# PEELING AWAY THE LAYERS OF NEWS: CLIMATE CHANGE SENTIMENTS AND FINANCIAL MARKETS.

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*Manchester, July 23, 2021.*

# Declaration

The candidate confirms that the work submitted is her own. Furthermore, the candidate has not submitted this thesis for any other qualification at this or any other institution. The candidate would like to give credit to those whose references have been used in this work. The following chapters of this thesis have been presented to conferences as well as submitted to peer-reviewed journals.

**Chapter 1** was used in Tran, Phuong Anh & Liu, Jia (2020), "PEELING AWAY THE LAYERS OF NEWS: CLIMATE CHANGE UNCERTAINTY AND DISAGREEMENT IN U.K STOCK MARKET.", BAFA Annual Conference and Master Class 2020.

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# List of abbreviations

| | |
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| **DoS:** | Divergence of sentiment (disagreement sentiment) index. |
| **UNC**: | Uncertainty sentiment index. |
| **LM**: | Loughran and McDonald text lexicon classification. |
| **WM**: | WMatrix semantic tagging classification. |
| **ESG**: | Environment – Social – Governance factors. |
| **OECD**: | Organisation for Economic Co-operation and Development. |
| **EUT:** | Expected Utility Theory. |
| **PT**: | Prospect Theory. |
| **MEU**: | Maxmin Expected Utility. |
| **FTSE100:** | share index of the 100 companies listed on the London Stock Exchange with the highest market capitalisation. |
| **SMB:** | Small minus big factor. |
| **HML:** | High minus low factor. |
| **PSM:** | Propensity Score Matching. |
| **DiD:** | Difference in difference model. |
| **POS**: | Part of speech. |
| **SIC:** | Standard Industrial Classification. |
| **BW**: | Baker and Wurgler's investor sentiment index. |
| **UM:** | University of Michigan's consumer sentiment index. |
| **EPU**: | Economic Policy Uncertainty. |
| **CCU**: | Climate-change induced uncertainty. |
| **PSU**: | Political stability uncertainty. |
| **IMF:** | International Monetary Fund . |
| **ND-GAIN:** | The Notre Dame Global Adaptation. |
| **MSCI:** | Morgan Stanley Capital International. |
| **ICLN:** | iShares Global Clean Energy ETF ticker. |
| **TAN:** | Invesco Solar ETF. |
| **CBI**: | Climate Bonds Initiative. |

# Abstract

Unlike other news, climate news conveys the uncertainty around the substantial trajectory and the economic consequences of climate change. Since solutions to climate change are uncertain, unknown, or undesirable, climate change news may trigger counter-productive responses like denial, avoidance, and disagreement; thus, news on climate change becomes an excellent source for disagreement and uncertainty. This thesis examines the effect of climate disagreement and uncertainty sentiments on stock performances in the U.K. Based on a large sample of climate news with data set of 3,747,807 daily observations in the sample window from 2008 to 2019, the results from panel regression models show that both disagreement and uncertainty sentiments are positively associated with daily trading volume and future stock price volatility. The positive relations between disagreement and uncertainty sentiments with stock volatility are vital for firms operating in environmentally sensitive industries. Furthermore, disagreement and uncertainty sentiments induce significantly more positive trading volumes but less positive abnormal returns for firms without ESG scores than those who have ESG score available. I also propose and implement a procedure to hedge climate change risk in the second chapter dynamically. As I found in the previous chapter that sentiments in climate change news significantly impact stock performance, the thesis builds a portfolio model to hedge against these news innovations (i.e., news-based sentiment or climate change topics) as well as other national-level uncertainties. A mimicking portfolio approach is then used to build climate change hedge portfolios. I discipline the exercise using ESG performance and ESG report scores for firms in different industries to model their climate risk exposures. The thesis constructs an effective hedge portfolio to mitigate the risk posed by climate change and national-level uncertainties. Climate risk does not impact only the stock market but also the bond market. The green bond market has been growing swiftly internationally since its first introduction in 2007. One of the biggest challenges the green bond market faces is the "greenwashing" concern. Greenwashing exploits investors' genuine environmental concerns, which create problems such as limiting investors' ability to make actual environmentally friendly decisions or generating confusion and skepticism towards all products promoting green credentials, including those that are genuinely more environmentally friendly. Using a sample of green bonds from five countries spanning from 2007 to 2019, this study is the first empirical study that detailed environmental performance's natural effect of green bond issuance by firms during 2007–2019, using propensity score matching and Difference in Difference model. Furthermore, the third chapter's results show strong evidence that climate communication plays an essential role in firms' commitment to improving their environmental footprint.

# Introduction

## 1. Research outline

### *1.1 Gaps of knowledge and research questions*

Threats from climate change and global warming pose the need to rethink our societies' structure and our economies' functioning. It is estimated that an amount of USD 6,9000 billion is needed for the next fifteen years for OECD countries to cope with the 2 degrees Celsius trajectory (OECD, 2017). In order to mobilise such amounts, both public fundings and private investments play essential roles.

Recently, financial investors have paid more significant attention to environmental topics and integrated them into their portfolios. Investors concerned about the environmental impacts of financial projects tend to modify their asset allocation by overweighting the assets provided by green companies while underweighting or disinvesting non-green companies. There are two main motives drivers of this asset allocation. Firstly, investors have pro-environmental non-pecuniary preferences that value green projects more highly, regardless of their expected returns. These investors are willing to sacrifice part of their returns by excluding polluting companies because of their environmental beliefs. The second motive is to hedge against environment-related financial risks. These risks involve litigation risks (Salzman and Hunter, 2007), environmental transition risks (Jakob and Hilaire, 2015), or physical risks (Arnell and Gosling, 2016). These risks are relatively new to the market; thus, they are likely to be imperfectly priced.

Regardless of the motivations, modification in the asset allocation of green investors may alter the prices and return equilibrium and affect firms' cost of capital. The former makes up the asset pricing approach of green investment in academic finance, while the latter represents part of the "impact investing" aspect that is newly introduced recently.

Up to date, there is little systematic research on these two impacts of climate-related investment. Significantly, the extends of climate change scales, and consequences up to this point are unknown and only approximately estimated. Thus, studies in climate communication also concern over fears that may appeal to climate change highlighted in the news, which may trigger counter-productive responses such as denial, avoidance, and disagreement since the solutions are uncertain, unknown, or undesirable (Lazarus, 1999, Hastings et al., 2004). Therefore, in this thesis, I focus on the following three main research questions:

- How do markets react to and price national-level climate change risks, especially climate-related disagreement and uncertainty sentiment risks conveyed in public news [Chapter 1].
- Whether firms' sustainability performance and reporting scores are sufficient to hedge against several sources of climate change risks [Chapter2].
- Are green-bond issuers genuinely committed to improving their footprint post-issuance and continue to do so when there are higher climate change uncertainties? [Chapter 3].

The three chapters in this thesis will concentrate on answering each of the above questions, respectively.

### *1.2 Aim of research.*

This thesis aims to evaluate the extensive impact of disagreement sentiments and different sources of uncertainty in the U.K stock market as well as the global market worldwide.

### *1.3 Justification for the research*

In this thesis, chapters 1 and 2 focus on the U.K stock market, while chapter 3 expanded the research to five other countries. The rationale for this choice is that the U.K stock market is one of the largest markets all over the world, while its capital – London – is said to remain Europe's and global financial capital (Bloomberg, 2017). The market, therefore, attracts many investors, both local and foreigners, as well as witnesses a considerable number of changes and movements of stock daily. As a result, it is crucial to investigate the causes of stock movements, from having a clear forecast for future performance.

The main climate risks measured in this thesis are sentiments retrieved from public news. The purpose of textual analysis is to find the tone in any written or spoken form. Throughout many years of research, it shows sufficient evidence on how information helped investors to increase their investment quality from the amount of time used for information search, several sources used for gathering integrated information for decision making (Claxton et al., 1974, Kiel and Layton, 1981, Klein and Ford, 2003). Many prior pieces of research prove that trading frequency is positively influenced by information acquisition (Abreu and Mendes, 2012, Barlevy and Veronesi, 2003). In order to theoretically explain this relationship, Peress (2004) states that the more information received or increased the precision, the more investors are willing to trade in riskier assets and expect higher returns. More information acquisition combined with riskier investment resulted in a frequent investor adjustment in their portfolio, thus boosting trading volume.

However, humans often have limited information and decide based on the small samples they got. As behavioural biases and sources of information are recognised as important factors to explain the market anomalies and stock moment, there must be a relationship between human cognitive biases and the news that investors receive. It is still argued how investors interpret textual sentiment and apply it to their decision-making process (Kearney and Liu, 2014). Identifying hidden sentiments that drive the stock market contributes to quantitative informational measures a step closer to a more accurate price formation process. It is essential to dredge all possible causes of price movement for academic use and study how different human cognitive truly impact decision-making processes.

## 2. Environmental investing.

### *2.1 Asset pricing approach*

The modern portfolio theory introduced by Markowitz (1952), as well as risk factors presented by Fama and French (1996) and Carhart (1997), are known to explain the dynamics of asset returns, they are often insufficient to explain the impact of climate change risks on asset return and performances. A host number of studies have highlighted the effects of climate change on firms' returns. Studies in the macroeconomy aspect recognized that climate change, which causes extreme weather (e.g., rising sea level, drought, and flooding), negatively affects economic development. Climate change can impact businesses in several ways (Henderson et al., 2018, Jia and Li, 2020). First, physical climate change can directly impact firms' intangible assets as well as their operation. For example, nearby coastal areas may have their property and equipment damaged directly by rising sea levels. Business activities and manufacturing activities may have to stop by flooding (e.g., flood affects logistic process) or drought (if water is required for operations. Vulnerabilities of firms' production processes to natural disasters raised by climate change can inflict significant loss to corporate profits. Second, policies on climate change may lead to firms' financial stability risk (Carney, 2015). For example, future carbon prices or taxes will damage firms with higher exposure to carbon assets. This problem is referred to "stranded asset issue". The impact of climate policy can be more severe for firms operating in the mining industry or those whose manufacturing process relies mainly on high-emission materials.

Due to the aforementioned potential risks brought by climate change, regulators are increasingly concerned about how efficiently the stock market price the climate change risks. Climate change emerges as an essential aspect for investors when accessing a firm's businesses and its related risks. Most investors, particularly long-term and ESG-oriented ones, choose risk management over divestment to be a better method for tackling climate risk (Krueger et al., 2020, Choi et al., 2018, Shmidt, 2015).

