PERCEIVED CLIMATE RISK AND STOCK PRICES:

AN EMPIRICAL ANALYSIS OF PRICING EFFECTS

Accepted at Risk Analysis (ABS-4)

Abstract

Increasing awareness of climate change and its potential consequences on financial markets has led to interest in the impact of climate risk on stock returns and portfolio composition, but few studies have focused on perceived climate risk pricing. This study is the first to introduce perceived climate risk as an additional factor in asset pricing models. The perceived climate risk is measured based on the climate change sentiment of Twitter dataset with 16 million unique tweets in the years 2010–2019. One of the main advantages of our proxy is that it allows us to capture both physical and transition climate risks. Our results show that perceived climate risk is priced into S&P 500 Index stock returns and is robust when different asset-pricing models are used. Our findings have implications for market participants, as understanding the relationship between perceived climate risk and asset prices is crucial for investors seeking to navigate the financial implications of climate change, and for policymakers aiming to promote sustainable financing and mitigate the potential damaging effects of climate risk on financial markets, and a pricing model that accurately incorporates perceived climate risk can facilitate this understanding.

Keywords: climate risk, physical climate risks, transition climate risks, perceived climate risk, asset pricing

1. INTRODUCTION

The literature has increasingly focused on the role of sentiment in decision-making since the 1990s, and numerous studies have investigated the impact of investor sentiment on financial markets. De Long et al. (1990) showed that the unpredictability of noise traders' sentiment leads rational investors to react aggressively, causing prices to deviate considerably from fundamental prices. Barberis et al. (1998) presented a model that considered investor sentiment as a source of both underreactions and overreactions to news. They concluded that sentiment plays an important role in financial markets. Other studies have shown that market sentiment impacts asset pricing with regard to predictability and asset pricing anomalies (e.g., Hirshleifer & Shumway, 2003; Böhm & Chiarella, 2005; Chiarella et al., 2006, 2009; He & Shi, 2012; Antoniou et al., 2013; Smales, 2014; Sun et al., 2016; Renault, 2017). The emergence of new technologies for textual analysis and evolution of sentiment analysis has facilitated the investigation of the emotional content of texts, and a new strand of literature has focused on news sentiment. Tetlock (2007) studied the impact of pessimism on stock market performance, and through a textual analysis of *The Wall Street Journal*, showed that pessimism can predict statistically significant changes in stock returns and the daily volume of U.S. equities. Additionally, Tetlock et al. (2008) highlighted the influence of negative information extracted from both the Wall Street Journal (WSJ) and Dow Jones News Service (DJNS) on future earnings and stock market returns the day after news publication. Grob-Klubmann and Hautsch (2011) showed that trading activity measured by volatility, trading volumes, and bid–ask spreads responds significantly to news sentiment. Smales (2014) and Sun et al. (2016) highlighted the impact of this sentiment measure on the return of the gold futures market and Standard and Poor's 500 (S&P 500) index, respectively. Smales (2015) and Hendershott et al. (2015) focused on the impact of Reuters' sentiment proxy on the time-varying beta by activity sector and institutional trading volume, respectively. Renault (2017) investigated the relationship between intraday investor sentiment and stock market returns. He proposed an online investor sentiment measure based on a large StockTwits dataset. Their findings support the idea that the first half-hour investor sentiment variations improve the forecast for the last half-hour market return. Griffith et al. (2019) analyzed the relationship between investor sentiment- based on media content extracted from the Thompson Reuters MarketPsych database, and market return and volatility. Interestingly, we use four proxies to reflect pessimism and optimism in investor behavior. Using a nonlinear framework, the author highlights that investor stress behavior has a low short-term effect on stock market returns. Investors' gloom and joy cannot predict stock market returns. However, investors' fear behavior plays an important role in the dynamics of stock market returns and volatility. Zhang et al. (2021) focused on the case of emerging markets, China, and investor sentiment, constructed based on textual analysis from a dataset containing articles on stock market analysis obtained from a Chinese investors' community. Their findings support a substantial nonlinear effect of their investor sentiment measures on stock market returns and volatility. Interestingly, they showed that investor sentiment helps predict stock volatility.

Recent studies have investigated the impact of climate risk on financial markets and stock returns and distinguished between physical and transition risks (e.g., Faccini et al., 2021; Bua et al., 2022). Faccini et al. (2021) constructed a textual measure for both types of climate risks and demonstrated that stock returns are impacted only by transition risk, as measured by the U.S. climate policy. Bressan and Romagnoli (2021) investigated the role of climate and weather derivatives as instruments for hedging climate risks. Interestingly, the authors assessed the impact of weather derivatives on climate risk and financial stability. They showed that bias in capital risk calculation (such as mispricing and over/under estimations), in the presence of climate change effect, might have the reverse effect of intensifying climate physical risk, and hence, the concerns for financial stability. Bua et al. (2022) introduced two innovative indicators derived from textual analysis to evaluate the physical and transition risks associated with climate change. Santi (2023) found that when investors' climate change sentiment is positive, clean firms outperform carbon-intensive firms. Their research underscored a noticeable escalation in climate risk premiums for both risk categories in the aftermath of the 2015 Paris Agreement on climate change, indicating heightened market sensitivity to environmental factors.

The debate over the pricing of climate risks has intensified and garnered attention from academics, policymakers, and both individual and institutional investors following the Paris Agreement on climate change. Nordhaus (2019) argued that financial markets do not adequately price climate risks because the externalities associated with climate change have led to a discrepancy between market prices and true social costs. Similarly, Campiglio et al. (2022) found that financial markets do not fully price climate risks. This perspective is supported by various financial institutions, including the Bank for International Settlements (BIS, 2020), International Monetary Fund (IMF, 2020), and European Central Bank (ECB, 2021). Interestingly, literature has investigated the pricing of climate risks by separately tackling the pricing of physical and transition risks. The literature is inconclusive and presents different findings regarding the physical and transition risks; some studies showed that physical risk is priced in credit market (Huynh and Xia, 2020), others suggest that it is priced in sovereign debt markets (Mallucci, 2022), and others show that it is not priced (Faccini et al., 2023). Bolton and Kacperczyk (2021) showed that firms with high total dioxide emissions earn high returns that are not accounted for by fundamental factors. Thus, suggesting that investors require premiums to compensate for their exposure to carbon risk. Alessi et al. (2021) explored how transition risks are priced by examining the risk premium associated with a firm's environmental sustainability. This study reveals a risk premium linked to a company's environmental practices and its transparency. In other words, investors are generally willing to accept lower returns on investments in greener and more transparent firms, all other factors being equal. Hsu et al. (2023) examined the concept of a pollution premium for public US companies. Their empirical design compared portfolios containing companies with high and low toxic emissions. The findings support the existence of a pollution premium that cannot be explained by fundamental factors. Bolton and Kacperczyk (2023) extended previous studies to international evidence with high- and low-carbon emission firms to investigate the pricing of transition risks. Their findings support the idea that higher stock returns correlate with increased levels and growth rates of carbon emissions across sectors in most countries. The carbon premium tied to emission growth is more pronounced in firms based in countries characterized by lower economic development, more substantial energy sectors, and less inclusive political systems.

Although the literature on pricing climate risks has grown substantially in the past decade, particularly following the 2015 Paris Agreement, it often separates the analysis of physical climate risks (extreme weather events) from transition risks (transition policy, transition regulation, and technological advancements), leading to inconclusive findings. This study advances the literature by examining the impacts of both physical and transition risks on asset pricing. Our study introduces a novel concept of "perceived climate risk" to bridge the gap between existing research on climate risk pricing and the role of behavioral finance in investment decisions. Moreover, our measure is based on investor sentiment, a crucial determinant of asset pricing (Antoniou et al., 2016).

From a theoretical perspective, we consider that both risks may affect investor behavior. Indeed, behavioral finance theory assumes that investor sentiment can be driven by cognitive biases, such as overconfidence, anchoring, and herding, which can lead to financial markets underreaction or overreaction to new information (Barberis et al., 1998), such as those related to climate risks. Tversky and Kahneman's (1974) availability heuristic posited that investors may assign excessive weight to recent or particularly noteworthy climate-related events such as natural disasters (physical risk) or prominent policy announcements (transition risk). Theoretically, physical risk may affect investors' behavior based on their perceptions of news. For example, dealing with excessive temperatures or risks of natural disasters might impact investors' mood, and therefore, their financial decisions. However, transition-policy news is perceived by investors and shapes their decisions and investments. For example, investors may perceive positive news coverage of climate policies as a decrease in transition risk, leading to a positive shock to the economy. Otherwise, perceived negative climate-policy news adversely affects the opportunities available to investors, and they react to hedge against this negative shock. Consequently, investors may opt to buy (short-sell) stocks with negative (positive) climate betas. Overall, we consider that the perceived climate risk originating from physical and/or transition risks might impact investors.

Beyond conventional media, social networks have become platforms for producing, reacting to, and sharing information and emotions. Investors rely on a wide range of information sources, including news and social media, to communicate and analyze data. This integration of information channels emphasizes the important role of social influence in spreading information. Furthermore, an emotional element, the market sentiment, accompanies this process and impacts the dynamics of financial markets. This study measured perceived climate risk through climate change sentiments using social media. Specifically, we referred to the Twitter climate change sentiment database. Climate change sentiment can be defined as investors' perceptions of the prospective impact of climate change on financial markets and individual assets. Several factors account for the emergence of climate change sentiment as a significant factor in financial markets. First, there is an increasing awareness of the physical and transitional risks of climate change. Physical risks encompass the direct impacts of climate change, such as extreme weather events, natural disasters, and long-term changes in temperature and precipitation patterns. Transition risks arise from the transition to a low-carbon economy, such as changes in policy and regulations, technological advancements, and shifts in market preferences (Bank of England, 2018). Second, responsible and sustainable investing (SRI) and environmental, social, and governance (ESG) factors are increasingly influencing investment decisions. The accumulation of environmental stresses has not only intensified environmental crises and increased their likelihood of occurrence but has also impacted the response of governments and investors (Jagannathan et al., 2017).

Although previous studies have investigated climate risk pricing in stock returns, a gap exists in the literature on perceived climate risk pricing. We tested whether perceived climate risk was priced at S&P 500 stock prices. We considered perceived climate risk rather than climate risk because measuring and evaluating climate risk is difficult and can introduce bias. To the best of our knowledge, this study is the first to introduce perceived climate risk as an additional factor in asset-pricing models. Our results demonstrate the fundamental role of perceived climate risk in asset pricing. Using the portfolio sorts approach and smart beta, we show that our results are robust, indicating that stock prices are affected by perceived climate risk.

Our study provides robust results, showing that perceived climate risk reflects both physical and transitional climate risks. Perceived climate risk based on Twitter reflects public perceptions, and thus may influence investment behaviors and the trading activity of both individual and institutional investors. Hence, a pricing model that accurately captures and incorporates perceived climate risk would be helpful for investors, hedgers, and portfolio managers.

The development of a perceived climate risk index that captures investor perceptions of the risks and opportunities associated with climate change can provide valuable insights into the impact of climate risk pricing. This study focuses on the incremental role of perceived climate risk in capital asset evaluation models. Interestingly, we consider various investor profiles related to climate, as we distinguish between climate risk sentiments associated with neutrals, believers, and deniers. To the best of our knowledge, this study is the first to examine the incremental role of perceived climate risk in capital asset valuation.

