifying for the first time a cap on greenhouse emissions.

June 2008: The Lieberman-Warner Climate Security Act reaches the Senate floor, initiating a debate on comprehensive climate change legislation.

January 2009: Obama takes office, setting the stage for reversing the lack of attention to climate change issues that characterized the Bush administration.

September 2009: The House of Representative passes the first comprehensive climate change bill, promoting the use of clean energy sources to suppress the use of fossil fuels.

April 2010: The BP oil spill in the Gulf of Mexico attracted vast media coverage. The political consequence was to upset hopes for winning bipartisan support to U.S. climate legislation, which rested on including measures to encourage more off-shore drilling, that were key to attract support from Republicans.

November 2010: Republicans took back control of the House of Representatives and gained seats in the Senate in the off-year elections. This decreased chances that the U.S. congress would pass a climate bill with substantial reforms, during President Obama's first term.

March 2011: Republicans in the U.S. House of Representatives introduced a bill that would permanently stop the environmental protection agency from regulating emissions blamed for warming the planet.

November 2012: Obama is confirmed president of the U.S. for another term, but Republicans confirm control over the House of Representatives. News coverage reflects on the implications for climate change policy.

February 2013: Obama's State of the Union Speech. He confirms again his commitment to fight climate change.

November 2014: The Democratic party loses control of the Senate in the mid-term elections. News coverage reflects on the implications for climate change policy.

January 2015: Republican Senators introduced a bill to approve the keystone XL pipeline, a major infrastructure for transporting oil from Canada to Texas, despite Obama's opposition.

November 2016: Donald Trump wins the elections, wowing to undo whatever progress Obama was able to make. In the first few months following his election, the news often report his claim that climate change is a hoax.

December 2016: Trump nominates Scott Pruitt to lead the Environment Protection Agency.

June 2017: Trump officially declares that the U.S. would abandon the Paris Agreement.

C Description of variables

Symbol	Description
aveBA	Average cross-sectional daily relative bid-ask spread BAS_t^i, where $BAS_t^i = (S_t^{ask,i} - S_t^{bid,i})/(0.5(S_t^{ask,i} + S_t^{bid,i}))$ for stock i on day t.
stedevSSD	Cross-sectional standard deviation of the synthetic-stock difference (SSD) measure of Hiraki and Skiadopoulos (2023)
Direct emissions intensity	Firm's Scope 1 plus Scope 2 CO_2 equivalent emissions to revenues USD in million
Scope 3 emissions intensity	Firm's Scope 3 CO_2 equivalent emissions to revenues USD in million
log(size)	The natural logarithm of market equity. Market equity is calculated as the product of the number of outstanding share with the price of the stock at the end of each month.
R&D /Sales	Research and Development expenses as a fraction of sales
GProf	Gross Profitability as a fraction of total assets
Return on Assets (ROA)	Operating Income before depreciation as a fraction of average total assets based on the two most recent periods
Inst. Own	Total Institutional Ownership per cent of outstanding shares. Institutional Ownership is computed using equity holdings by institutions which Thomson-Reuters file 13F reports. Total institutional ownership level is calculated by adding all shares for each security for each quarter. Total Institutional Ownership per cent of outstanding shares is the institutional ownership level divided by total shares outstanding at quarter end.

Table A.2. Description of variables