Although there is evidence of growing attention from investors on climate change risk, the markets have had little experience dealing with such risks; thus, they may either overreact or underreact to these risks as a result. Chapter 1 in this thesis focuses on studying climate change risks from different resources on stock markets.

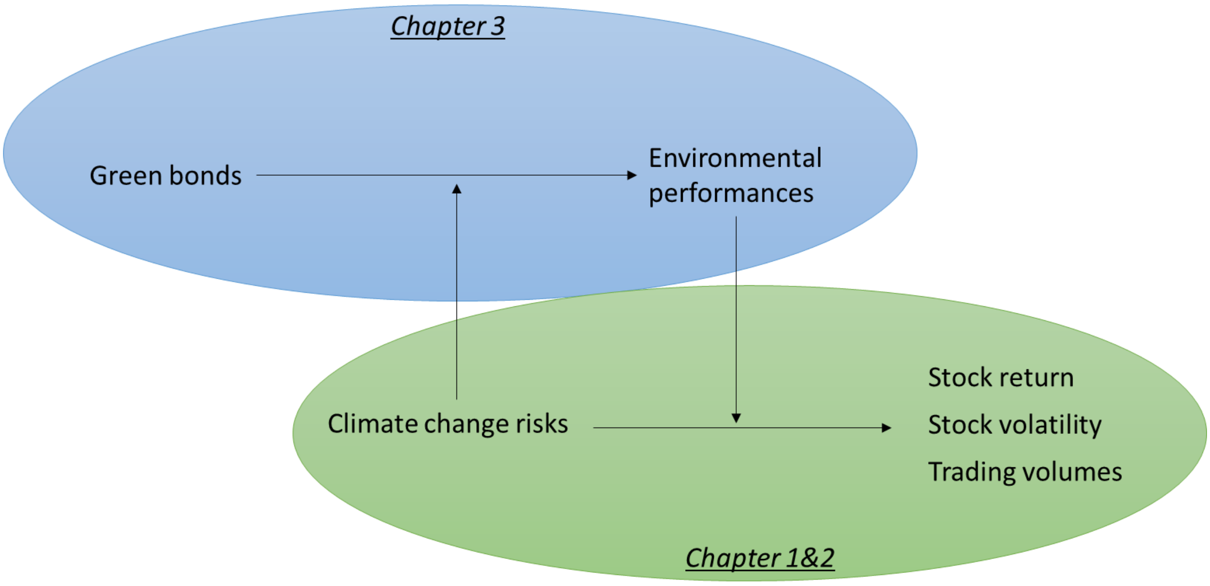
Since climate change risk may drive firms' stock returns and stock volatility, it poses an asset pricing risk to investors' portfolios. Pro-environmental investors, driven by pecuniary motive, may seek solutions to hedge against these risks. One way to form a climate-related hedge portfolio is to use firms' environmental ratings. A host number of researchers have pursued to shed light on how firms' sustainability engagements can impact their returns. However, up to this point, results from this line of literature are mixed. For example, Barber et al. (2020) and Renneboog et al. (2008) demonstrate that firms' environmental performances are negatively associated with their financial performance. Especially, El Ghoul et al. (2011) and Chava (2014) observe the same relationship with expected returns. Interestingly, Bolton and Kacperczyk (2020b) and Hsu et al. (2019) indicate that companies with higher greenhouse gas emissions experience higher returns than those with lower emissions. On the other hand, the positive relationship between firms' environmental and financial performances are found in the researches of Eccles et al. (2014a), Krüger (2015), and Statman and Glushkov (2016). Notably, Krüger (2015) reveals that investors react significantly negatively when there is more negative news regarding corporate environmental engagement. In addition, some other studies do not find any significant association of firms' environmental performance with their financial performances (e.g., Bauer et al. (2005) and Galema et al. (2008)).

Based on the literature on decision-making theory, especially on uncertainty and disagreement theories, I shed empirical light on the benefit of using firms' environmental rankings to hedge against climate change risks in the second chapter of this thesis.

### *2.2 Impacting investing approach*

As discussed in the first two chapters of this thesis, firms' environmental investments impact their asset' expected returns; thus, it may also change capital costs for firms. For example, Pastor et al. (2019) demonstrate that the most polluting firms suffer a higher cost of capital than those who are less polluting. With a lower cost of capital, companies have a better resource to improve the environmental theory footprint and mitigate their environmental effect. However, firms with extra resources may not always be committed to improving their environmental footprints. One problem with this asset pricing perspective concerns greenwashing activities, especially in the bond market. This concern results from a lack of uniform standards that validate that the funds are used accurately to green projects that firms marketed. The emergence of green bonds, especially the growing liquidity of these assets, presents a favourable framework for identifying the impact of financial investment flows on the environment. In the third chapter of this thesis, I approach this impact investing perspective by investigating whether green bonds issuers improve their green investments post-issuance.

***Figure 1: Main research approaches in the thesis***




## 3. Decision-making theory and information.

Decision theory studies the reasons for an agent's choices. In order to explain the question of why people make such choices, decision theory includes two branches: normative (prescriptive) or positive (descriptive) decision theory (Hansson, 2005).

On the one hand, normative decision theory looks for the best decision within a particular circumstance. Decision-makers in normative decision theory are entirely rational and able to make perfect accuracy. On the other hand, positive decision theory tends to describe decision makers' behaviours and identify the consistent rules out of it.

Risk management is one of the most critical participants in the decision-making process. Interestingly, the risk perception of each individual is influenced by psychology.

### *3.1. Normative decision theory – Expected Utility Theory (EUT)*

Bernoulli (1954) is one of the most well-known and preferred theories by many researchers since it represents the rational behaviour of people under uncertainty. First introduced by Bernoulli (1954), the theory promotes the importance of people's preferences regarding decisions that have uncertain results (such as gambles). According to the theory, the expected value is the probability-weighted average of a mathematical outcome. In contrast, if some specific axioms are met, the subjective value of an individual's gamble will be equal to that individual's expected valuations from that gamble's outcome.

In 1944, von Neumann and Morgenstern introduce the utility theorem, which provides sufficient conditions for EUT (Von Neumann and Morgenstern, 1944). Four axioms define an entirely rational decision-maker in the theorem, including independence, transitivity, completeness, and continuity. If an individual always behaves like those four axioms, there will be a utility function in which that person will prefer one gamble to others if and only if the expected utility of that one is more than that of the others. This model has been used as a descriptive model of economic behaviour and is considered a normative decision-making model of choice under uncertainty. The model suggests that rational people would take riskier actions to maximise their expected value.

However, EUT is also put under criticism since many violations have been found in the empirical application, and the theory has been questioned for many events as it contains "systematically mispredicted human behaviour" (Shiller, 1999). The utility of wealth in Bernoulli's theory states that if two people with the same amount of wealth and other things are equal, then those two people should be happy equally. However, in practice, it is argued by Rabin and Thaler (2001) that the utility of wealth cannot mathematically explain the loss aversion since one person with £2m but has just lost £1m cannot be as happy as another one who had £500 and just gained £500 even though eventually both of them hold £1m in hand.

One of the vital behavioural assumptions of EUT, which is the “independence axiom”, has been proved to be systematically violated in experimental studies. Allais (1953) presents the Allais paradox as a choice problem that illustrates the inconsistency between the observed choices with EUT's prediction. While EUT predicts that when the certainty increases but not the price, people are supposed to stick with their preference, Allais paradox proved that if the certainty of an outcome increases either in constant or the price, individuals will change their preference toward a more certain outcome. In 1982, Mark J. Machina challenged the normative and descriptive power of EUT by proving that the results of EUT analysis do not base on the independence axiom (Machina, 1982).

**Ambiguity aversion theory**

Even though in normative theory, Savage (1954) states that there is no difference between the choices containing clear outcomes (risk) and the choices containing vague outcomes (ambiguity), in practice, people do prefer the former to the latter in the process of making a decision. This phenomenon is the ambiguity aversion which is discovered by the work of Ellsberg (1961a). Since the introduction of ambiguity aversion, studies in psychology and experimental economics have proved that people incline to hate feelings to events of ambiguity, in which the outcomes related to different nature states are unidentified. Many economists have claimed that ambiguity is linked to financial markets because the probabilities of profit distribution are not acknowledged. Driven by this remark, the concept of ambiguity is tested for many applications in finance. One of the robust estimations from theoretical portfolio choice models is that, with the existence of ambiguity, stock market participation has a tendency to be lower than forecasted from the basic EUT model and has negative relation with the changes of ambiguity in the market (Maenhout, 2004a, Cao et al., 2005a, Epstein and Schneider, 2010). This prediction, later, is tested with raw financial data in the paper of Antoniou et al. (2015). The researchers conclude that the hypothesis that rises in ambiguity is related to the outflows of equity funds and significantly lessens the likelihood that households invest in stocks.

### *3.2. Descriptive decision theory – Prospect Theory (P.T.)*

As the emergence of human behavioural aspects and in line with RDU, Prospect Theory (P.T.) is introduced by Kahneman and Tversky (1979) as evidence and solution of the EUT's systematic behavioural violation. The theory challenges the use of utility functions by taking risk aversion into account and becomes the most competing model of EUT in the line of non-expected utility.

As a behavioural economic theory, Kahneman and Tversky discovered three regularities in P.T. as the decision-making process of humans while the probabilities of outcomes are unknown. Firstly, losses emerge more apparent and more significant than gains in the real-life human decision-making process. The second indicates that people pay more attention to changes in their preferred utility than absolute utilities. Moreover, the last one implies that the prediction of subjective probabilities is biased due to anchoring. In order to extend the previous work, Tversky and Kahneman (1992) estimate that with the coefficient of loss aversion of 2.25, the value function is moderately convex (concave) over losses (gains).

In 1995, Benartzi and Thaler (1995) bring the prospect theory into practice using prospect theory utility functions to calculate portfolios. Two researchers improve the richness of the model with an investor's characteristic named myopic loss aversion, where loss-averse investors tend to accept higher risk when they rarely evaluate their investment performance. Barberis and Thaler (2002) suggest that among all non-expected utility theories, the prospect theory may be considered the most promising for successfully capturing the experimental results. Barberis and Thaler (2002) study the economy in that investors' utilities is not only arose from consumption but also the instabilities in the value of their wealth. In the argument of those two researchers, investors are loss aversion also against the fluctuations in their total wealth, and the level of loss aversion depends on the results of previous investment results. By incorporating the prospect theory, their models can explain the additional volatility, the predictability of the stock market, and especially the low connection between returns and consumption development.