This paper is organized as follows. Section 2 presents a literature review. In Section 3, we construct a measure of perceived climate risk. Section 4 presents the data and Section 5 discusses the main findings. Finally, Section 6 concludes the paper.

2. LITERATURE REVIEW

2.1. The Relationship between Market Sentiment, and Physical and Transition Risks

Understanding the relationship between market sentiment and climate risk (both physical and transition risks) is crucial for investors seeking to navigate the financial implications of climate change and for policymakers aiming to promote sustainable financing and mitigate the potential damaging effects of climate risk on financial markets. Recent studies show that climate change sentiment is influenced by investors' perceptions of the potential consequences of physical and transition risks for individual companies, industries, and financial markets (Antoniuk & Leirvik, 2021; Zhang, 2022).

The growing awareness of climate risk among investors, coupled with policy and regulatory pressures, has contributed to the increasing influence of climate change sentiment on overall market sentiment (Campiglio et al., 2018). Negative climate change sentiment can result from heightened concerns about the physical risks associated with climate change, such as the increased frequency and severity of extreme weather events, which can lead to disruptions in business operations, damage to assets, and increased insurance costs (Bessec and Fouquau, 2020; Zhang, 2022). Negative climate change sentiments stem from growing apprehensions about transition risks, such as the risk of stranded assets due to changes in regulations, technological advancements that render carbon-intensive assets obsolete, and shifts in consumer preferences towards sustainable products and services. Kölbel et al. (2020) showed that climate risk disclosure after the 2015 Paris Agreement negatively impacted credit default swap (CDS) spreads for non-material industries but did not find such an effect on physical risk. Conversely, positive climate risk sentiment can arise from increased optimism about opportunities associated with the transition to a low-carbon economy, such as the potential for innovative low-carbon technologies, green infrastructure investments, and growth of renewable energy markets (Engle et al., 2020). Stroebel and Wurgler (2021) showed that asset prices may underestimate, rather than overestimate, climate risk.

The interconnection between market and climate change sentiment highlights the critical role of policy and regulation in shaping investors' perceptions of climate risk and its impact on financial markets. Campiglio et al. (2018) found that carbon pricing policies significantly affect the valuation of firms with high carbon emissions, reducing their market capitalization. Governments and regulatory bodies can help improve both perceived climate risk and overall market sentiment by implementing policies and regulations aimed at mitigating climate risk and promoting sustainable financing.

2.2. The Impact of Climate Risk on Asset Valuation Models

Several studies have explored the integration of climate risk into traditional asset valuation models, often by incorporating climate risk as an additional factor or modifying existing factors to account for climate risk (Bolton & Kacperczyk, 2020, Faccini et al., 2021; Bua et al., 2022). These studies extend the Fama–French three-factor model and the standard capital asset pricing model (CAPM) by adding climate risk factors that capture the excess returns of stocks with low exposure to climate risks or strong environmental performance compared to those with high exposure to climate risks or weak environmental performance.

This augmented model acknowledges the growing importance of climate risk considerations in asset pricing and facilitates investors' understanding of the impact of climate risk on expected returns and portfolio performance. Antoniou et al. (2016) showed that during periods of optimism, the positive pricing of covariance risk may be obscured because of the active participation of simple traders in risky equities, whereas during periods of pessimism, traders tend to remain inactive, resulting in prices that are more closely aligned with the underlying fundamentals.

Hong et al. (2019) showed that stock markets exhibit inefficiencies in processing information pertaining to drought trends, which climate scientists consider one of the most critical climate risks that are either induced or intensified by climate change. Bolton and Kacperczyk (2020) found robust evidence that carbon emissions significantly and positively affect stock returns; Trinks et al. (2018) found that portfolios divested from fossil fuels do not experience significant underperformance compared with unconstrained market portfolios over an extensive period.

The extant literature appears to reach a consensus on the role of investor climate sentiment in the financial market. Our study considers this issue differently. We considered a Bayesian estimation for all types of Fama–French models. This approach allows us to incorporate prior information, provide a natural framework for uncertainty, and handle complex hierarchical data structures. These advantages make Bayesian estimation an attractive alternative to traditional estimation methods for financial models, particularly in the context of incorporating climate change sentiment, where data limitations, model complexity, and uncertainty are key challenges that need to be addressed. This approach yields pertinent information for investors, financial institutions, and policymakers who aim to comprehend and tackle the financial implications and possibilities linked to climate change.

3. METHODOLOGIES

We considered perceived climate risk as measured by climate change sentiment. Previous studies have used newspapers to gauge climate change sentiments (Engle et al., 2020; Ardia et al., 2022; Bua et al., 2022; Pástor et al., 2022). Newspapers may incorporate journalistic biases, including tendencies toward personalization, dramatization, and novelty (Boykoff & Boykoff, 2007). This can hinder the accurate representation of public opinion and pose challenges for individuals with diverse backgrounds to comprehend the conveyed information. To gain a more comprehensive understanding of public perceptions of climate change, several studies have explored climate change sentiment on online social media and social networking site Twitter (Kirilenko & Stepchenkova, 2014; Cody et al., 2015; Dahal et al., 2019; Loureiro & Allo, 2020). The platform offers an invaluable resource for investigating societal viewpoints, as users freely express opinions and share thoughts on various trending topics such as climate change or global warming.

The following section provides an overview of the Twitter climate change sentiment databases used in prior studies. First, we emphasize the adequacy, comprehensiveness, and novelty of the selected database. Next, we elucidate the methodology employed to measure climate change sentiments in this database. Finally, we analyzed the key characteristics and descriptive statistics pertaining to Twitter climate change sentiments.

3.1. Twitter Climate change Sentiment Database

Numerous studies have explored climate change sentiments by analyzing Twitter posts. Kirilenko and Stepchenkova (2014) employed the keywords, *global change* and *climate change*, to filter Twitter posts from 2012 to 2013. Williams et al. (2015) expanded the set of relevant keywords to include *climate change*, resulting in a collection of 590,608 tweets during the first half of 2013. Cody et al. (2015) focused on a single keyword, *climate*, and generated a large and novel Twitter climate change database comprising 1.5 million tweets collected from 2008 to 2014, a span of seven years. The dataset size continued to increase following Yeo et al. (2017), who gathered 3.7 million observable tweets using the keywords, *climate change* and *global warming*, during 2012–2014. Other investigations, such as Dahal et al. (2019), Abdar et al. (2020), and Loureiro and Alló (2020), have focused on Twitter climate change sentiment with thousands of tweets for analysis.

In this study, we used the Twitter climate-change dataset[1] of Effrosynidis et al. (2022), which is the most recent and largest Twitter post database on climate change. Our sample contained approximately 16 million unique tweets between 2010 and 2019. This database was constructed by merging three substantial climate change-related Twitter databases: (1) credibility of climate change denial (Samantray and Pin, 2019), (2) climate change tweet IDs data (Littman and Wrubel, 2019), and (3) Twitter archive data (Effrosynidis et al., 2022). This database contains an extensive relevant keyword list, which includes

- *climatechange*
- *climatechangeisreal*
- *actonclimate*
- *globalwarming*
- *climatechangehoax*
- *climatedeniers*
- *climatechangeisfalse*
- *climatechangenotreal*.

[1] Assess The Climate Change Twitter Dataset: https://www.kaggle.com/datasets/deffro/the-climate-change-twitter-dataset.

We consider this comprehensive database to be the most suitable for capturing public perceptions of climate change. We extracted all observations from this database for the years 2010–2019, aligned with the specific timeframe of our investigation.

In addition to containing information pertaining to Twitter posts, the database offers supplementary dimensions encompassing geolocation, sex (categorizing the owners of each post as male or female), stance (classifying individuals as climate believers, deniers, or neutral), aggressiveness (distinguishing between aggressive and non-aggressive languages), temperature, environmental disasters, and topics (such as extreme weather events, resource overconsumption, and politics). This database includes climate change sentiment scores for each post, which we used in our investigation.

3.2. Climate Change Sentiment Scores: Measurement of Perceived Climate Risk

Climate change sentiment score plays a pivotal role in our analysis and asset pricing methodology. We focused on understanding the construction of this sentiment database and explored methods for transforming and effectively utilizing these scores to achieve our research objectives.

Following the methodology of Effrosynidis et al. (2022), after the initial pre-processing procedures aimed at cleansing the textual content and converting it into vectorized representations, each tweet underwent sentiment analysis. The tweets were subjected to sentiment analysis using four popular unsupervised machine learning techniques: VADER (Hutto and Gilbert, 2014), Textblob (Loria, 2018), pre-trained RNN model, and pre-trained BERT model using the Flair framework (Akbik et al., 2019). Given the limited number of predefined labels for sentiments, unsupervised machine learning offers advantages such as greater adaptability, scalability, and bias reduction. To ensure reliability and validity, the sentiment score was calculated as the average across all four models, encompassing a range from -1 (indicative of the most negative sentiment) to 1 (reflecting the most positive sentiment). Table 1 displays examples of climate change sentiment scores for Twitter posts (Effrosynidis et al., 2022).

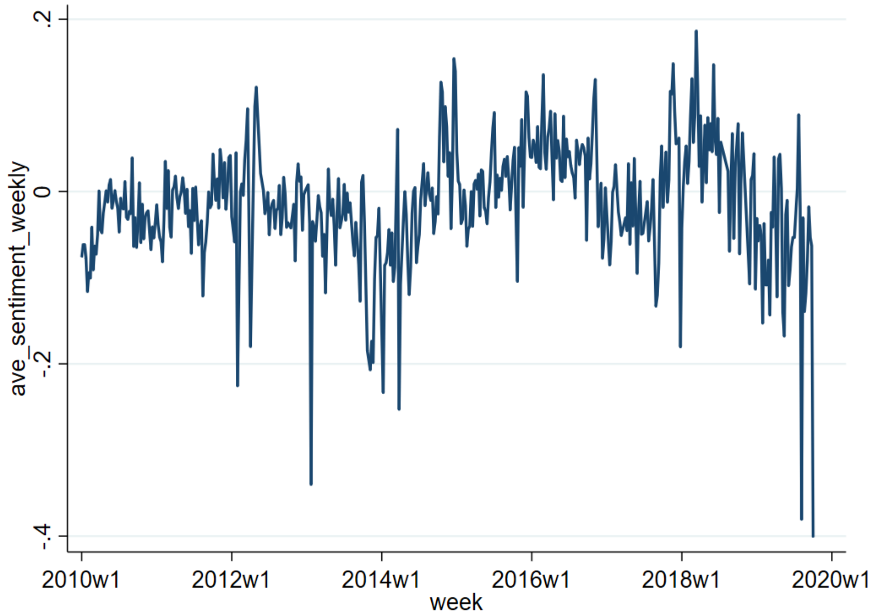
<Table 1 is about here>

Given the availability of climate change sentiment scores for each post, it was necessary to convert them into weekly scores by calculating the average sentiment scores across all posts within a given week. To conduct more comprehensive analyses incorporating additional dimensions every week, such as the total number of posts categorized by sex, aggressiveness level, or stance, we transformed the data by summing the corresponding number of posts for each criterion.