**Risk aversion theory**

According to behavioural finance, gains and losses experienced previously by humans will affect behaviour differently. The behavioural theory emphasises risk aversion theory that investors will brace risk-taking according to the prior losses they get while exhibiting risk aversion (loss aversion) when they have prior gains. This behaviour encourages investors to gamble and "to seek risk when faced with possible losses, and to avoid risk when a certain gain is possible" (Kahneman and Tversky, 1979, Benartzi and Thaler, 1995). Risk aversion follows the psychology principle that a decline in utility rising out of the awareness of losses relative to gains encourages investors to sell good performance stocks rather than losing stocks. Through the disposition effect, evidence of this phenomenon is found by Odean (1998) and Barber and Odean (2001), who show that investors tend to hold on to the losers and sell winners.

### *3.2.1 Disagreement theory*

Another factor of ambiguity in the decision-making process is disagreement. One might argue that it is inevitable that there will be disagreement where scientific uncertainty exists; however, these two do not amount to the same scale. It might be disagreement among people on the origins and extent of particular subjects where uncertainty occurs. Especially, climate change news is now filled with disagreement and uncertainty. It is unknown how much damage global warming would cost for the economies and lives on Earth, and people usually disagree with each other on how humans should act to protect everyone's life. However, the scale of disagreement is different by the topic. Most people agree that people need to reduce their waste and companies need to decrease carbon emission usage, but when it comes to the question 'How?', they often disagree more with current eco-solutions, since they may produce even more carbon than they save and if it is worth to sacrifice the business for an uncertain future.

Our prediction is developed from the literature of disagreement with evidence from Karpoff (1986), Atmaz and Basak (2018) that the more disagreement occurs, the higher frequency of trading. Furthermore, Banerjee and Kremer (2010) point out that when investors disagree about interpreting a piece of information, the level of disagreement is reflected through the trading volume, thus affecting volatility.

While there are some characteristic differences, disagreement and uncertainty still have a similar upshot in the decision-making model: they do not deliver an exact source of the decision problem as required by the standard decision-making model, and both can drive investors away from the correct decisions.

### *3.2.2 Cognitive bias theory*

a. Cognitive bias: ambiguity effect

Among cognitive biases related to the theory of ambiguity, aversion is the ambiguity effect, which affects individual investors' formation, thus impacting business and economic decisions. Ellsberg (1961a) first introduces this cognitive bias, describing that when information received is missing or vague, decision-makers tend to prefer the options for which the probability of favourable income is known rather than unknown probability.

A host number of theoretical models can predict more robustly than the original Expected Utility (E.U.) model that when people have to face ambiguity, financial market participation is reduced (Easley and O'Hara, 2009, Cao et al., 2005a). Epstein and Schneider (2010) stress that ambiguity can induce investors' willingness to invest in financial markets.

Epstein and Schneider (2008), Illeditsch (2011) suggest that ambiguous information received by investors can lead to enormously high price volatility. Ozsoylev and Werner (2011) prove that ambiguity can raise the price volatility in which the excess volatility is when that price volatility surpasses payoff volatility.

b. Cognitive bias: Negativity bias

The negativity effect is when there is a more significant negative effect (e.g., unpleasant news, emotions, risk facing) versus positivity stimuli on a subject. That foundation logic is developed by Peeters (1971) and is proved and explained in the papers of Beach and Strom (1989). Extensive research has been done on the advantage of negative information in processing positive information. Researchers argue that this process might be an essential part of human evolution and survival function (Rozin, 2001). It is proved that negative information can be detected easier and quicker than positive information (Aarts and Dijksterhuis, 2003). Negative information is said to prepare humans the cautiousness, thus, avoiding potential dangers. These findings are consistent with the loss aversion theory of Tversky and Kahneman (1992), which indicates that people tend to avoid losses rather than gaining profit even though they are equal possibilities.

Because negative information is detected and preferentially processed, it is predicted that negative information is more likely to survive through social transmission. Negativity bias was investigated initially in examining rumour spread. Fessler et al. (2014) discovered three times of hazards information in urban legends more than that of benefits one. However, it is argued that this evidence is only indirect as only the products of social transmission were used for the methodological approach. In order to test whether a negativity bias shapes the contents of stories, psychologists examined the social transmission process directly through the reproduction method. Such research results from Bebbington et al. (2016) revealed that unambiguously adverse events preferentially survive across successive transmission processes.

c. Negativity and uncertainty relation

The impact of individual negativity or uncertainty has been well documented in neoclassical and behavioural finance literature. Some studies in behavioural literature suggest that when investors face a high possibility of losses, they tend to embrace the ambiguity, while in case of a high possibility of gains, they may decide based on ambiguity aversion. For instance, the 'fear' effect (ambiguity aversion) is found in the paper of Viscusi and Chesson (1999) for little possibilities of loss, while the 'hope' effect (ambiguity-seeking) is detected for the significant possibility of gain. When the risk is neutral, Maffioletti and Santoni (2005) and Wakker et al. (2007a) find the ambiguity seeking in trading behaviour of the individual agent. The combined effect, thus, has been proved to be significant, and one should not study risk-return relation without taking ambiguity into account (Brenner and Izhakian, 2018). Since uncertainty sentiment represents ambiguity and negative sentiment represents a risk, it raises the question of how ambiguity will move the prices with negativity. The question of how exactly the combined effect of both risk and uncertainty (or negativity bias and ambiguity effect) has on returns has not been studied widely. In the paper of Bird et al. (2013), more significant price drift is detected when the market received greater information uncertainty. The researchers also find higher expected returns towards good news and lower expected returns towards bad news due to larger information uncertainty. My prediction is in line with theoretical models developed within ambiguity effect and negativity bias and is hoped to provide the same evidence. Thus, the paper wishes to detect stronger stock price movement and volume when uncertainty is taken under consideration along with other negativities compared to solely uncertainty sentiment.

## 4. Contributions

### *4.1. Chapter 1*

In the first chapter, I demonstrate from a practical perspective how climate change risks are drawn from the news affect investors' trading behaviours and drive the stocks' abnormal returns. In particular, for climate change risk, I focus on the climate-related disagreement and uncertainty sentiments conveyed in public news. This collection of climate news is collected from four broadsheets (The Wall Street Journal, The Financial Times, the Daily Telegraph, The Guardians) and two more middle-class publications (The Times and The Independent) to have a well-mixed news source of intelligent and respectable news. The index of disagreement and uncertainty sentiments are then constructed from this climate change news based on a well-known dictionary of (Loughran and Mcdonald, 2011) (hereafter L.M.) and corpus analysis and comparison tool developed by Lancaster University (Rayson, 2008) (hereafter L.M.). For brevity, I only report results from the model using Loughran and McDonald's dictionary in chapter 1.

Several studies in the literature have evidenced the impact of sentiments on stock markets. For example, it is found that negative sentiment induces the market prices instantly (Tetlock, 2007, García, 2013) and negatively impacts next-day abnormal returns. On the other hand, Jegadeesh and Wu (2013) and Davis et al. (2015) claim that both positive and negative sentiments significantly influence the event or post/event returns. The news, which is of more attention, regardless of negative or positive, all have power in changing the subsequent trading period returns.

Instead of examining the negative and positive sentiments separately, I followed Siganos et al. (2017) and study the relationship of these two sentiments and form a disagreement sentiment measure. In addition, I also investigate the impact of uncertainty sentiments in the stock market. I show that climate-related disagreement and uncertainty sentiments are positively associated with daily trading volume changes and future volatility when controlling for a large set of firm-level and economic variables. These results are in line with disagreement theory and ambiguity theory that when investors interpret the same piece of news differently, they trade according to their diverged beliefs, leading to higher stock trading volumes and volatility (Banerjee and Kremer, 2010).

Furthermore, I also documented that climate-related disagreement sentiments reduce stock's abnormal returns while uncertainty sentiments increase. These different reactions of abnormal stock return to disagreement and uncertainty sentiments justify our motivation to study disagreement and uncertainty separately. I argue that these two sentiments have a different impact on stock markets and should be studied thoroughly, especially regarding climate change. One might argue that it is inevitable that there will be disagreement where scientific uncertainty exists; however, these two do not amount to the same scale (Glas and Hartmann, 2016b, Rich and Tracy, 2018). There may be disagreement among people on the origins and extent of climate change uncertainty.

Lastly, I demonstrate that firms sensitive to climate change news (e.g., those operating in environmentally sensitive industries, have lower ESG scores, or do not disclose sustainability information) face significantly higher stock volatility than other firms during higher disagreement uncertainty sentiments. Also, firms' stock volatility is affected more when disagreement and uncertainty sentiments are associated with the news's physical climate and social climate topics.

One possible explanation why news disagreement and uncertainty sentiments can lead to positive abnormal stock returns while leading to an increase in stock volatility is noise trading theory (Trueman, 1988). There could be noise traders or sentiment traders who actively trade in the stock market, especially in active trading months (e.g., January). When climate change news is first released, it will be interpreted differently between optimistic and pessimistic traders. Diverging opinions of investors lead to widespread stock prices, resulting in higher stock price volatility. Additionally, price is also pushed far away from its fundamental value, creating high returns for stock at the beginning. After a short time, rational and informed traders will eventually step in, and prices are set up back to fair value.

### *4.2. Chapter 2*

As described in the first chapter, since climate change risks in news increase firms' stock volatility and firms sensitive to climate change news tend to face significantly higher stock volatility, investors need to hedge against these risks. I extend the mimick portfolio approach studied in Engle et al. (2020). Specifically, I use four hedge targets that present climate risks: disagreement sentiments, uncertainty sentiment, physical climate coverage, and climate change-induced uncertainty. The findings reveal that throughout all models of the four hedge targets, the hedge portfolio constructed using either environmental reporting scores or performance scores performs similarly to each other in in-sample models. Nevertheless, the former performs better in out-of-sample models than the latter. Noticeably, when comparing out-of-sample and cross-validation fit, the significant differences in the results between these two measures imply that our hedge portfolios' returns are dependent on the training set's time series. This result may be due to the lack of consistent ESG and environment scores for all firms. Since the growing evidence that a firm's sustainable engagement connects strongly to performance focuses on the investor's attention on ESG, our hedge portfolio can benefit from a more completed and regulated ESG data system.