3.3. Analysis of Climate Change Sentiment

Figure 1 illustrates the weekly climate change sentiment scores for the years 2010–2019, traducing our variable perceived climate risk. Figure 1 shows that perceived climate risk measures exhibited fluctuations around neutral levels but displayed negativity during two distinct periods: (1) 2012–2014 and (2) from 2019 onward. Specifically, a shift toward more positive sentiment occurred in 2015 and persisted until 2018. This shift can be attributed to updated public perceptions following the Paris Agreement adopted at the UN Climate Change Conference in Paris in 2015, which likely influenced attitudes towards climate change. The subsequent decrease in sentiment scores during the second negative phase after 2019 can be attributed to the COVID-19 pandemic, during which society shared negative views on general climate change concerns and the pandemic.

FIGURE 1 Perceived Climate Risk measured as the weekly climate change sentiment score

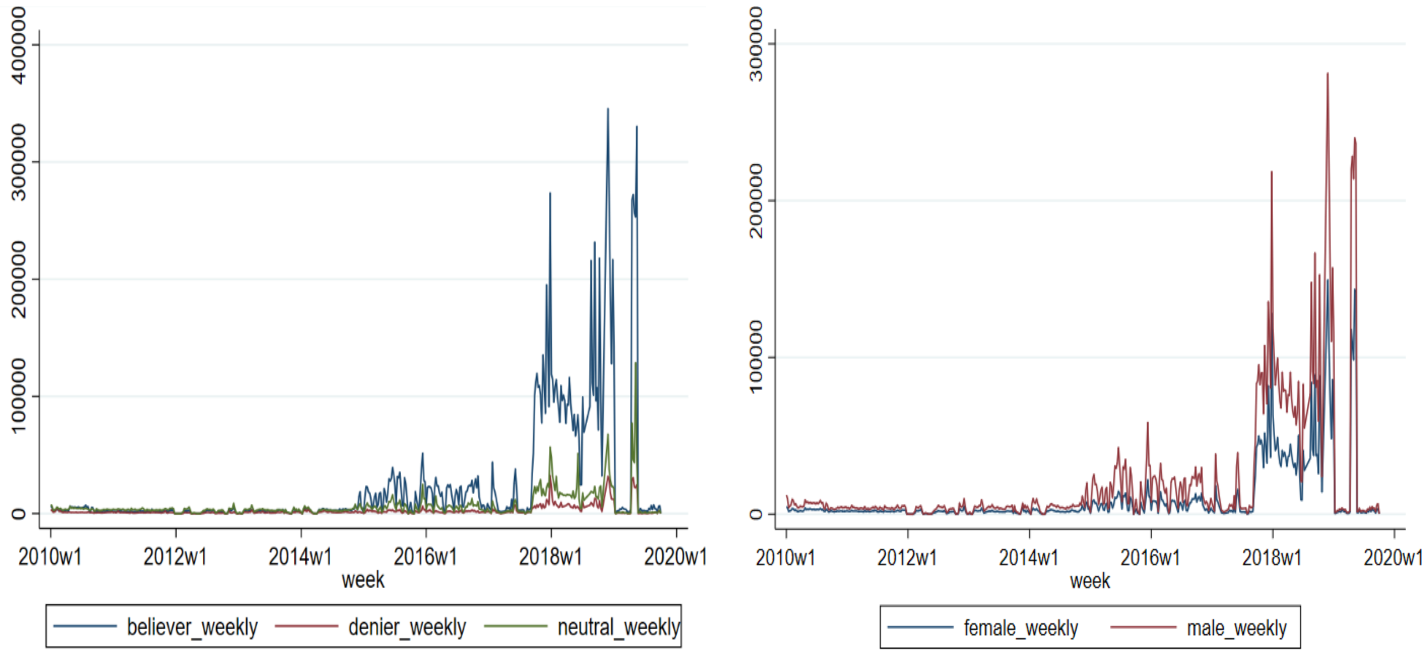


Note: The figure displays average climate change sentiment scores by week (average sentiment score of all posts in the corresponding week). It is based on data sourced from Effrosynidis et al. (2022).

Figure 2 shows additional analyses regarding different dimensions, namely, stance and sex. The graph demonstrates that Twitter posts expressing belief in climate change surpassed those adopting a denier or neutral stance. Our data analysis revealed two distinct waves of climate awareness: the first originating in 2015 and the second emerging in 2018. The year 2015 signifies the initiation of an initial wave that coincided with the inception of the Paris Agreement. Moreover, 2018 marked the commencement of the subsequent wave owing to numerous instances of extreme weather phenomena and climatic events observed throughout the year (NOAA Climate[2]).

[2] Access here: https://www.climate.gov/news-features/blogs/beyond-data/2018s-billion-dollar-disasters-context#:~:text=During%202018%2C%20the%20U.S.%20experienced,storms%2C%20drought%2C%20and%20wildfires.

FIGURE 2 Weekly statistics for climate change stance and sex of post owners



Note: The figure displays total number of posts by week with each criterion of stance (believer/denier/ neutral) and sex (female/male). It is based on data sourced from Effrosynidis et al. (2022).

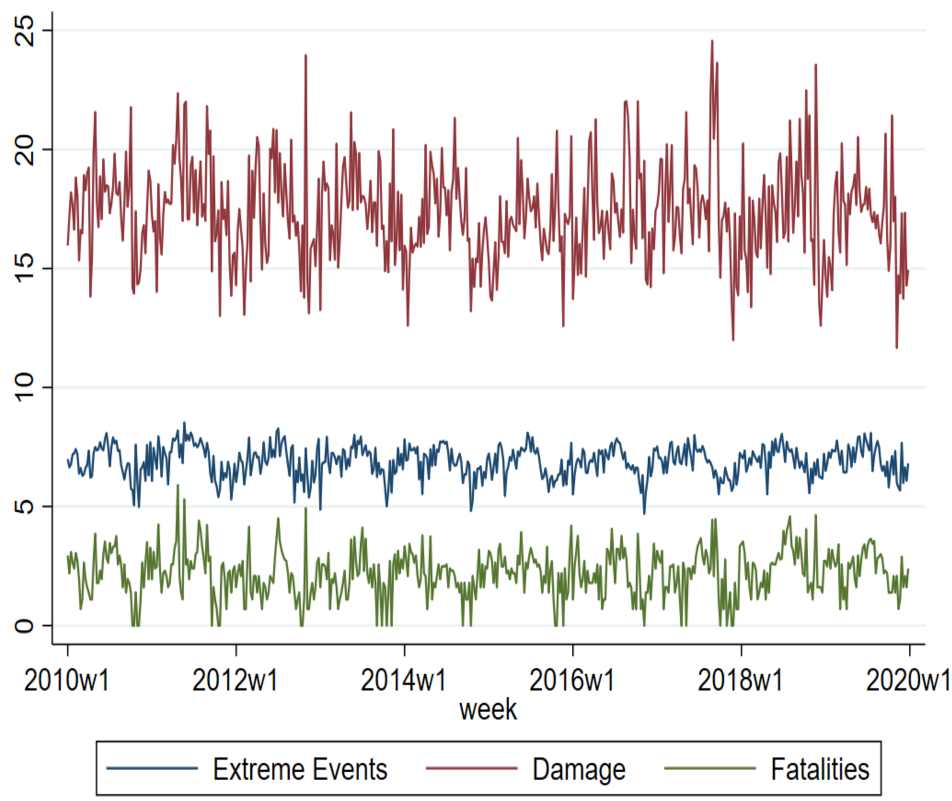
4. DATA

4.1. Physical Climate Risks

To investigate the implications of physical climate risks, we obtained data from the National Oceanic and Atmospheric Administration (NOAA)[3] recorded by the National Center for Environmental Information. This database documents instances of severe storms and abnormal weather phenomena[4] that resulted in considerable damage and losses across the United States from 1950 to 2023.

[3] Access Storm Events Database (NOAA): https://www.ncdc.noaa.gov/stormevents/
[4] Extreme events include the following: blizzard, coastal flood, cold/wind chill, debris flow, dense fog, drought, excessive heat, extreme cold/wind chill, flash flood, flood, frost/freeze, funnel cloud, hail, heat, heavy rain, heavy snow, high surf, high wind, hurricane, ice storm, lake-effect snow, lightning, marine. thunderstorm wind, storm surge/tide, strong wind, thunderstorm wind, tornado, waterspout, wildfire, winter storm, winter weather.

FIGURE 3 Physical climate risks



Note: The figure displays the logarithm number of total extreme events, total property damage (thousand USD), and total fatalities (both direct and indirect) with weekly frequencies in the United States from 2010 to 2019. It is based on data sourced from the Storm Event Database (NOAA).

Our approach involved aggregating the data every week, encompassing the cumulative occurrence of events, extent of damage incurred, and number of fatalities per week. By examining the periodic patterns of extreme weather over the years, we identified a notable correlation among these three indicators, as illustrated in Figure 3. Consequently, in our model testing, we used the logarithm of the number of extreme events as a proxy for assessing physical climate risks.

4.2. Transition Climate Risk

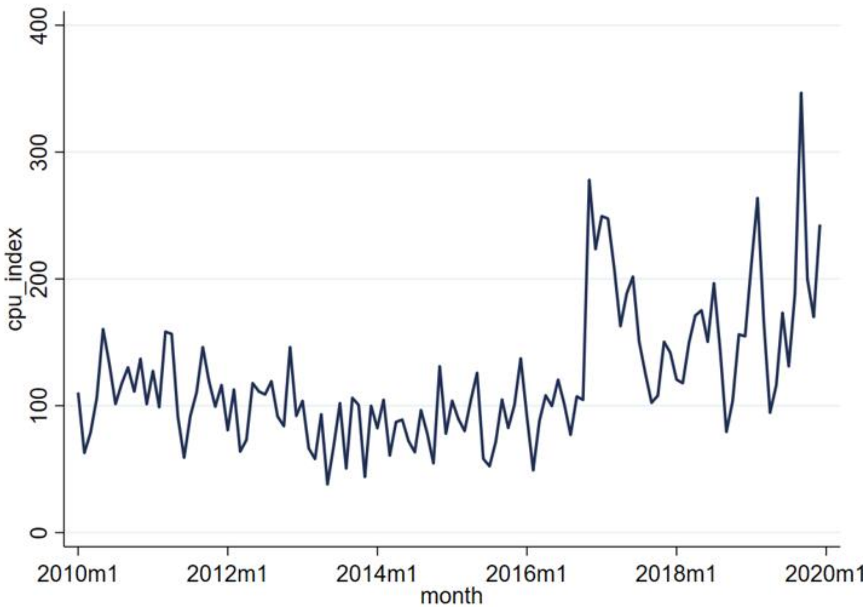
We investigated transition climate risk using the U.S. Climate Policy Uncertainty (CPU) index[5] built by Gavriilidis (2021). This index is based on a corpus of climate articles published monthly in eight leading U.S. newspapers: *The Boston Globe*, *Chicago Tribune*, *Los Angeles Times*, *Miami Herald*, *The New York Times*, *Tampa Bay Times*, *USA Today*, and *The Wall Street Journal*. The climate-policy keywords used to classify the climate articles included the following terms:

- *uncertainty* or *uncertain*;
- *carbon dioxide*, *climate*, *climate risk*, *greenhouse gas emissions*, *greenhouse*, CO_2, *emissions*, *global warming*, *climate change*, *green energy*, *renewable energy*, or *environmental*;
- *regulation*, *legislation*, *White House*, *Congress*, *EPA*, *law* or *policy;* and
- variants such as *uncertainties*, *regulations*, or *policies*.