### *4.3. Chapter 3*

In the third chapter, I show how green investing can influence companies' environmental practices, especially green bonds issuers who promised to improve environmental theory practices. Being motivated by a growing discussion around green investments and bridging the literature gap, I examine the green bond's role in reducing information asymmetry and potential factors that may impact firms' environmental performance post-issuance. I design a quasi-experimental model that studies the changes in firms' (i) emissions consumption, (ii) ESG, and environment scores between the green bond issuers and non-green bond issuers. The findings disclose that post green bonds issuance;

firms' $CO_2$ consumption still increases. This result is because most green bond issuers have the environment as the core to the firms' operations (e.g., utilities, energy, transportation).

In contrast, I observe that $CO_2$ per one million in marker value significantly dropped 12.9% after issuing green bonds. Consistently, after issuing green bonds, the issuers' environment and social score increase significantly by 4.6 and 9.8 points, respectively. Our results support the signaling argument that green bonds serve as a credible signal that shows the market that firms intend to improve their environmental footprint.

Additionally, I use disagreement and uncertainty sentiment in climate change news, climate change-induced uncertainty, economic policy uncertainty, and political uncertainty to show that national-level uncertainty is negatively related to firms' environmental performance following green bond issuance. From a theoretical standpoint, these findings support the real options theory.

Last, I evidence that climate communication plays an essential role in firms' commitment to improving their environmental footprint. Especially, climate news related to physical climate change and climate policy encourages firms to commit better to sustainability. In particular, green bond issuance signals an increase in firms' environmental engagement, and climate change topics related to physical climate and climate policy help to boost this development by 25.07 times and 10.79 times, respectively.

## 5. Significant implications for the finance industry

The findings of this thesis have several implications for finance industries. Firstly, my studies show that apart from generic sentiments being studied (e.g., positive, and negative sentiments), disagreement and uncertainty sentiments are also crucial in asset pricing models. For the research that focuses on the association between sentiment levels and investors' behaviours, controlling the disagreement and uncertainty sentiments is necessary. I also demonstrate that disagreement and uncertainty impact stock markets differently. This finding justifies my rationale to study these two sentiments separately in this thesis. It might be argued that it is inevitable that there will be disagreement where uncertainty exists; however, there may be disagreement regarding the origins and scale of uncertainty. Thus, these two sentiments do not amount to the same and require separate investigations in future researches. Second, this thesis highlights the importance of transparency regarding companies' environmental information. Firms that provide more and better environmental performances are less sensitive to climate change risk. This study may help investors to form efficient hedging portfolios using firms' environmental information to prevent climate change risks from several sources. Third, the thesis stresses the importance of climate policy. Since external uncertainties regarding climate change have adverse effects on a firm's sustainability performance, such policy or political uncertainties can be reduced by introducing appropriate public policies.

Furthermore, and more generally, my study underlines the necessity of development in green finance. Public support of green finance's development should be boosted, especially through uniform standards for ratings and green investment classification. These standards will offer investors more truthful information on the environmental impacts of firms in which they seek to invest. Lastly, as climate change information highlighted in media can either encourage better environmental practices or create counter-productive responses like denial or avoidance, news media should present specific facts regarding global warming to fully understand the issues, especially news related to physical climate change or climate policies.

# Chapter 1:

PEELING AWAY THE LAYERS OF NEWS: CLIMATE CHANGE UNCERTAINTY AND DISAGREEMENT IN U.K STOCK MARKET.

## 1. Overview of the chapter

The growing global concern over climate change has recently sparked a new systematic risk on future stock value. Although the impacts of climate change have become more visible[1], it is uncertain about the extent to which investors price climate risks into their portfolio decisions. Researches in climate communication suggest that extreme weather or climate change highlighted in media will help elicit public concern and promote protective actions. However, it is warned against fear appeals that they may trigger counter-productive responses like denial, avoidance, and disagreement because climate solutions are uncertain, unknown, or undesirable (Lazarus, 1999, Hastings et al., 2004). As many previous studies have stated, human-induced climate change is potentially a key source of uncertainty that has significant impacts over a long period (Jensen and Traeger, 2014, Cai et al., 2015, Cai and Lontzek, 2019, Hambel et al., 2018, Nordhaus, 2017). Therefore, disagreement and uncertainty regarding climate change can be a reliable source to examine how markets price climate risk. Up to this point, the relation between climate change risk and the stock market is unclear ex-ante. There is little systematic empirical evidence on the relationship between climate risk and stock market efficiency to date.

An investigation on the impact of climate change risk on a firm's stock performance is subject to at least two empirical challenges. First, the lack of a market-wide measure of uncertainty among individual investors prevents researchers from generalizing the findings. Although the impacts of uncertainty and disagreement are well studied in the finance literature, their existing measures obtain notable disadvantages. For instance, these measures indirectly proxy for dispersion of opinions (e.g., historical trading volume, return volatility, firm age, or volatility of accounting performance)[2] , and the most well-known measure of dispersion in analyst forecast is generated from analyst's opinions, which may not fully represent market-wide disagreement (Bamber et al., 2011). Second, the decision on the level of investment exposure to climate change risk and investment decision may be jointly determined, or both may be associated with unobservable risks. Although the effect of climate change

[1] Anecdotal evidence about climate change can be found in news media. For example, Europe was affected by unusually hot weather in 2018, causing extreme drought and agriculture losses SCHIERMEIER, Q. 2018b. Droughts, heatwaves and floods: How to tell when climate change is to blame. *Nature,* 560**,** 20-22., while farmers in Australia have also felt the threat from climate change CHAN, G. 2019a. 'Action now': the farmers standing up against 'wilful ignorance' on climate. *The Guardian*.. HANSEN, J., SATO, M. & RUEDY, R. 2012. Perception of climate change. *Proceedings of the National Academy of Sciences,* 109**,** E2415-E2423., and GILLIS, J. 2012. Clouds' Effect on Climate Change Is Last Bastion for Dissenters. provide more comprehensive discussion about climate change.

[2] See, e.g., LI, G. & LI, D. 2011. Belief Dispersion Among Household Investors and Stock Trading Volume. *SSRN Electronic Journal*., BERKMAN, H., DIMITROV, V., JAIN, P., KOCH, P. & TICE, S. 2009. Sell on the News: Differences of Opinion, Short-Sales Constraints, and Returns Around Earnings Announcements. *Journal of Financial Economics,* 92**,** 376-399., GIANNINI, R., IRVINE, P. & SHU, T. 2019. The convergence and divergence of investors' opinions around earnings news: Evidence from a social network. *Journal of Financial Markets,* 42**,** 94-120.

on firms’ operations has been discussed in few studies, the relationship between climate change and market efficiency is mainly unexplored. Grasping this research opportunity, I investigate how climate change risks imposed from news affect firms’ stock performance and how firms’ sustainability engagement may be beneficial in reducing these risks.

This paper bridges the gaps and addresses the challenges mentioned above in two ways. First, I yield daily sentiment measures from news stories to address the disagreement and uncertainty measurement challenge. Comparing to the other two common sentiment sources (e.g., corporation-expressed and internet-expressed), the media-based sentiments used in this paper can be used in both market-level and firm-level contexts (Kearney and Liu, 2014). Textual sentiments from news directly provide a better market-wide disagreement and uncertainty sentiment than dispersion in analyst forecast while limit the noise level contained by internet messages. Second, to alleviate endogeneity concern, I control macroeconomic news to confirm that the determined relations are not simply resulting from macroeconomic information driving sentiment. Besides, I also include sentiment level in our baseline model to ensure that the results are robust even when different news is available among investors.

Our main prediction is that days with a high level of divergence or uncertainty regarding climate change are associated with daily trading volumes. An increase in climate change risk may encourage investors to invest in green firms while discouraging them from placing their money in firms with lower sustainability engagement. However, due to differences in interpretations of the same disclosed information, climate change risk is lower for optimistic investors’ perspectives while higher for those who are more pessimistic. Consequently, during the days with a high divergence of sentiment or high uncertainty sentiment, public information is interpreted differently, leading to differences in judgments.

Our predictions are drawn from theoretical models established in disagreement and uncertainty literature. Hong and Stein (2007) predict that heterogenous priors create diverging views on the “value” of new information even when investors receive the news simultaneously. Banerjee and Kremer (2010), Atmaz and Basak (2018), and Siganos et al. (2017) suggest that higher belief dispersion results in more trading. Belief heterogeneity is often the answer to the questions: Why does stock value be driven far away from its fundamental value, and why is it volatile? (Coudert and Gex, 2008, Lee et al., 2015, Shen et al., 2017). Prior research has linked investors sentiment to expected return (Heston and Sinha, 2017, Griffith and Reisel, 2019), stock volatility (Rupande et al., 2019, Jiao et al., 2020), and trading volume (Kostopoulos et al., 2020). I follow the disagreement measure suggested by Siganos et al. (2017) for both disagreement and uncertainty sentiments.

This paper also studies the impacts of disagreement and uncertainty sentiments on stock price volatility and abnormal return. Because high disagreement and uncertainty sentiments can result in more significant absolute changes in prices (e.g., Banerjee and Kremer (2010)), one can expect that these two sentiments will positively relate to stock volatility and a negative relation with stock returns.

To the best extent of our knowledge, this paper is the first to investigate the disagreement and uncertainty sentiments extensively in the context of climate change and global warming. In the setting of this study, I mainly focus on the climate change area through both news sentiments and new topics.

We contribute to the finance literature in several ways. First, I contribute to the disagreement literature a valuable measure of market-wide disagreement and uncertainty sentiments. This measurement can also be computed in a higher frequency than most other disagreement and uncertainty sentiments. In literature, the relations between sentiment levels and stock markets are well studied (Baker and Wurgler, 2006, Kearney and Liu, 2014); however, most of the papers in the literature focus mainly on positivity and negativity or the average level of sentiment[3] while neglecting the sentiment variations (e.g., disagreement and uncertainty) hidden within daily information. Our paper contributes to the literature by investigating both divergence of sentiment and uncertainty sentiment rather than simple negative, positive, or average sentiment levels. This paper should be of broad interest to scholars studying individual investors' behaviors and the market's microstructure because our sentiments are developed based on textual analysis, which contains investor sentiment and reflects conditions of markets and firms. Furthermore, as a direct measure of sentiments, our divergence of sentiment and uncertainty are less likely to proxy for other market forces irrelevant to disagreement or uncertainty, such as investors' liquidity needs

Second, I extend the empirical studies on climate change risk. Most studies in this field mainly focus on carbon exposure and raw natural disaster (Dong et al., 2019, Hong et al., 2019). Although these indicators directly represent climate risk, they lack investors' genuine reactions to climate risks. I differ from them by explicitly focusing on sentiments conveyed in climate change news. The paper's findings have critical implications for the stock market efficiency in the U.K as well as in investors' effective decision-making in terms of portfolio investment. Lastly, I add to a growing body of literature investigating the consequences of climate change risks (Diaz-Rainey et al., 2017). Our study is different because I focus on both prospects and risks arising from significant climate change news. As news

[3] See, e.g, ANTWEILER, W. & FRANK, M. 2004. Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards. *Journal of Finance,* 59**,** 1259-1294., TETLOCK, P. 2007. Giving Content to Investor Sentiment: The Role of Media in the Stock Market. Ibid.62**,** 1139-1168., GARCÍA, D. 2013. Sentiment during Recessions. *The Journal of Finance,* 68**,** 1267-1300., CHEN, M.-P., CHEN, P.-F. & LEE, C.-C. 2013. Asymmetric effects of investor sentiment on industry stock returns: Panel data evidence. *Emerging Markets Review,* 14**,** 35–54.

covers all possible public information regarding climate change, it is likely to obtain both changes in environmental regulation, physical climate events, and climate-related developments[4].