This index is measured in a series of steps. First, the number of relevant articles per month was adjusted for each newspaper based on the total number of articles published in the same month. This normalization process ensures a fair comparison across newspapers. Subsequently, the resulting eight series were standardized to achieve a uniform standard deviation and mean value of 100. The larger the index, the higher the uncertainty in climate policies. The data were collected from 2010 to 2019 and are shown in Figure 4.

[5] Access Climate Policy Uncertainty (CPU) index: https://www.policyuncertainty.com/climate_uncertainty.html

FIGURE 4 Transition climate risk



Note: This figure shows the climate policy uncertainty (CPU) index with monthly frequency in the United States for 2010–2019. It is based on data sourced from Gavriilidis (2021).

Our analysis revealed a noteworthy surge in climate-policy uncertainty from 2016 after the Paris Agreement, a legally binding international treaty on climate change signed by 196 countries at the 2015 UN Climate Change Conference (COP21). This increase in climate policy uncertainty signified heightened media attention to the U.S. government's regulatory actions in response to this landmark event. The second surge, which occurred after 2019, highlighted growing global concern regarding policies to address climate change.

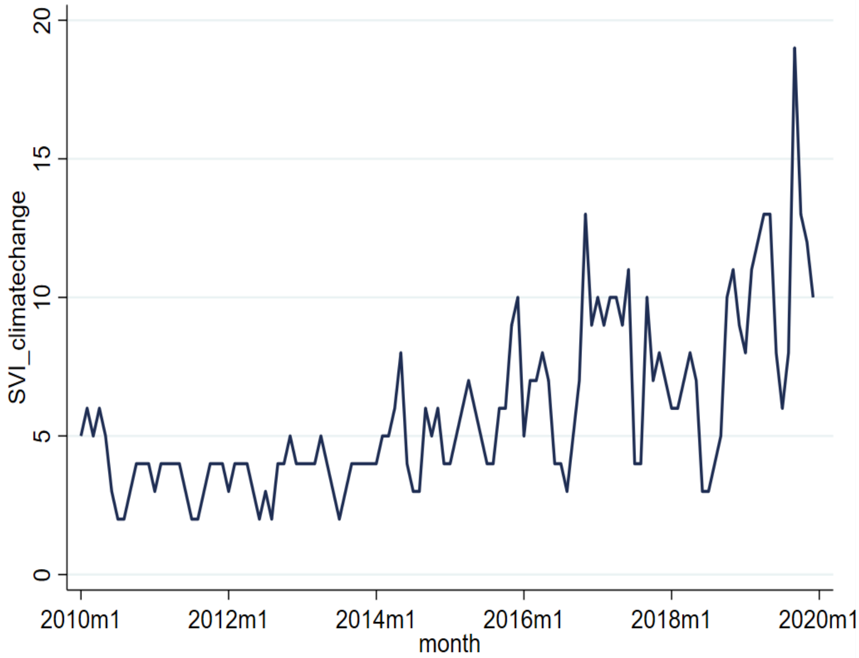
4.3. Climate Attention

Following previous studies that investigated Internet searches for climate change to measure attention (Choi et al., 2020; Ding et al., 2022; Santi, 2023), we employed Google's Search Volume Index (SVI)[6] as a metric to gauge attention toward climate-related issues. Specifically, we gathered monthly frequency data reflecting the number of Google user

[6] Assess Google SVI: https://trends.google.com.

searches for the keyword *climate change*. The SVI climate change index exhibited higher values when a greater level of attention was directed towards climate change. Our analysis revealed a noticeable trend in 2014, when societal attention to climate change progressively increased and experienced a significant surge until 2020.

FIGURE 5 Climate attention



Note: This figure shows the climate attention with monthly frequency in the United States for 2010—2019. It is based on data sourced from Google Trends.

4.4. Fama-French Factors Data

Our study focuses on pricing stocks on the S&P 500 Index, which includes the 500 largest market capitalization stocks listed on the New York Stock Exchange, with weekly frequencies from 2010 to 2019. We obtained stock risk-adjusted returns, prices, volumes, and shares outstanding daily for each stock from Wharton Research Data Services (WRDS). We transformed these into weekly indicators. Given that our observations were derived from the S&P 500 Index, no abnormal fluctuations in stock prices were detected in the dataset.

To incorporate the Fama–French factor into the asset pricing model, we collected three Fama–French factors (market, size, and value), five factors (adding profitability, and investment), and five factors plus the momentum factor in daily frequency from WRDS and Kenneth French's data library.[7] It is necessary to transform the daily frequency into a weekly frequency.

5. RESULTS AND DISCUSSION

5.1. The Relationship between Climate Risks and Perceived Climate Risk

We first examined whether perceived climate risk, measured by climate change sentiment, is determined by climate risks (physical and transition). Second, given the importance of attention in shaping investor sentiment (Barber et al., 2022; Barber & Odean, 2008; Da et al., 2011, among others), we investigate how climate attention can moderate the potential relationship between climate risks and perceived climate risk.

To address this first question, we proposed two models corresponding to the effect of physical risk (Model 1) and transition risk (Model 2), and the interaction effect between these two risks (Model 3). We used the weekly logarithm of the number of extreme events as a proxy for physical climate risk. In terms of transitional climate risk, we proposed that policy uncertainty may have a lagging effect. Thus, we employed a one-month lag in the policy uncertainty index as a proxy for the transition climate risk. There are three models for each week *t*:

$$\text{Percevied}_t = a_0 + \beta_1 \text{PCR}_t + e_t \ (1)$$

$$\text{Percevied}_t = a_0 + \beta_1 \text{TCR}_t + e_t \ (2)$$

$$\text{Percevied}_t = a_0 + \beta_1 \text{PCR}_t + \beta_2 \text{TCR}_t + \beta_3 \text{PCR}_t * \text{TCR}_t + e_t \ (3)$$

[7] Access Fama–French factors: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

where ***Perceived:*** perceived climate risk, ***PCR:*** physical climate risk, ***TCR:*** transition climate risk, $\boldsymbol{e_t}$**:** i. i.d. error term.

The empirical findings presented in Table 2 encompass the outcomes of the three models with approximately 470 weekly observations from 2010 to 2019. Models 1 and 2 revealed a significant negative impact of both physical and transition climate risks on perceived climate risk, indicated by the negative signs and statistical significance of the coefficients of the primary independent variables. Specifically, higher levels of climate risks (physical and transition) were associated with more negative perceived climate risks and an increased prevalence of negative news shared on social media platforms. In Model 3, when both types of risks were considered in conjunction and interaction with each other, it was evident that they acted as substitutes in terms of their impact on perceived climate risk. This implies that when both physical and transition climate risks coexist, public perceptions of these two risks differ. The result of Model 3 motivated us to use perceived climate risk rather than climate risk measures because a substitution effect exists when both occur.

<Table 2 is about here>

To address how climate attention can moderate the negative relationship between climate risk and perceived climate risk, we interacted with climate attention in the full model (Model 3) with both physical and transition climate risks. We used two proxies for climate attention: (1) Google SVI_Climatechange and (2) the Paris Agreement event, which was a control variable that received 1 if after 2015 and 0 otherwise. Model 4 is shown below:

$$\text{Perceived}_t = a_0 + \beta_1 \text{PCR}_t + \beta_2 \text{TCR}_t + \beta_3 \text{CCA}_t + \beta_4 \text{PCR}_t * \text{TCR}_t + \beta_5 \text{PCR}_t * \text{CCA}_t + \beta_6 \text{TCR}_t * \text{CCA}_t + e_t \quad (4)$$

where ***Perceived:*** perceived climate risk, ***PCR:*** physical climate risk, ***TCR:*** transition climate risk, ***CCA:*** climate change attention, $\boldsymbol{e_t}$**:** i.i.d error terms.

Table 3 presents the findings derived by employing two indicators as proxies for measuring climate attention (SVI_Climatechange in Model 4a and Paris Agreement in Model 4b). Both models indicated that an increase in climate attention negatively moderated the impact of climate risk on perceived climate risk, as is evident from the negative coefficient values and the statistical significance of the interaction variables. From an economic perspective, heightened public concern about climate change corresponds to increased attention being paid to the consequences of extreme events and policy uncertainty. More public attention may lead to greater intention to share climate news and express opinions. Consequently, these risks become more prominent and exert a more pronounced negative influence on perceived climate risk.

<Table 3 is about here>

After showing a strong relationship between climate risk and perceived climate risks (physical and transition risks), we tested whether perceived climate risk is priced into stock prices. To test this hypothesis, we used the Portfolio Sorts approach and checked its robustness using the Fama-Macbeth approach and factor-zoo tests.

5.2. Modelling Perceived Climate Risk

Although previous studies investigated the pricing of climate risk in financial markets (Faccini et al., 2021), there is a gap in the literature on perceived climate risk. We followed the Portfolio Sorts approach as the main method, Fama Macbeth approach and factor-zoo tests as the robustness tests, and implemented the Smart Beta strategy.

5.2.1. Portfolio Sorts Approach

To model perceived climate risk, we employed a portfolio orts approach as the primary methodology. Our dataset consisted of stocks listed on the S&P 500 Index, which have been adjusted over time to account for changes in the composition of stock lists. Thus, we calculated the perceived climate risk beta for each stock and sorted the stocks weekly based on their perceived climate risk beta, which ranged from the highest to the lowest. Subsequently, we established long positions in the portfolio of stocks with the highest perceived climate risk beta and short positions in the portfolio of stocks with the lowest perceived climate risk beta. By taking long and short positions, we created a long–short spread, referred to as alpha, for each week.

To determine whether this alpha contributed to excess returns, we employed cross-sectional regression analysis to assess the statistical significance of the relationship between the alpha generated from the long–short portfolios and the excess returns observed. If alpha yields statistically significant results, we can infer that perceived climate risk is priced in stock returns. Conversely, if the results are not statistically significant, then no discernible pricing effect is associated with perceived climate risk.

First, to calculate the beta for each stock *i* in each week *t*, we used the following model:

$$R_{i,t} - R_{f,t} = a_i + \beta_i \text{Perceived}_t + \gamma_i X_{i,t} + e_t \quad (5)$$

where $\boldsymbol{R_{i,t}}$: the weekly return on stock i in week t; $\boldsymbol{R_{f,t}}$: the risk-free rate in week t;

Perceived: perceived climate risk; $\boldsymbol{X_{i,t}}$: Fama-French factor, $\boldsymbol{e_t}$**:** i. i.d. error term.

We computed the beta by regressing recursively using a rolling window of 12 weeks, which means that the beta of stock *i* in each week was defined by the total observations of each stock in the previous three months (12 weeks). Each week, after identifying the perceived climate risk beta (β_i), we ranked this beta from highest to lowest and grouped it into decile and quintile portfolios. We long the highest quintile–decile perceived climate risk (quintile 5, decile 10) and short the lowest quintile–decile perceived climate risk (quintile 1, decile 1). We computed the returns of each portfolio and the long–short spread (alpha) using equally weighted returns. Market cap-weighted returns were also implemented, and the results were consistent. We report the results of the equally weighted returns for all tests. We again estimated the significance of alpha using Model 5.

Table 4 shows the outcomes of the two specifications: quintiles and deciles with five panels, including Panel A: market model; Panel B: Fama–French 3-factor model (Fama and French, 1993); Panel C: Fama–French 5-factor model (Fama and French, 2015); Panel D: Carhart model, including Fama–French 3-factor model and momentum factor (Carhart, 1997), and Panel E: Fama–French 5-factor model plus momentum factor model. Across all five panels and two specifications, we consistently found a positive and statistically significant coefficient for alpha, indicating that perceived climate risk is priced into stock returns.

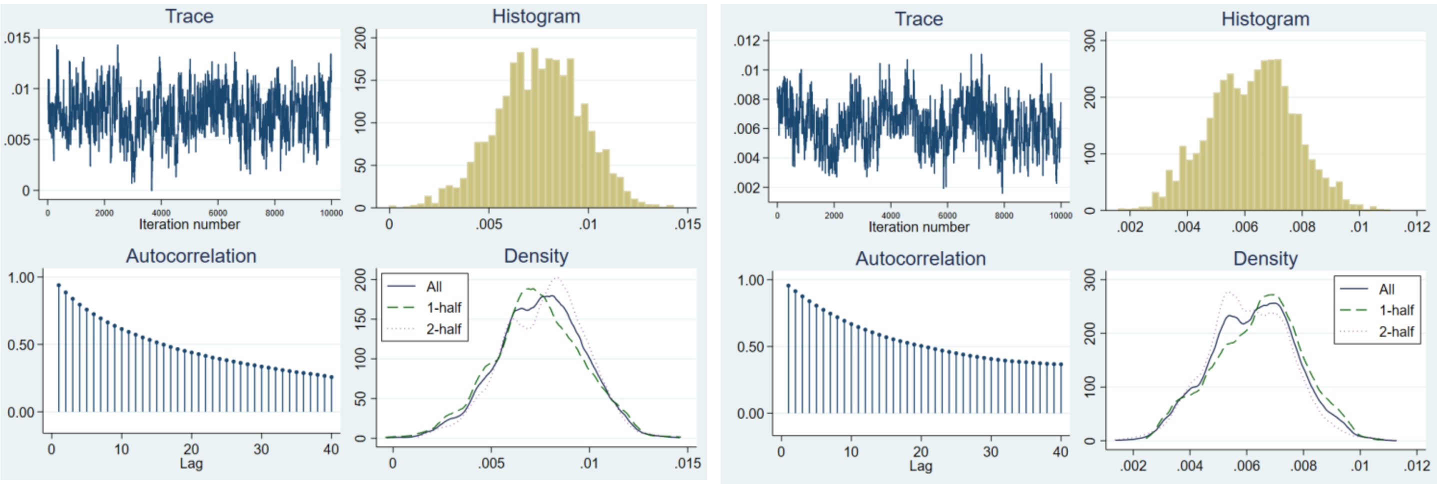
The positive sign of alpha may imply that when the perceived climate risk measured by climate change sentiment is positive, investors tend to buy (or sell) stocks with a positive (or negative) perceived climate risk beta, which increases excess returns. This behavior suggests that investors incorporate a climate risk premium into their decisions, acknowledging that stocks with higher perceived climate risk might also offer higher potential returns as compensation for this risk. Conversely, when the perceived climate risk measured by climate change sentiment is negative, investors would buy (or sell) stocks with a negative (or positive) perceived climate risk beta, thereby decreasing excess returns. Here, the climate risk premium adjusts in the opposite direction as investors demand less compensation for holding stocks perceived as less risky in terms of climate impact.

<Table 4 is about here>

To validate the effect of alpha on excess returns, we examined the quantile regression bootstrap standard error with different levels of excess returns (quantile 10th, 25th, 50th, 75th, 90th) with both specifications (quintiles and deciles). Quantile regression models are prominent in economics and finance (Koenker & Bassett, 1978; Koenker & Machado, 1999), and are used to assess extreme outcomes and high volatility in Fama–French model (Wang et al., 2023). Table 5 shows that the coefficient of alpha was positive and statistically significant at the 1% level in quantile levels 50^{th}, 75^{th}, and 90^{th}. This outcome highlighted that the significance of the pricing effect became increasingly apparent and impactful when average and higher levels of excess returns were examined. Our results highlight the positive effect of alpha and show that perceived climate risk is priced into stock returns.

<Table 5 is about here>

FIGURE 6 Bayesian adaptive Markov chain Monte Carlo (MCMC) estimations



Quintile | Decile

Note: The figure shows the relevant statistics (trace, histogram, autocorrelation, and density) for the Fama–French 5-factor model plus momentum factor model.

We also ran a Bayesian adaptive Markov chain Monte Carlo (MCMC) model to examine the alpha parameter in the model. This method has been adopted in previous studies to estimate parameters (Chen et al., 2012; Chen & Gerlach, 2013; Chen et al., 2017). Additionally, random walk Metropolis–Hastings sampling was employed to adapt the posterior distributions. We ran Bayes estimations using 12500 MCMC iterations, 2500 Burn-in, and 10000 MCMC sample sizes; the outcomes are presented in Table 5, with specific attention paid to the parameters associated with the coefficients of perceived climate risk across different panels and models. The 95% credible intervals for these parameters consistently fell within positive ranges, indicating a robust and enduring positive effect of perceived climate risk factors.

<Table 6 is about here>

5.2.2. Fama–MacBeth Approach

We employed the Fama–MacBeth approach to assess the pricing effect of perceived climate risk. We ran it in two steps with a rolling window of 12 weeks (three months) as the portfolio-sorting approach in Step 1 and cross-sectional regressions of the perceived climate risk beta in Step 2 over the next week. Table 7 presents the results for the Fama–MacBeth approach with all five panels, and shows that our results were robust. These findings confirmed that perceived climate risk is priced into stock returns.

<Table 7 is about here>

In assessing the robustness of the impact of perceived climate risk on stock returns, the Portfolio Sorts approach and Fama-MacBeth regression provide complementary insights. The portfolio sorting approach (Table 4) groups stocks into portfolios based on characteristics, such as perceived climate risk and assesses average returns, effectively highlighting the influence of specific factors. This approach is beneficial for its intuitive representation of investment strategies and ability to highlight the role of perceived climate risk in shaping stock returns. For example, in this method's Market Model, both quintiles and deciles show a significant positive relationship with stock returns at the 1% level, emphasizing the relevance of perceived climate risk. However, the Fama-MacBeth regression (Table 7), a two-step econometric procedure, offers a more nuanced statistical test. The first step involves cross-sectional regressions of stock returns against risk factors, including perceived climate risk. The second step computes the average of these coefficients over time. This method addresses the issue of multicollinearity and captures the dynamic nature of risk premiums.

The convergence of the findings of these two approaches is notable. Despite their methodological differences, both approaches consistently identify perceived climate risk as a significant factor influencing stock returns. In both methods, the impact of perceived climate risk, while varying across models, remained significant. Its effect is more pronounced in simpler models and is somewhat reduced in more complex models, such as the Fama-French five-factor plus momentum model. This indicates that the influence of perceived climate risk is robust, yet moderated when other factors are considered.

The consistent statistical significance of perceived climate risk in various models and approaches underscores its importance in empirical asset pricing. This finding is crucial for investors and analysts and suggests that perceived climate risk should be considered in investment strategies and risk assessment models. Moreover, the significance of other factors, such as market, size, and value across different models aligns with traditional asset pricing theory, further validating the comprehensive nature of these analytical approaches.

5.2.3. Factor-zoo Robustness Tests

To ensure the resilience of our perceived climate risk factor, we conducted robustness tests against the factor zoo using the methodology outlined by Feng et al. (2020). This study underscores the potential for bias in the robustness and significance of the newly proposed factors, based on the selection of relevant factors within the model. We tested the statistically significant explanatory power of our proposed factor (perceived climate risk factor) beyond the hundreds of factors proposed in the past (up to 2016, with 150 factors following the database referenced in this paper).

Given the monthly frequency of the factors in the referenced study, we adopted a portfolio sorts approach to construct monthly quintile equally weighted alphas for perceived climate risk factors. We tested our monthly perceived climate risk factor with six panels: Panel A (Fama-French three factors), Panel B (Fama-French five factors), Panel C (Fama-French five-factor plus momentum factor), Panel D (15 recent factors proposed from 2012–2016 following Feng et al. (2020)), Panel E (all 150 factors), and Panel F (Double Selection Lasso method with 200 random seeds). Feng et al. (2020) applied the double-selection lasso method to evaluate the contribution of a factor in explaining asset prices, specifically in a high-dimensional setting. The results presented in Table 8 across these panels consistently demonstrate the significance and validity of our proposed perceived climate risk factor within the asset pricing model, underscoring its meaningful contribution.

<Table 8 is about here>

5.2.4. Extending Analysis (Pre and Post Paris Agreement; Energy and Non-energy Sectors)

Furthermore, we tested whether the pricing effect differed before and after the 2015 Paris Agreement. We divided our 2010–2019 sample into two subgroups: pre-2015 and post-2015. There was heightened awareness of climate risk in the post-2015 period. The results in Table 9 support the hypothesis that the pricing effect of perceived climate risk on stock returns was substantially greater during the post-2015 period in comparison to the pre-2015 period. In all panels (except Panel E, where the coefficient of alpha was insignificant in both periods), the coefficient of alpha was insignificant in the pre-2015 sub-sample but positive and significant post-2015. This result indicates that the pricing effect of perceived climate risk was stronger and more pronounced when there was an elevated level of concern about climate change. This finding aligns with earlier studies on transition risk pricing and the impact of climate disclosures on stock markets since the Paris Agreement of 2015 (Kölbel et al., 2020; Santi, 2023).

<Table 9 is about here>

To investigate the difference in the perceived climate risk effect between firms in the energy sector and those in other sectors, we replicated our main method, Portfolio Sorts, using a sub-sample analysis. We classified the sub-sample based on The Global Industry Classification Standard (GICS), in which the energy sector is defined as code "10."

Table 10 shows the results with sub-sample analysis. These outcomes offer insight that perceive climate risk factor indeed affects the pricing of stocks in both energy and non-energy sector; however, the sensitivity is more pronounced in firms in energy sector. Given that companies within the energy sector are likely to be more acutely affected by climate-related risks, such an analysis confirms a better pricing effect of perceived climate risk in energy sector.