Our findings obtain several implications for managers, investors, and policy makers. First, I expect investors to be interested in our discoveries due to the rapid growth of socially responsible investment globally (Connaker and Madsbjerg, 2019, Renneboog et al., 2008). I report evidence supporting that in addition to institutionalized characteristics, the dynamic characteristics (e.g., disagreement and uncertainty over climate change news) are also associated with firms' stock performances. Thereby, for investors who integrate sustainability issues in their investment portfolios, disagreement and uncertainty over climate change news should be considered. Second, it is helpful to managers and directors in terms of corporate sustainability to recognize the benefit of reporting corporate's exposure to climate risk. This study identifies and examines the importance of environmental disclosures in inclining climate risk imposed by newspaper articles. Third, uncertainty is of primary concern to directors and managers in several countries (PwC, 2019, Henderson et al., 2018); our results should be of their interest since I show that sustainability performance can alleviate the negative effect of disagreement and uncertainty over climate change news. Therefore, it makes economic sense to accelerate environmental performances under the existence of disagreement and uncertainty sentiment. Fourth, as our source of disagreement and uncertainty can be alleviated by public policy (e.g., climate change induced uncertainty can be mitigated by public policy), it is expected that policymakers will be interested in our findings. Our results indicate method to promote firms' commitment towards the resolution of environmental and social issues, e.g., mitigating impact of disagreement and uncertainty over climate change news.

The following part of the paper is structured as follows. Section 2 provides a brief literature review and our hypothesis drawn from prior research gaps, followed by methodology discussion and data description in Section 3. Empirical results will be analyzed in section 4. Section 5 provides robustness tests for our models and alternative explanation. The last section will conclude this paper with proposed areas for further research.

## 2. Theoretical background, literature review, and hypothesis development

### *2.1. Climate change risk and market efficiency*

In the literature, studies from the macroeconomy aspect recognized that climate change, which causes extreme weather (e.g., rising sea level, drought, and flooding), has an observable adverse effect

[4] Climate-change risk involves risks driven by changes in regulations, changes in physical climate parameters, and changes in other climate-related developments MATSUMURA, E. M., PRAKASH, R. & VERA-MUNOZ, S. 2014. Firm-Value Effects of Carbon Emissions and Carbon Disclosure. *The Accounting Review,* 89**,** 695-724..

on economic development. Climate change can impact businesses in several ways (Henderson et al., 2018, Jia and Li, 2020). First, physical climate change can directly impact firms' intangible assets as well as their operations. For example, firms located near coastal areas may have their property and equipment damaged directly by rising sea levels. Business activities and manufacturing activities may have to stop by flooding (e.g., flood affects logistic process) or drought (if water is required for operations. Due to the nature of businesses, agriculture, mining, utility, tourism, and insurance firms can be influenced more profoundly (IPCC, 2014). Thus, vulnerabilities of firms' production processes to natural disasters raised by climate change can inflict significant losses to corporate profits. Second, policies on climate change may lead to firms' financial stability risk (Carney, 2015). For example, future carbon prices or taxes will impose more damage on firms with higher exposure to carbon assets. This issue is referred to as a "stranded asset issue". The impact of climate policy can be more severe for firms operating in the mining industry or those whose manufacturing process rely mainly on high-emission materials.

Due to the aforementioned potential risks brought by climate change, regulators are increasingly concerned about how efficiently the markets price climate change risks. As a result, climate change emerges as an essential aspect for investors when accessing a firm's businesses and its related risks. Although there is evidence of growing attention from investors on climate change risk[5], the markets have had little experience dealing with such risks; thus, they may either overreact or underreact to these risks as a result. Most investors, particularly long-term and ESG-oriented ones, choose risk management over divestment to be a better method for tackling climate risk (Krueger et al., 2020).

### *2.2. Behavioural finance: disagreement and uncertainty sentiments.*

Behavioural finance has long imposed a significant challenge to neoclassical finance, which relaxes the assumption that investors are rational and the risk-return relationship is sufficient to determine asset prices (Selden, 1912, Festinger, 1962). In the aspect of investor sentiments, many preferences and behavioural biases can act as the outcome of investor sentiment and cognitive biases, optimistic sentiment: familiarity (Huberman, 2001) and loyalty (Cohen, 2009), and pessimistic sentiments, such as ambiguity aversion (Antoniou et al., 2015), which may cause overreaction and underreaction anomalies. The ambiguity aversion phenomenon is first established by Ellsberg (1961b). Since the

[5] Media attention to climate change is higher in years with record-breaking warm weather than non-recorded ones SHMIDT, G. A. 2015. Thoughts on 2014 and ongoing temperature trends. *RealClimate*.; retail investors sell carbon-intensive firms in abnormally warm weather, causing carbon-intensive stock to underperform low carbon-emission stock in such weather CHOI, D., GAO, Z. & JIANG, W. 2018. Attention to Global Warming. *SSRN Electronic Journal*.; most of surveyed institutional investors in study of KRUEGER, P., SAUTNER, Z. & STARKS, L. T. 2020. The Importance of Climate Risks for Institutional Investors. *The Review of Financial Studies,* 33**,** 1067-1111. have taken at least first step in climate risk management with half of them have applied carbon footprint analysis and stranded asset risk analysis.

introduction of ambiguity aversion, studies in psychology and experimental economics have proved that people incline to hate feeling to events of uncertainty, in which the outcomes related to different nature states are unidentified.

One branch of ambiguity aversion is the uncertainty aversion bias. Gilboa and Schmeidler (1989) established uncertainty literature, assuming that the decision-makers, when face uncertainty, will make their decision based on the Maxmin Expected Utility (MEU). Several economists have claimed that uncertainty is linked to financial markets since the probabilities of profit distribution are not clearly acknowledged (Miao et al., 2012, Augustin and Izhakian, 2019). One of the robust estimations from theoretical portfolio choice models is that, with uncertainty, stock market participation tends to be lower than forecasted from the basic Expected Utility Theory (EUT) model. Moreover, market participants are also negatively associated with the changes in uncertainty level in the market (Maenhout, 2004b, Cao et al., 2005b, Epstein and Schneider, 2010, Antoniou et al., 2015). For example, Antoniou et al. (2015) find that the low-volatility anomaly emerges when the stocks with greater valuation uncertainty are overvalued during the high sentiment period, the effect of which is strengthened by investor overconfidence.

Another branch of ambiguity in the decision-making process is disagreement. One might argue that it is inevitable that there will be disagreement where scientific uncertainty exists; however, these two do not amount to the same scale. There may be disagreement among people on the origins and extent of particular subjects where uncertainty occurs. The concept that investors' disagreement implies an asset-pricing model is originated in the paper of Miller (1977), which suggests that, unlike optimistic opinions, pessimistic opinions are not reflected in market price due to short-sale constraints. Subsequent empirical researches support the argument of Miller (1977) and document that disagreement among investors' opinions lead to overpricing when there are short-sale constraints (e.g., Park (2005), Yu (2011), and Hong and Sraer (2016)).

While disagreement and uncertainty have some characteristic differences (D'Amico and Orphanides, 2008, Glas and Hartmann, 2016a, Rich and Tracy, 2010, Rich and Tracy, 2018), they still have a similar upshot in the decision-making model: they do not deliver an exact source of the decision problem as required by standard decision-making model, and both can drive investors away from the correct decisions (Giordani and Söderlind, 2003). Therefore, this paper distinguishes disagreement and uncertainty as two different textual sentiments to study their impact on the stock market differently.

### *2.3. Hypotheses development*

We predict that both disagreement and uncertainty sentiments conveyed in climate change news significantly impact trading volume. When the same information is available to investors, the divergence between positivity and negativity in the news generates disagreement, while uncertain information can be interpreted as either good or bad news. These differences in interpretation lead to a difference of opinions. When investors trade based on their diverging beliefs, days with higher disagreement and uncertainty sentiments are expected to be associated with higher trading volume.

Our prediction is aligned with theoretical models generated in disagreement literature, that the more disagreements occur, the more trading is executed (Karpoff, 1986, Banerjee and Kremer, 2010, Atmaz and Basak, 2018). It is suggested that disagreement is directly proportional to the trading volume, and due to the different manner in interpreting public information, investors will trade in a way that is revising their disagreement; thus, the more they differ in understanding the news, the higher volume stocks will be traded (Banerjee and Kremer, 2010, Atmaz and Basak, 2018). According to Hong and Stein (2007), heterogeneous is the cause of investors' disagreement on valuing the same new piece of information although they receive that news simultaneously. Furthermore, Banerjee and Kremer (2010) state that different investors have different interpretations of the same piece of information, and thus, higher disagreement leads to higher trading volume.

**Hypothesis 1 (H1):** *Uncertainty and disagreement sentiments in climate change news induce increased future trading volume.*

Next, I also examine the relationships between our climate change disagreement, uncertainty sentiments, and stock price volatility. As mentioned above, since the divergence of sentiments and interpretation of uncertain news can lead to diverging belief on a firm's values, they can also result in higher absolute price changes. In disagreement theory, Banerjee and Kremer (2010) show that the level of disagreement is reflected in return volatility, and higher volatility is observed in the period of higher disagreement. Besides, according to unicertainty theory, uncertainty is noted to impact investors' consumption and portfolio approach, resulting in changes in asset prices (Drechsler, 2013). Significantly, economic policy uncertainty (EPU) generated in the study of Baker et al. (2016) is shown to be related to higher stock volatility. However, if trades are idiosyncratic, disagreed trades may automatically cancel each other out; thus, it may not leave such an effect on the prices of stocks. Thereby, I treat the connection between disagreement and uncertainty sentiment and stock price volatility as an empirical question, as Siganos et al. (2017) suggested.