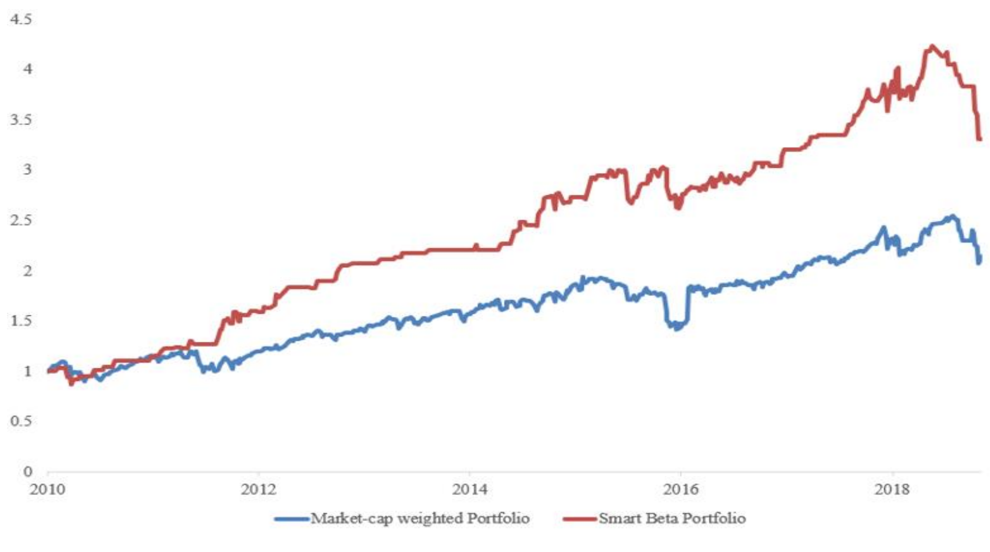
<Table 10 is about here>

5.2.5. Smart Beta Portfolio with Perceive Climate Risk

The increasingly obvious impact of perceived climate risk on financial markets calls for new investment approaches to manage them. The following section proposes an application of the Smart Beta approach to consider perceived climate risk in financial markets.

After identifying the pricing effect of perceived climate risk, we proposed a smart beta portfolio to capture the exposure to the perceived climate risk beta. A smart beta portfolio is also known as factor investing, in which a portfolio is built based on factor weighting rather than on market capitalization weighting. The smart beta portfolio included only the long positions. In adopting the smart beta portfolio strategy, our primary motivation was to exploit the unique pricing effect associated with perceived climate risk, which is increasingly recognized as a significant influencer in financial markets. Unlike traditional market capitalization-weighted portfolios, smart beta allows for greater diversification and targeted exposure, particularly to specific market inefficiencies or factors; in this case, the perceived climate risk beta. This approach offers an enhanced risk management framework as it aligns the portfolio more closely with stocks that demonstrate higher sensitivity to shifts in environmental sentiment, providing a clearer understanding and management of risk exposure. Additionally, the adaptability of the smart beta strategy through weekly rebalancing based on the perceived climate risk beta ensures that the portfolio remains responsive, dynamic, and capable of capturing short-term trends and reacting promptly to new market information. The potential of smart beta portfolios to outperform traditional indices is particularly compelling in scenarios where selected factors, such as perceived climate risk, play a crucial role in driving market dynamics.

FIGURE 7 Market cap-weighted (S&P500) portfolio and smart beta portfolio



Note: The figure shows the cumulative returns of the two portfolios in the years 2010–2019.

Figure 7 clearly shows the effectiveness and efficiency of the smart beta portfolio compared with the market cap-weighted portfolio when investors can obtain significantly higher returns. The smart beta portfolio's outperformance over the market capitalization-weighted portfolio, which began in late 2011, coincided with a period marked by significant volatility in perceived climate risk alongside a pronounced negative peak in this index, as illustrated in Figure 1. This correlation demonstrates the impactful relationship between perceived climate risk and valuation of financial assets. This change in perceived climate risk underscores the increasing relevance of environmental factors in financial decision-making processes.

This smart beta strategy aims to exploit market inefficiencies and align the risk-return profile more closely with investor objectives, unlike conventional market-cap-weighted indexes. This phase of perceived climate risk provides key insights into the intricate relationship between non-financial factors, such as environmental sentiment and financial market performance.

6. CONCLUSIONS

Although previous studies have investigated the pricing of climate risk in stock returns, a gap still exists in the pricing of perceived climate risk. To the best of our knowledge, this study is the first to introduce perceived climate risk as an additional factor in asset-pricing models. Previous studies (Faccini et al., 2021; Bua et al., 2022) have considered climate risk. This study considered perceived climate risk rather than climate risk as fundamental because previous studies have failed to capture the effect of physical risk (Faccini et al., 2021). In this study, we developed a measure for perceived climate risk using Twitter. We then tested whether perceived climate risk is priced at the S&P 500 stock prices. Our findings highlighted the key role of perceived climate risk in asset pricing. Using the Portfolio Sorts approach, the Fama-

Macbeth approach, and factor-zoo tests, we showed that our results were robust. Our study provides robust results, showing that perceived climate risk captures both physical and transition risks. As climate change sentiment on Twitter reflects public perceptions, it may affect the investment behavior and trading activity of both individual and institutional investors. Hence, a pricing model that accurately captures and incorporates perceived climate risk would be helpful for investors, hedgers, and portfolio managers.

This study offers compelling evidence on the influence of perceived climate risk on financial markets, leading to several important policy implications. The observation that perceived climate risk is priced into stock returns, as indicated by the positive and statistically significant coefficient for alpha across various models, emphasizes the need for a more nuanced approach to financial decision-making. Moreover, the pricing effect is more pronounced for firms in the energy sector. These findings suggest that investors, fund managers, and regulatory bodies should consider the sentiment around climate change as a significant factor when assessing the value and risk of assets and that perceived climate risk is an essential factor in asset pricing. This calls for a reassessment of traditional investment strategies, encouraging investors and asset managers to incorporate perceived climate risk data into their risk assessments and portfolio allocations.

Furthermore, this study highlights the relationship between climate risk and perceived climate risk. Both physical and transition climate risks had significant negative impacts on perceived climate risk. This is a crucial insight for investors and policymakers because it highlights the importance of considering these risks in investment strategies and policy formulations. The rise in climate policy uncertainty after the Paris Agreement indicates the impact of international treaties and global events on financial markets, which also signals the need for more transparent and consistent climate policy frameworks. This suggests that investors and financial analysts need to be cognizant of such events and their potential effects on market sentiment, and consequently, on asset valuations. Investors and companies require predictable frameworks to make long-term decisions and erratic policy environments can lead to increased market volatility. This would enable investors to make informed decisions and facilitate the development of more resilient financial markets that are better equipped to handle the challenges posed by climate change and related risks. One key implication is the potential for smart beta portfolios to outperform traditional market capitalization-weighted portfolios, particularly during periods marked by volatility in perceived climate risk. The study's analysis, which shows that the smart beta portfolio began to significantly outperform the market cap-weighted portfolio in late 2011, coinciding with notable shifts in perceived climate risk, underscores the strategic advantage of incorporating sentiment analysis into investment strategies.

The integration of perceived climate risk analysis into investment decision-making could lead to more resilient portfolios, better risk management, and a greater alignment of financial markets, with a broader societal shift towards acknowledging and addressing climate change.

Our study's focus on the American market assets highlights the significance of perceived climate risk in influencing financial market dynamics in the U.S. This finding opens avenues for further research to explore how these dynamics might differ across various global markets, considering diverse economic, regulatory, and cultural landscapes. Additionally, a longitudinal study could examine the long-term effects of perceived climate risk on financial markets to better understand the evolution and lasting impacts of such sentiments over time. Furthermore, the development of predictive models that assess market responses to major global events, such as international treaties or pandemics, could offer invaluable tools for investors and policymakers. Such models could aid in understanding whether the trends identified in the American markets are consistent with or diverge from those in other parts of the world, thereby helping to tailor region-specific investment strategies and policies.

REFERENCES

Abdar, M., Basiri, M. E., Yin, J., Habibnezhad, M., Chi, G., Nemati, S., & Asadi, S. (2020). Energy choices in Alaska: Mining people's perception and attitudes from geotagged tweets. *Renewable and Sustainable Energy Reviews*, 124, 109781.

Akbik, A., Bergmann, T., Blythe, D., Rasul, K., Schweter, S., & Vollgraf, R. (2019, June). FLAIR: An easy-to-use framework for state-of-the-art NLP. *In Proceedings of the 2019 conference of the North American chapter of the association for computational linguistics (demonstrations)* (pp. 54-59).

Alessi, L., Ossola, E., & Panzica, R. (2021). What greenium matters in the stock market? The role of greenhouse gas emissions and environmental disclosures. *Journal of Financial Stability*, *54*, 100869.

Antoniou, C., Doukas, J.A., & Subrahmanyam, A.~~,~~ (2013). Cognitive dissonance, sentiment, and momentum. *Journal of Financial and Quantitative Analysis*, 48, 245–275.

Antoniou, C., Doukas, J. A., & Subrahmanyam, A. (2016). Investor sentiment, beta, and the cost of equity capital. *Management Science*, *62*(2), 347-367.

Antoniuk, Y., & Leirvik, T. (2021). Climate change events and stock market returns. *Journal of Sustainable Finance and Investment,* 1-26.

Ardia, D., Bluteau, K., Boudt, K., & Inghelbrecht, K. (2022). Climate change concerns and the performance of green vs. brown stocks. *Management Science*.

Bank of England (2018). Transition in thinking: The impact of climate change on the UK banking sector. Available at: https://www.bankofengland.co.uk/prudential-regulation/publication/2018/transition-in-thinking-the-impact-of-climate-change-on-the-uk-banking-sector

Bank for International Settlements (BIS) (2020): The green swan: Central banking and financial stability in the age of climate change, January, www.bis.org/publ/othp31.htm.

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies*, 21(2), 785-818.

Barber, B. M., Huang, X., Odean, T. & Schwarz, C. (2022). Attention-Induced Trading and Returns: Evidence from Robinhood Users. *The Journal of Finance*, 77, 3142-3290.

Barberis, N., Shleifer, A., & Vishny R. (1998). A model of investor sentiment. *Journal of Financial Economics*, 49, 307-343.

Bessec, M.,–& Fouquau, J. (2020, October). Green sentiment in financial markets: A global warning. In *Proceedings of Paris December 2020 Finance Meeting EUROFIDAI-ESSEC, Université Paris-Dauphine Research Paper* (No. 3710489).

Böhm, V., & Chiarella, C., (2005). Mean variance preferences, expectations formation, and the dynamics of random asset prices. *Mathematical Finance*. 15, 61–97.

Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, *142*(2), 517-549.

Bolton, P., & Kacperczyk, M. (2023). Global pricing of carbon-transition risk. *The Journal of Finance*, *78*(6), 3677-3754.

Bolton, P., & Kacperczyk, M. (2024). Are carbon emissions associated with stock returns? Comment. *Review of Finance*, *28*(1), 107-109.

Boykoff, M. T., & Boykoff, J. M. (2007). Climate change and journalistic norms: A case-study of US mass-media coverage. *Geoforum*, 38(6), 1190-1204.

Bressan, G. M., & Romagnoli, S. (2021). Climate risks and weather derivatives: A copula-based pricing model. *Journal of Financial Stability*, *54*, 100877.

Bua, G., Kapp, D., Ramella, F., & Rognone, L. (2022). Transition versus physical climate risk pricing in European financial markets: A text-based approach.