**Hypothesis 2 (H2):** *Uncertainty and disagreement sentiments in climate change news induce an increase in future stock price volatility.*

In addition to trading volume and stock price volatility, this paper also examines the relationship between climate change disagreement and uncertainty sentiments and abnormal stock return.

Empirically, based on ambiguity theory, disagreement and uncertainty sentiments have been shown to affect asset prices and have explanatory power on some well-recognized anomalies (Fama and French, 2007, Carlin et al., 2014, Baker et al., 2016, Antoniou et al., 2015, Banerjee et al., 2019). For instance, using theoretical models of portfolio choice that incorporate ambiguity, Antoniou et al. (2015) show that the low-volatility anomaly emerges when the stocks with greater valuation uncertainty are overvalued during the high sentiment period, the effect of which is strengthened by investor overconfidence. Banerjee et al. (2019) show that investors systematically choose to diverge from rational expectations, leading to higher return volatility, trading volume, and return predictability. It is expected that when volatility is high, the price will be pushed up, leading to lower returns as in the notion of efficient market hypothesis.

**Hypothesis 3 (H3):** *Uncertainty and disagreement sentiments in climate change news negatively affect the abnormal stock return.*

Climate change information is usually available to investors, yet firms' environmental activities are often hidden from outsiders. This information asymmetry is the reason behind the increase in transaction costs when investors look for suitable stocks for their portfolios. Therefore, it is in the companies' best interest to make this information available to attract a clientele that is sensitive to the environment. Over the past few years, there has been a promising trend in reporting and disclosing corporate social responsibility information voluntarily and mandatorily[6].

Nevertheless, studies related to the relationship between stock performance and environmental activities have shown different outcomes. Several pieces of research indicate that corporate sustainability outlines a long-term business approach to generate long-term shareholder value (Wang and Bansal, 2012, Malik, 2015, Friede et al., 2015). For instance, Lins, Servaes, and Tamayo (2017) discover that companies whose better sustainability engagement during financial crises earned higher stock returns for their investors. On the other hand, Barnea and Rubin (2010) argue that excessive investing into sustainability can generate conflicts among different shareholders due to the reduction in shareholders' wealth and value of corporations. Besides, information on firms' commitments towards sustainability initiatives may also create asymmetric information problems. Some researchers find no effect of ESG on expected return (e.g., Bauer et al. (2005) and Galema et al. (2008)). Notably, Bolton and Kacperczyk (2020a) find that heavy emitter companies achieve higher stock returns than those who emit less.

[6] Examples of the more prominent voluntary disclosure initiatives include the Carbon Standards Disclosure Board, Integrated Reporting, the Carbon Disclosure Project, and the UN Principles for Responsible Investment.

It is crucial to understand how investors act against firms' environmental information since this can support the decisions of firms' managers and directors on voluntary sustainability disclosures. For instance, knowing that investors value green practices and drive the companies' future cash flow could help to explain the swift development of Socially Responsible Investment (SRI). On a larger scale, a complete understanding of the direction of investors' reaction towards the green and non-green company will help portfolio managers to build more efficient portfolios better, forecasting more accurately future expected returns and sufficiently estimate related risks. Furthermore, knowing the reason why managers are investing more in environmental practices will help to settle the ongoing debate regarding whether every socially responsible activity is needed to maximize shareholder values (Friedman, 1970, Karnani, 2010); or whether profits will be sacrificed for the interest of society (Kolstad, 2007, Reinhardt and Stavins, 2010, Benabou and Tirole, 2010). Therefore, our research sheds some light on the role of environmental performances in reducing the impact of climate change risks on future stock performance.

**Hypothesis 4 (H4):** *Climate-related uncertainty and disagreement sentiments impact green firms and non-green firms differently.*

## 3. Research design

### *3.1. Data and sample selection*

For disagreement and uncertainty measures, I collect daily climate change news from 01/01/2008 to 31/12/2019 using the advanced search function in ProQuest with keywords: 'Climate change' or "Global Warming". This search aims to capture climate change-related news but not limit it to too narrowed topics. Following Tetlock (2007), I narrow our search and download news from well-known The Wall Street Journal and other U.K broadsheets (The Financial Times, the Daily Telegraph, The Guardians, The Times, and The Independent) in order to have a well-mixed source of intelligent and respectable newspaper articles. The index of disagreement and uncertainty sentiments are then constructed from this climate change news based on a well-known dictionary of (Loughran and Mcdonald, 2011) (hereafter LM) and corpus analysis and comparison tool WMatrix developed by Lancaster University (Rayson, 2008) (hereafter WM). For brevity, I only report results from the models using Loughran and McDonald's dictionary since sentiment constructed from WMatrix classification gets similar results.

We obtain firm-level trading volume, stock price volatility, and abnormal stock returns for a broad cross-section of all companies listed in the U.K stock markets from DataStream. I include both live and delisted stock in order to avoid survivorship bias. Financial data are collected from DataStream, while macroeconomic data are downloaded from Bloomberg. The sample period is from 2008 to 2019 to provide a relatively complete picture of how disagreement and uncertainty sentiment in climate change news impact firms' stock performance. After synthesizing databases and dealing with missing data, the final sample consisted of 3,747,807 firm-year observations from 1,197 individual firms domiciled in the U.K. Table 1 presents the descriptive statistics of our final samples. The mean of disagreement and uncertainty sentiment constructed from the LM dictionary are 0.981 and 0.746, respectively, while the mean of disagreement and uncertainty sentiment constructed from WMatrix are 1.111 and 0.766, respectively. Thus, significant variation in disagreement and uncertainty introduced by climate change news was found in this sample.

Results for Spearman correlation are shown in Panel B of Table 1. Both dictionaries' disagreement and uncertainty are positively related to firms' trading volume and stock price volatility, indicating that disagreement and uncertainty in climate change news are positively associated with firms' stock performance.

### *3.2. Variables and their measurements*

#### *3.2.1. Dependant variable – trading volume, stock price volatility, and abnormal returns*

As mentioned in Section 3.1, I collected stock market data from DataStream to construct our trading volume, stock price volatility, and abnormal stock returns.

First, stock trading volume is the average number of shares traded for individual stocks in a day gathered from DataStream. I calculate the stock trading volume changes as the first difference of trading volume:

$$\Delta Volume_t = Volume_t - Volume_{t-1}$$

Second, I calculate simple volatility proxy as the first logarithmic difference of low and high price (Gallant et al., 1999b):

$$V_{S,t} = \ln(H_t) - \ln(L_t)$$

In which, $H_t$ and $L_t$ are high and low prices at day $t$, respectively, and are collected from DataStream in local currency. Differentiating our research from Siganos et al. (2017), I do not use squared stock market return as a measure of volatility since it is suggested that range volatility is more reliable than log-squared return (Chan and Lien, 2001). Furthermore, in a regression model, it is suggested that a few large volatilities can mainly influence estimations because of large variance. Therefore, using logarithmic ranged volatilities can deal with limited data obtained and produce more efficient coefficient estimates, avoiding the need for positivity constraint.

Third, in order to calculate abnormal stock returns, I estimate the beta within the window of 300 to 50 trading days before the day that climate change news is released. As all our stock data is from the U.K thus, I use the FTSE100 index for market return and 10-year Gilt bond yield for the risk-free rate, both retrieved from Bloomberg.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_1 \left(R_{m,t} - R_{f,t}\right) + \beta_2\, SMB + \beta_3\, HML + e_{i,t}$$

In which $R_{i,t}$ is the stock return of firm *i* at day *t,* $R_{f,t}$ and $R_{m,t}$ are the log return of 10-year Gilt bond yield and FTSE100 Index. *SMB* and *HML* indexes are downloaded from Gregory et al. (2013) from 2008 to 2017 since it is the last available data on their website. I calculated *SMB* and *HML* for the years 2018 and 2019 following their method. From the above model, I obtain estimated parameters $\alpha_i$ and $\beta_i$ and use them in the following model to calculate expected $\hat{R}_{it}$:

$$\hat{R}_{i,t} - R_{f,t} = \hat{\alpha}_i + \hat{\beta}_1 \left(R_{m,t} - R_f\right) + \hat{\beta}_2 SMB + \hat{\beta}_3 HML + e_{i,t}$$

In addition to the abnormal return obtained from the Fama French 3-factor model, I also employ the CAPM model for robustness with the model below.

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i \times (R_{m,t} - R_{f,t}) + e_{i,t}$$

$$\hat{R}_{i,t} - R_{f,t} = \hat{\alpha}_i + \hat{\beta}_i \times (R_{m,t} - R_f) + e_{i,t}$$

The result of $\hat{R}_{i,t}$ for both Fama-French 3 factors and CAPM models, then will be used to estimate abnormal returns for firm *i* and event day *t* as below:

$$AR_{i,t} = R_{ii} - \hat{R}_{it}$$

From the daily abnormal return $AR_{i,t}$, I constructed expected cumulative abnormal return for three days interval [-1 +1] around the day of news and five days interval [+1 +5] after the day of news for our models.