Campiglio, E., Dafermos, Y., Monnin, P., Ryan-Collins, J., Schotten, G., ~~and~~ & Tanaka, M. (2018). Climate change challenges for central banks and financial regulators. *Nature Climate Change*, *8*(6), 462-468.

Campiglio, E., Daumas, L., Monnin, P., & von Jagow, A. (2023). Climate-related risks in financial assets. *Journal of Economic Surveys*, *37*(3), 950-992.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, 52(1), 57-82.

Chen, M. H., Shao, Q. M., & Ibrahim, J. G. (2012). Monte Carlo methods in Bayesian computation. *Springer Science and Business Media*.

Chen, C. W., & Gerlach, R. (2013). Semi-parametric quantile estimation for double threshold autoregressive models with heteroskedasticity. *Computational Statistics*, 28, 1103-1131.

Chen, C. W., Li, M., Nguyen, N. T., & Sriboonchitta, S. (2017). On asymmetric market model with heteroskedasticity and quantile regression. *Computational Economics*, 49, 155-174.

Chiarella, C., Dieci, R., & Gardini, L. (2006). Asset price and wealth dynamics in a financial market with heterogeneous agents. *Journal of Economic Dynamics and Control*, 30, 1755-1786.

Chiarella, C., Iori, G., & Perelló, J., (2009). The impact of heterogeneous trading rules on the limit order book and order flows. *Journal of Economic Dynamics and Control*. 33, 525–537.

Choi, D., Gao, Z., & Jiang, W. (2020). Attention to global warming. *The Review of Financial Studies*, 33(3), 1112-1145.

Cody, E. M., Reagan, A. J., Mitchell, L., Dodds, P. S., & Danforth, C. M. (2015). Climate change sentiment on Twitter: An unsolicited public opinion poll. *PloS One*, 10(8), e0136092.

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The Journal of Finance*, 66(5), 1461-1499.

Dahal, B., Kumar, S. A., & Li, Z. (2019). Topic modeling and sentiment analysis of global climate change tweets. *Social Network Analysis and Mining*, 9, 1-20.

De Long, J.B., Shleifer, A., Summers, L.H., & Waldmann, R.J., (1990). Noise trader risk financial markets. *Journal of Political Economy*, 98, 703–738.

Ding, Q., Huang, J., & Zhang, H. (2022). Time-frequency spillovers among carbon, fossil energy and clean energy markets: The effects of attention to climate change. *International Review of Financial Analysis*, 83, 102222.

Effrosynidis, D., Karasakalidis, A. I., Sylaios, G., & Arampatzis, A. (2022). The climate change Twitter dataset. *Expert Systems with Applications*, 204, 117541.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging climate change news. *The Review of Financial Studies*, *33*(3), 1184-1216.

European Central Bank (2021): Climate-related risk and financial stability, July,

www.ecb.europa.eu/pub/pdf/other/ecb.climateriskfinancialstability202107~87822fae81 .en.pdf

Faccini, R., Matin, R., & Skiadopoulos, G. (2021). Are climate change risks priced in the us stock market? (No. 169). *Danmarks Nationalbank Working Papers*.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics,* 33(1), 3-56.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1), 1-22.

Feng, G., Giglio, S., & Xiu, D. (2020). Taming the factor zoo: A test of new factors. *The Journal of Finance*, 75(3), 1327-1370.

Gavriilidis, K. (2021). Measuring Climate Policy Uncertainty. *Available at SSRN*: https://ssrn.com/abstract=3847388.

Groß-Klußmann, A., & Hautsch, N. (2011). When machines read the news: Using automated text analytics to quantify high frequency news-implied market reactions. *Journal of Empirical Finance*, 18, 321–340.

Griffith, J., Najand, M., & Shen, J. (2020). Emotions in the stock market. *Journal of Behavioral Finance*, 21(1), 42-56.

He, X.Z., & Shi, L., (2012). Boundedly rational equilibrium and risk premium. *Accounting and Finance*, 52, 71–93.

Hendershott, T., Livdan, D., & Schürhoff, N. (2015). Are institutions informed about news? *Journal of Financial Economics,* 117, 249–287.

Hirshleifer, D. A., & Shumway, T., (2003). Good day sunshine: Stock returns and the weather. *The Journal of Finance,* 58,1009-1032.

Hong, H., Li, F. W., & Xu, J. (2019). Climate risks and market efficiency. *Journal of Econometrics*, *208*(1), 265-281.

Hsu, P. H., Li, K., & Tsou, C. Y. (2023). The pollution premium. *The Journal of Finance*, *78*(3), 1343-1392.

Hutto, C., & Gilbert, E. (2014, May). Vader: A parsimonious rule-based model for sentiment analysis of social media text. *In Proceedings of the international AAAI conference on web and social media* (Vol. 8, No. 1, pp. 216-225).

Huynh, T. D., & Xia, Y. (2021). Climate change news risk and corporate bond returns. *Journal of Financial and Quantitative Analysis*, *56*(6), 1985-2009.

International Monetary Fund (2020): "Chapter 5: Climate change: physical risk and equity prices", Global Financial Stability Report, no 2020/001, April, www.imf.org/en/Publications/GFSR/Issues/2020/04/14/global-financial-stabilityreport-april-2020#Chapter5.

Jagannathan, R., Ravikumar, A., & Sammon, M. (2017). Environmental, social, and governance criteria: Why investors are paying attention (No. w24063). *National Bureau of Economic Research.*

Kirilenko, A. P., & Stepchenkova, S. O. (2014). Public microblogging on climate change: One year of Twitter worldwide. *Global Environmental Change*, 26, 171-182.

Koenker, R., & Bassett Jr, G. (1978). Regression quantiles. *Econometrica: Journal of the Econometric Society*, 33-50.

Koenker, R., & Machado, J. A. (1999). Goodness of fit and related inference processes for quantile regression. *Journal of the American Statistical Association*, 94(448), 1296-1310.

Kölbel, J., Leippold, M., Rillaerts, J., & Wang, Q. (2020). Does the CDS market reflect regulatory climate risk disclosures? *SSRN*, (3616324).

Littman J., & Wrubel L. (2019): Climate change tweets Ids, *Harvard Dataverse*

Loria, S. (2018). textblob Documentation. *Release 0.15*, 2(8), 269.

Loureiro, M. L., & Alló, M. (2020). Sensing climate change and energy issues: Sentiment and emotion analysis with social media in the UK and Spain. *Energy Policy,* 143, 111490.

Mallucci, E. (2022). Natural disasters, climate change, and sovereign risk. *Journal of International Economics, 139*, 103672.

Nordhaus, W. (2019). Climate change: The ultimate challenge for economics. *American Economic Review*, *109*(6), 1991-2014.

Pástor, Ľ., Stambaugh, R. F., & Taylor, L. A. (2022). Dissecting green returns. *Journal of Financial Economics,* 146(2), 403-424.

Renault, T. (2017). Intraday online investor sentiment and return patterns in the US stock market. *Journal of Banking and Finance*, 84, 25-40.

Samantray, A., & Pin, P. (2019). Credibility of climate change denial in social media. *Palgrave Communications*, 5(1).

Santi, C. (2023). Investor Change Sentiment and financial markets. *International Review of Financial Analysis*, 102490.

Smales, L-L. (2014). News sentiment in the gold futures market. *Journal of Banking and Finance,* 49, 275-286.

Smales, L-L. (2015). Time-variation in the impact of news sentiment, *International Review of Financial Analysis*, 37, 40-50.

Stroebel, J., & Wurgler, J. (2021). What do you think about climate finance? *Journal of Financial Economics*, *142*(2), 487-498.

Sun, L., Najand, & M., Shen, J. (2016). Stock return predictability and investor sentiment: a high-frequency perspective. *Journal of Banking and Finance,* 73, 147–164.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market, *The Journal of Finance*, 62, 1139–1168.

Tetlock, P. C., Saar-Tsechansky, M., & Macskassy, S. (2008). More than words: Quantifying language to measure firms' fundamentals. *The Journal of Finance*, 63, 1437-1467.

Trinks, A., Scholtens, B., Mulder, M., & Dam, L. (2018). Fossil fuel divestment and portfolio performance. *Ecological Economics*, *146*, 740-748.

Tversky, A., & Kahneman, D. (1974). Judgment under Uncertainty: Heuristics and Biases: Biases in judgments reveal some heuristics of thinking under uncertainty. *Science*, 185(4157), 1124-1131.

Wang, K. Y., Chen, C. W., & So, M. K. (2023). Quantile three-factor model with heteroskedasticity, skewness, and leptokurtosis. *Computational Statistics and Data Analysis*, 182, 107702.

Williams, H. T., McMurray, J. R., Kurz, T., & Lambert, F. H. (2015). Network analysis reveals open forums and echo chambers in social media discussions of climate change. *Global Environmental Change*, 32, 126-138.

Yeo, S. K., Handlos, Z., Karambelas, A., Su, L. Y. F., Rose, K. M., Brossard, D., & Griffin, K. (2017). The influence of temperature on #–ClimateChange and #–GlobalWarming discourses on Twitter. *Journal of Science Communication*, 16(5), A01.

Zhang, W., Gong, X., Wang, C., & Ye, X. (2021). Predicting stock market volatility based on textual sentiment: A nonlinear analysis. *Journal of Forecasting*, 40(8), 1479-1500.

Zhang, S. Y. (2022). Are investors sensitive to climate-related transition and physical risks? Evidence from global stock markets. *Research in International Business and Finance*, *62*, 101710.

Table 1: Examples of Climate Change Sentiment Scores (Perceived Climate Risk Proxy)

#	Tweet text	Topic	Sentiment	Stance	Aggressiveness
1	Canada's Prime Minister Stephen Harper announces a new $1.3bn fund to combat climate change.	Importance of Human Intervention	−0.12	believer	not aggressive
2	Well, no snow. At least I'm not in Alaska where its -78 degrees! That's NEGATIVE SEVENTY-EIGHT flippin degrees! Damn that global warming.	Weather Extremes	−0.74	believer	aggressive
3	Why does MSM always accept assumption that CO2 emissions cause global warming? Fail. #msmbias #tcot	Seriousness of Gas Emissions	−0.54	denier	not aggressive
4	Gov. Rick Scott banned the term 'climate change' in Florida. The state was just hit by its worst storm ever.	Importance of Human Intervention	−0.94	believer	not aggressive
5	This humidity is oppressive. It's 6:10am and 27C with 88% humidity. That's unnatural. Which moron said climate change doesn't exist?!	Weather Extremes	−0.93	believer	aggressive
6	Wrapping up a wonderful presentation from IFTF board member, Larry Smarr, on climate change opportunities and dilemmas in the ICT world.	Global stance	0.93	believer	not aggressive
7	Congrats to Paul and the environment team! And thank you to all the residents and groups over the years for pushing our city to do our part in fighting climate change. Amazing work to celebrate today and build upon in days to come! #ygk #ClimateAction	Importance of Human Intervention	0.91	believer	not aggressive
8	30 degrees Celsius outside? So much for global warming...Canada could use warmer winters! #copenhagen #climate #climatechange	Weather Extremes	0.07	denier	not aggressive
9	Anti-Trump chef to Trump: If climate change isn't real, why are you building a sea wall at your golf course?	Donald Trump versus Science	−0.44	believer	aggressive
10	If at this point you still don't believe human activity has a huge effect on #climatechange you are either really uninformed or an idiot.	Ideological Positions on Global Warming	−0.55	believer	aggressive

Source: Effrosynidis et al. (2022)

Table 2: The Effect of Climate Risks on Perceived Climate Risk

Dependent var: Perceived Climate Risk	**Model 1**	**Model 2**	**Model 3**
Physical Climate Risk	-0.019***		-0.064***
	(0.006)		(0.015)
Transition Climate Risk		-0.018***	-0.286***
		(0.007)	(0.080)
Physical Climate Risk * Transition Climate Risk			0.039***
			(0.012)
Constant	0.118***	0.009	0.449***
	(0.044)	(0.009)	(0.104)
Month FE	Yes	Yes	Yes
Observations	472	468	468
R-squared	0.055	0.048	0.087

Robust standard errors are indicated in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3: The Moderation Effect of Climate Attention

Dependent var: Perceived Climate Risk	**Model 4a**	**Model 4b**
Physical Climate Risk	-0.022	-0.049***
	(0.016)	(0.014)
Transition Climate Risk	-0.148	-0.213***
	(0.094)	(0.082)
Physical Climate Risk * Transition Climate Risk	0.031**	0.034***
	(0.013)	(0.011)
SVI_ClimateChange	0.055***	
	(0.013)	
Physical Climate Risk * SVI_ClimateChange	-0.006***	
	(0.002)	
Transition Climate Risk * SVI_ClimateChange	-0.011***	
	(0.002)	
ParisAgreement		0.225***
		(0.066)
Physical Climate Risk * ParisAgreement		-0.016*
		(0.009)
Transition Climate Risk * ParisAgreemen		-0.071***
		(0.016)
Constant	0.056	0.293***
	(0.119)	(0.100)
Month FE	Yes	Yes
Observations	468	468
R-squared	0.159	0.206

Robust standard errors are indicated in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4: Portfolio Sorts Approach

	Perceived Climate Risk	Market Factor	Size Factor	Value Factor	Profitability Factor	Investment Risk Factor	Momentum Factor
Panel A: Market Model							
Quintiles	**0.012*** **	0.976***					
	(0.002)	(0.003)					
Deciles	**0.009*** **	0.976***					
	(0.002)	(0.003)					
Panel B: Fama-French three-factor model							
Quintiles	**0.008*** **	0.960***	0.042***	0.111***			
	(0.002)	(0.003)	(0.006)	(0.006)			
Deciles	**0.006*** **	0.960***	0.042***	0.111***			
	(0.002)	(0.003)	(0.006)	(0.006)			
Panel C: Fama-French 5 factors model							
Quintiles	**0.008*** **	0.984***	0.057***	0.059***	0.103***	0.163***	
	(0.002)	(0.004)	(0.006)	(0.007)	(0.010)	(0.012)	
Deciles	**0.006*** **	0.984***	0.056***	0.059***	0.103***	0.163***	
	(0.002)	(0.004)	(0.006)	(0.007)	(0.010)	(0.012)	
Panel D: Fama-French-Carhart model							
Quintiles	**0.009*** **	0.959***	0.038***	0.089***			-0.039***
	(0.002)	(0.003)	(0.006)	(0.006)			(0.004)
Deciles	**0.006*** **	0.959***	0.038***	0.089***			-0.039***
	(0.002)	(0.003)	(0.006)	(0.006)			(0.004)
Panel E: Fama-French five-factor plus momentum factor model							
Quintiles	**0.008*** **	0.983***	0.051***	0.030***	0.096***	0.178***	-0.057***
	(0.002)	(0.004)	(0.006)	(0.007)	(0.010)	(0.012)	(0.006)
Deciles	**0.006*** **	0.983***	0.050***	0.030***	0.096***	0.178***	-0.044***
	(0.002)	(0.004)	(0.006)	(0.007)	(0.010)	(0.012)	(0.004)

Robust standard errors are indicated in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Quantile Regressions Estimations

	Perceived Climate Risk		
	Quantile = 0.5	**Quantile = 0.75**	**Quantile = 0.90**
Panel A: Market Model			
Quintiles	**0.006****	**0.013*****	**0.022*****
	(0.002)	(0.002)	(0.003)
Deciles	**0.005*****	**0.009*****	**0.015*****
	(0.002)	(0.002)	(0.004)
Panel B: Fama-French three-factor model			
Quintiles	**0.004*****	**0.006*****	**0.008*****
	(0.001)	(0.002)	(0.003)
Deciles	**0.005*****	**0.007*****	**0.010*****
	(0.002)	(0.002)	(0.003)
Panel C: Fama-French 5 factors model			
Quintiles	**0.005*****	**0.007*****	**0.007****
	(0.002)	(0.002)	(0.003)
Deciles	**0.005*****	**0.008*****	**0.010****
	(0.001)	(0.002)	(0.004)
Panel D: Fama-French-Carhart model			
Quintiles	**0.003***	**0.006*****	**0.010*****
	(0.002)	(0.002)	(0.004)
Deciles	**0.005*****	**0.007*****	**0.012*****
	(0.001)	(0.002)	(0.003)
Panel E: Fama-French five-factor plus momentum factor model			
Quintiles	**0.004*****	**0.006*****	**0.006****
	(0.001)	(0.001)	(0.003)
Deciles	**0.005*****	**0.008*****	**0.009*****
	(0.001)	(0.002)	(0.002)

Robust standard errors are indicated in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6: Bayesian adaptive Markov Chain Monte Carlo (MCMC)

	Perceived Climate Risk					
	Mean	Standard deviation	MSCE	Median	2.5th	97.5th
Panel A: Market Model						
Quintiles	**0.012*** **	0.002	0.000	0.012	0.007	0.016
Deciles	**0.009*** **	0.002	0.000	0.009	0.005	0.012
Panel B: Fama-French three-factor model						
Quintiles	**0.008*** **	0.002	0.000	0.008	0.004	0.013
Deciles	**0.006*** **	0.002	0.000	0.006	0.003	0.009
Panel C: Fama-French 5 factors model						
Quintiles	**0.008*** **	0.002	0.000	0.008	0.004	0.012
Deciles	**0.006*** **	0.002	0.000	0.006	0.003	0.009
Panel D: Fama-French-Carhart model						
Quintiles	**0.009*** **	0.002	0.000	0.009	0.004	0.013
Deciles	**0.006*** **	0.002	0.000	0.006	0.003	0.010
Panel E: Fama-French five-factor plus momentum factor model						
Quintiles	**0.008*** **	0.002	0.000	0.008	0.004	0.012
Deciles	**0.006*** **	0.001	0.000	0.006	0.003	0.009

Bayes Estimations with 12500 MCMC iterations, 2500 Burn-in, 10000 MCMC sample size
Robust standard errors are indicated in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Fama-Macbeth Approach

VARIABLES **Dep var: Excess Return**	**Panel A: Market model**	**Panel B: Fama-French 3 factors model**	**Panel C: Fama-French 5 factors model**	**Panel D: Fama-French-Carhart model**	**Panel E: Fama-French five-factor plus momentum factor model**
Perceived Climate Risk	**0.003**	**0.005***	**0.005***	**0.005***	**0.005***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Market Factor	-0.001	-0.001	-0.001	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Size Factor		0.001	-0.001	0.001	-0.001
		(0.000)	(0.001)	(0.000)	(0.001)
Value Factor		-0.001	-0.001	-0.001	-0.001
		(0.000)	(0.001)	(0.000)	(0.001)
Profitability Factor			0.001		0.001
			(0.000)		(0.000)
Investment Factor			-0.001		-0.001
			(0.000)		(0.000)
Momentum Factor				0.001	-0.001
				(0.001)	(0.001)
cons	0.002**	0.002***	0.003***	0.002**	0.002***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
Observations	195,882	195,882	195,882	187,547	187,547
R-squared	0.193	0.388	0.611	0.468	0.681
Number of groups	423	423	423	406	406

Newey Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Factor Zoo Tests (monthly frequency)

VARIABLES **Dep var: Excess Return**	**Panel A: Fama-French 3 factors model**	**Panel B: Fama-French 5 factors model**	**Panel C: Fama-French five-factor plus momentum factor model**	**Panel D: 15 recent factors from 2012 - 2016**	**Panel E: All 150 factors**	**Panel F: Double Selection Lasso**
Perceived Climate Risk	**0.066*****	**0.064*****	**0.067*****	**0.164*****	**0.074****	**0.158****
	(0.008)	(0.008)	(0.008)	(0.009)	(0.037)	(0.077)
Observations	56,407	56,407	56,407	44,502	44,502	44,502

Robust standard errors are indicated in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9: Pricing effect of perceived climate risk with subgroups: (1) Pre-2015; (2) Post-2015

	Perceived Climate Risk	
	Pre-2015	**Post-2015**
Panel A: Market Model		
Quintiles	**0.005***	**0.016*****
	(0.003)	(0.004)
Deciles	**0.003**	**0.012*****
	(0.002)	(0.002)
Panel B: Fama-French three-factor model		
Quintiles	**0.005***	**0.010*****
	(0.003)	(0.003)
Deciles	**0.003**	**0.009*****
	(0.002)	(0.002)
Panel C: Fama-French 5 factors model		
Quintiles	**0.005***	**0.008****
	(0.003)	(0.003)
Deciles	**0.003**	**0.008*****
	(0.002)	(0.002)
Panel D: Fama-French-Carhart model		
Quintiles	**0.005***	**0.009*****
	(0.003)	(0.003)
Deciles	**0.003**	**0.008*****
	(0.002)	(0.002)
Panel E: Fama-French five-factor plus momentum factor model		
Quintiles	**0.005***	**0.007****
	(0.003)	(0.003)
Deciles	**0.003**	**0.007*****
	(0.002)	(0.002)

Robust standard errors are indicated in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 10: Pricing effect of perceived climate risk with subgroups: (1) Non-Energy Sector; (2) Energy Sector

	Perceived Climate Risk	
	Non-Energy Sector	**Energy Sector**
Panel A: Market Model		
Quintiles	**0.007*****	**0.077*****
	(0.002)	(0.012)
Deciles	**0.005*****	**0.056*****
	(0.002)	(0.009)
Panel B: Fama-French three-factor model		
Quintiles	**0.006****	**0.057*****
	(0.002)	(0.012)
Deciles	**0.004****	**0.042*****
	(0.002)	(0.008)
Panel C: Fama-French 5 factors model		
Quintiles	**0.004***	**0.056*****
	(0.002)	(0.012)
Deciles	**0.004****	**0.042*****
	(0.002)	(0.008)
Panel D: Fama-French-Carhart model		
Quintiles	**0.006****	**0.060*****
	(0.002)	(0.012)
Deciles	**0.004****	**0.042*****
	(0.002)	(0.008)
Panel E: Fama-French five-factor plus momentum factor model		
Quintiles	**0.005****	**0.059*****
	(0.002)	(0.011)
Deciles	**0.004****	**0.044*****
	(0.002)	(0.008)

Robust standard errors are indicated in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$