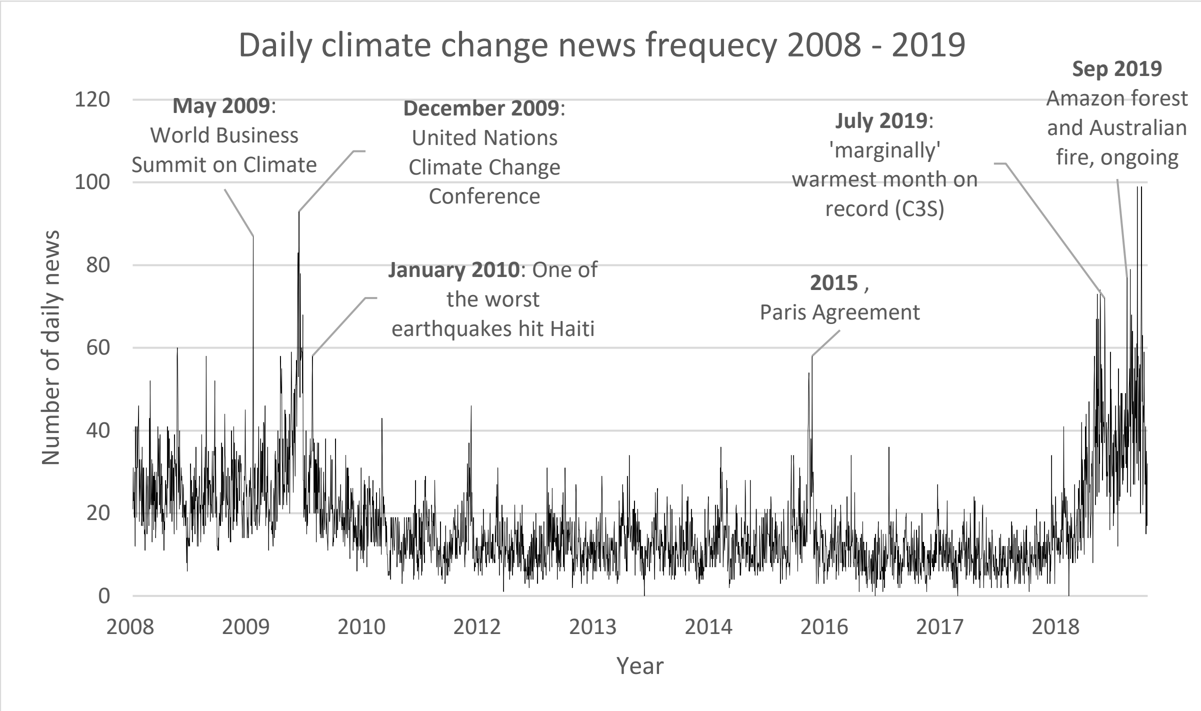
### *3.2.2. Independent variables – disagreement and uncertainty sentiments*

We construct the daily disagreement and uncertainty sentiment index based on the aggregated textual tone in climate change news from 1st January 2008 to 31st December 2019. In order to avoid fake news issues, following Tetlock (2007), I specifically download climate change news from trustworthy news outlets, namely: The Financial Times, the Daily Telegraph, The Guardians and The Times, The Wall Street Journal, and The Independent.

Figure 1 shows a time series of climate change news from our data source. It shows that the number of climate-related news spike at the time of significant climate change events, such as the United

Nations Climate Change conference in 2009 or the latest Amazon Forest and ongoing Australian fire began in September 2019 and lasts months after that.

**Figure 2: News frequency and events graph 2008 - 2019**




Our text dataset is then cleaned and classified into positive, negative, and uncertainty sentiment based on (i) financial lexicon dictionary from (Loughran and Mcdonald, 2011) and (ii) semantic tagging from the WMatrix tool (Rayson, 2008).

Following Siganos et al. (2017)'s paper, I employ sentiment analysis to calculate the disagreement sentiment as the divergence of positive and negative as follow:

$$DoS_t = \left| \frac{x_{p,t} - x_{p,all}}{\sigma_{p,all}} + \frac{x_{n,t} - x_{n,all}}{\sigma_{n,all}} \right|$$

In which, $\frac{x_{p,t} - x_{p,all}}{\sigma_{p,all}}$ and $\frac{x_{n,t} - x_{n,all}}{\sigma_{n,all}}$ are positive and negative sentiments where $x_{p,all}$ and $x_{n,all}$ are the average percentage of positive and negative sentiment detected during the time frame of the data set and $\sigma_{p,all}$ and $\sigma_{n,all}$ are standard deviation for those variables. Similarly, I also calculate the uncertainty sentiment to be the absolute value of change in uncertainty proportion:

$$UNC_t = \left| \frac{x_{u,t} - x_{u,all}}{\sigma_{u,all}} \right|$$

In which, $x_{u,t}$ is the uncertainty proportion calculated as the number of uncertainty words over the total of words in day *t*, $X_{u,t} = \frac{N_{u,t}}{N_{all,t}}$ ; $x_{u,all}$ is the average percentage of uncertainty that appeared during the dataset and $\sigma_{u,all}$ is the standard deviation of these variables. The absolute value indicates the distance of uncertainty counts on day $t$ to the mean uncertainty of the whole sample.

To validate our arguments for the use of sentiments retrieved from climate change news and the relevance of using textual analysis methods, I cross-validate the interpretation of our disagreement and uncertainty sentiments as a measure of investor sentiment. First, I run a regression of disagreement sentiments on other alternative proxies for investor sentiments, including Baker and Wurgler (2006)'s investor sentiment index (BW) and the University of Michigan consumer sentiment index (UM). Second, I run a regression of uncertainty sentiments on other alternative uncertainty proxies, such as Baker et al. (2016) Economic Policy Uncertainty (EPU) and IMF (2020) World Uncertainty Index (WUI). I find that both our disagreement and uncertainty sentiments appear to have significant and positive relations with their respective alternative proxy. This evidence indicates that our disagreement and uncertainty sentiments can capture investor sentiments. More detail on our construction of disagreement and uncertainty sentiments are presented in Appendix B. For brevity, I only present results from regression with sentiments classified by Loughran and MacDonald's dictionary.

#### *3.2.3. Control variables*

In addition to disagreement and uncertainty variables, I also include several economic and financial covariates. Controlling such variables avoids the biases caused by the exclusion of related variables when estimating the influence of our targeted disagreement and uncertainty sentiment variables. Several papers in the literature suggest that trading volume and volatility forecasting models can be enhanced by including financial and macroeconomic data, such as Paye (2012), Christiansen et al. (2012), Mittnik et al. (2015), and Nonejad (2017). Christiansen et al. (2012) show that funding liquidity and credit risk proxies consistently appear as predictors that enhance volatility forecast across asset classes. Besides, it is found in the paper of Nonejad (2017) that some of the most important predictors for volatility in the S&P 500 are risk premia, past volatilities, corporate bond's default spread, and interest rate over a short period. It is also possible that the predictive power of disagreement and uncertainty in the news for stock return originated from business cycle information. In order to control for the impact of the business cycle, I apply several macroeconomic and financial variables that are connected directly to macroeconomic fundamentals, as below:

For firm-level data, I follow Fama and French (1992) and Sloan (1996) papers and include book-to-market (BTM), log of the total asset (SIZE), and leverage (LEV).

Regarding equity market variables, I follow Audrino et al. (2020) include past stock returns and the major UK FTSE100 stock indices. In the beginning, I also consider the FTSE All-Share index; however, it shows multiple correlations with the FTSE 100 index; thus, I only consider one of them in our models. I also consider Fama-French risk factors (SMB, HML, and risk-free market rate are downloaded from Gregory et al. (2013) from 2008 to 2017 and calculated by the author from 2017 to 2019 as it is not available elsewhere). Besides, the well-established equity market valuation ratio - dividend-price ratio (DP), earning price ratio (EP), and the implied volatility FTSE100 VIX as tested for robustness is also included.

Another aspect of the capital market – the bond market – also potentially influences the risk and return forecast of stock. In this data set, I follow Welch and Goyal (2008) and employ UK 3-month Treasury Bill, 10 Years Gilt rate, their 12-month moving average, and their difference (term spread).

Stock price volatility and trading volume are well-known to be strongly positively related (Lustig et al., 2014); therefore, I consider a set of variables that can be proxies for financial markets' liquidity. First, I include the turnover ratio of both researched stocks and FTSE100 indexes. Besides, I also take the differences between the 3-month GBP LIBOR rate and the 3-month Treasury Bill. Moreover, finally, I obtain the bid-ask spread of important currencies, namely: USD, EUR, CHF, and JPY.

Last but not least, our model also contains a series of macroeconomic variables. Based on several pieces of research in the literature (e.g., Christiansen et al. (2012), Mittnik et al. (2015), and Nonejad (2017), I take in industrial production, employment growth, consumer confidence and sentiment, inflation, housing starts and money supply.

In summary, I take into account 25 financial and macroeconomic covariates. A complete detailed description is provided in Appendix A. Noticably, seven variables are recorded monthly and three variables annually. In order to obtain these variables in our model, I follow Audrino et al. (2020) and impute daily observation of these variables by linear interpolation of their logarithmic monthly values.

**Table 1: Descriptive statistics of the final sample**

This table presents the descriptive statistics of the final sample. Definitions and construction details for each variable can be found in Appendix A. With regards to brevity, I do not include control variables in our correlation matrix.

| Variables | N | Mean | 25th Percentile | Median | 75th Percentile | Standard Deviation |
|---|---|---|---|---|---|---|
| *Panel A. Descriptive Statistic* | | | | | | |
| *Dependent variables* | | | | | | |
| ΔVolume (t) | 2,997,288 | 33.398 | -6.100 | 0.000 | 7.100 | 6295.981 |
| Volatility (t+1) | 2,730,413 | -0.1986 | -1.171 | 0.000 | 0.938 | 6.077 |
| CAR_FF3 [-1 +1] | 3,747,807 | -0.0472 | -0.306 | 0.000 | 0.287 | 1.673 |
| CAR_FF3 [+1 +5] | 3,746,610 | -0.060 | -0.359 | 0.000 | 0.341 | 1.926 |
| *Independent variables* | | | | | | |
| DoS_LM | 3,747,807 | 0.981 | 0.379 | 0.790 | 1.369 | 0.814 |
| DoS_WM | 3,747,807 | 1.111 | 0.420 | 0.908 | 1.563 | 0.914 |
| UNC_LM | 3,747,807 | 0.746 | 0.277 | 0.592 | 1.017 | 0.673 |
| UNC_WM | 3,747,807 | 0.766 | 0.290 | 0.594 | 1.073 | 0.658 |
| *Control variables* | | | | | | |
| *Firm-level financial variables* | | | | | | |
| BTM | 2,563,078 | 6.511 | 5.834 | 6.556 | 7.129 | 1.181 |
| SIZE | 2,592,688 | 10.383 | 8.516 | 10.209 | 12.085 | 2.848 |
| LEV | 1,585,688 | -1.324 | -2.286 | -0.945 | -0.026 | 2.071 |
| *Equity market variables* | | | | | | |
| DP | 1,472,106 | -3.875 | -4.184 | -3.596 | -3.129 | 1.357 |
| DP_FTSE100 | 718,200 | -7.850 | -8.752 | -7.767 | -6.816 | 1.301 |
| MKT | 3,647,259 | 0.000 | -0.005 | 0.000 | 0.006 | 0.011 |
| SMB | 3,647,259 | 0.000 | -0.004 | 0.000 | 0.004 | 0.007 |
| HML | 3,647,259 | 0.000 | -0.003 | 0.000 | 0.003 | 0.006 |
| VIX_FTSE100 | 3,602,970 | 0.000 | -0.042 | -0.004 | 0.036 | 0.075 |
| VIXC_FTSE100 | 3,602,970 | 0.001 | -0.884 | -0.007 | 0.952 | 1.518 |
| *Bond market variables* | | | | | | |
| Rltv_TB3 | 3,632,895 | -0.208 | -0.084 | -0.007 | 0.035 | 0.679 |
| Rltv_G10 | 3,632,895 | -0.179 | -0.459 | -0.121 | 0.100 | 0.406 |
| TermSpread | 3,632,895 | 1.500 | 0.867 | 1.384 | 2.339 | 1.044 |
| *Macroeconomic variables* | | | | | | |
| CPIC | 3,625,713 | -0.002 | -0.054 | 0.003 | 0.047 | 0.095 |
| EXPINFC | 3,625,713 | 0.001 | -0.100 | 0.000 | 0.127 | 0.271 |
| IPIM | 3,625,713 | -0.001 | -0.005 | 0.000 | 0.005 | 0.010 |
| HSNSA | 3,625,713 | -0.006 | -0.096 | 0.010 | 0.090 | 0.147 |
| HSSA | 3,625,713 | -0.005 | -0.060 | 0.012 | 0.050 | 0.099 |
| M1M | 3,625,713 | 0.005 | 0.000 | 0.004 | 0.009 | 0.009 |
| CAPC | 3,625,713 | 0.000 | -0.012 | 0.002 | 0.013 | 0.020 |
| SENT | 3,625,713 | 0.001 | -0.012 | 0.000 | 0.013 | 0.024 |
| CONF | 3,625,713 | -0.001 | -0.055 | -0.002 | 0.053 | 0.217 |
| EMP | 3,625,713 | 0.001 | 0.000 | 0.001 | 0.002 | 0.002 |
| *Liquidity variables* | | | | | | |
| TURN | 2,180,921 | 4.554 | 2.754 | 4.615 | 6.477 | 2.629 |
| TURNC_FTSE100 | 3,747,807 | -0.121 | -0.121 | 0.000 | 0.131 | 0.274 |

| Panel B. Spearman Correlation | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Variables | **DoS_LM** | **DoS_WM** | **UNC_LM** | **UNC_WM** | **Volume (t+1)** | **Volatility (t+1)** | **CAR_FF3 [-1 +1]** | **CAR_FF3 [+1 +5]** |
| DoS_LM | 1 | | | | | | | |
| DoS_WM | 0.188*** | 1 | | | | | | |
| UNC_LM | 0.110*** | 0.152*** | 1 | | | | | |
| UNC_WM | 0.185*** | 0.348*** | 0.207*** | 1 | | | | |
| Volume (t+1) | 0.002*** | 0.0012* | 0.0011** | 0.002 | 1 | | | |
| Volatility (t+1) | 0.0002* | 0.0010* | -0.0008* | 0.012*** | 0.004*** | 1 | | |
| CAR_FF3 [-1 +1] | 0.0013** | -0.002*** | 0.004*** | 0.006*** | -0.0008 | -0.002*** | 1 | |
| CAR_FF3 [+1 +5] | -0.003*** | -0.007*** | 0.013*** | -0.006*** | 0.0008 | -0.0003 | 0.451*** | 1 |

**** p<0.01, ** p<0.05, * p<0.1*

### *3.3. Econometric models*

As per our research questions, I utilize panel regression models for our study.

The regression models of the relationship between trading volume and disagreement/sentiment variables are as below:

$$\Delta Volume_t = \alpha + \beta_1 DoS_t + \beta_2 VO_{t-1} + \beta_3 Control_t + \varepsilon_{t+1} \qquad \textit{(Equation 1)}$$

$$\Delta Volume_t = \alpha + \beta_1 UNC_t + \beta_2 VO_{t-1} + \beta_3 Control_t + \varepsilon_{t+1} \qquad \textit{(Equation 2)}$$

In which, $\Delta Volume_t$ is the average daily trading volume from collected DataStream, $DoS_t$ denotes for our disagreement sentiments at day *t,* and $UNC_t$ represents uncertainty sentiment at day $t$. In order to alleviate the time trends issue within the trading volumes, I deal with time and firm fixed effects in our regression. Following Siganos et al. (2017), I also use one lag of volume $VO_{t-1}$ to control the possibility that past volume is related to the sentiments that appeared in today's news. I further add other firm-level and macroeconomic variables to control for the macroeconomic development and the company's performance in the model.

For the model of volatility, according to Mandelbrot (1963), it is common for volatility clustering to happen in real-life data where a large return follows a previous large return and small returns follow previous small returns. This volatility clustering results from the arrival of information in a short time. In order to deal with the long-memory behaviour of volatility, I follow the work of Audrino et al. (2020) and employ the Heterogeneous Autoregressive model (HAR) as below:

$$Vs_{t+1}^{(d)} = \alpha + \beta_1 DoS_t + \beta^{(d)} Vs_t^{(d)} + \beta^{(w)} Vs_t^{(w)} + \beta^{(m)} Vs_t^{(m)} + \beta_3 Control_t + \varepsilon_{t+1} \qquad \textit{(Equation 3)}$$

$$Vs_{t+1}^{(d)} = \alpha + \beta_1 UNC_t + \beta^{(d)} Vs_t^{(d)} + \beta^{(w)} Vs_t^{(w)} + \beta^{(m)} Vs_t^{(m)} + \beta_3 Control_t + \varepsilon_{t+1} \qquad \textit{(Equation 4)}$$

In which $\beta^{(w)} logVs_t^{(w)} = \frac{1}{5}\sum_{i=1}^{5} logVs_{t-i+1}^{(d)}$ and $\beta^{(m)} logVs_t^{(m)} = \frac{1}{22}\sum_{i=1}^{22} logR = Vs_{t-i+1}^{(d)}$ are the weekly and monthly averages of daily ranged volatilities, respectively and $\varepsilon_t$ is a zero-mean innovation process. In this model, I deploy the range volatility as the first logarithmic difference between high and low prices rather than plain volatility, following Audrino et al. (2020), because plain volatility is may have a skewness issue (Goncalves and Meddahi, 2011).

For the model of abnormal stock return,

$$CAR_{[i,j]} = \alpha_i + \beta_1 DoS_t + \beta_2 R_{t-1} + \beta_3 Control_t + e_{i,t} \qquad \textit{(Equation 5)}$$

$$CAR_{[i,j]} = \alpha_i + \beta_1 UNC_t + \beta_2 R_{t-1} + \beta_3 Control_t + e_{i,t} \qquad \textit{(Equation 6)}$$

In which $CAR_{[i,j]}$ is the cumulative abnormal return from day *i* to day *j* around the released date of the news. Following prior studies, such as Sun et al. (2016), I also include lagged return $R_{t-1}$ as a predictor. In order to observe a longer effect of sentiment on abnormal return, I run regressions where our response variables are $CAR_{[-1+1]}$ and $CAR_{[+1+5]}$ as described in Section 3.2.

Because our dataset includes fewer observed years than firms, I follow Petersen (2009) and use standard errors clustered by firms to capture the possible correlation between observations of the same firm but in different years. I also include dummy variables for each period to control for possible correlation of observations in the same year but belong to different firms. According to White (1980), these standard errors are robust to heteroskedasticity.

## 4. Empirical results

### 4.1. *Disagreement and uncertainty sentiments and stock trading volume changes*

We first examine the prediction that our climate-related disagreement and uncertainty sentiments are positively related to trading volume. Table 2 presents the regression estimation results of Eq. 1. It shows that there are strong positive relations between disagreement sentiments and daily stock trading volumes. In column (3) of Table 2, the estimation coefficient of *DoS_LM* is statistically significant at the 5% level, showing that an increase in climate-related disagreement in a day will increase daily average trading volume. The parameter coefficient of *DoS_LM* is at a value of 15.13. This value suggests that when our *DoS_LM* measure increases by 0.814 (the standard deviation of *DoS_LM*), the firm-level trading volume will increase by 0.814 × 15.13 = 12.315 standard deviation to a rise of approximately 411,296 in trading volume changes.

**Table 2: Model of daily trading volume with change in investor disagreement with lagged trading volume**

This table report results from the following predictive regression:

$\Delta VO_t = \alpha + \beta_1 DoS_t + \beta_2 Vo_{t-1} + \beta_3 Control + \varepsilon_t$ and $\Delta VO_t = \alpha + \beta_1 UNC_t + \beta_2 Vo_{t-1} + \beta_3 Control + \varepsilon_t$

VO is the average daily trading volume from collected DataStream, DoS_LM, and UNC_LM are disagreement and uncertainty sentiment variables classified by Loughran and McDonald's' lexicon. $VO_{t-1}$ is one day lag of volume (volume of one day before the date of news) to control the possibility that past volume is related to the sentiments that appeared in today's news. Robust t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively. The data is in daily frequency, and the sample period is from January 2008 to December 2019.

| | *Dependent: ΔVolume (t)* | | | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| DoS_LM | 14.07*** | | 15.13** | |
| | (2.607) | | (2.136) | |
| UNC_LM | | 11.59* | | 14.57* |
| | | (1.787) | | (1.731) |
| VO (t-1) | 0.319*** | 0.319*** | 0.334*** | 0.334*** |
| | (610.8) | (610.8) | (489.5) | (489.5) |
| Return | 55.87*** | 55.86*** | 50.22*** | 50.22*** |
| | (42.46) | (42.46) | (29.41) | (29.41) |
| Constant | -340.3*** | -334.9*** | -456.2*** | -453.0*** |
| | (-47.72) | (-49.67) | (-4.333) | (-4.303) |
| Controls included | No | Yes | No | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Company FE | Yes | Yes | Yes | Yes |
| Observations | 2,243,977 | 2,243,977 | 1,414,218 | 1,414,218 |
| R-squared | 0.144 | 0.144 | 0.146 | 0.146 |
| Number of Ticker | 1,165 | 1,165 | 942 | 942 |

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As column (4) of Table 2 presents, uncertainty sentiment is positively related to stock trading volume. However, the estimation coefficient of *UNC_LM* is only significant at the 0.1% level. Considering economic significance, the regression results imply that uncertainty sentiments improve approximately 15% (a coefficient of 14.57 on the scale of 100) of firms' stock trading volumes. Taken together, our results indicate that both disagreement and uncertainty sentiments derived from climate change news are positively related to stock trading volumes, which supports our H1. Our findings align with prior researches, including Atmaz and Basak (2018), Siganos et al. (2017), which found that disagreement and uncertainty sentiments encourage investors to trade more.

Regarding theoretical perspective, our results support disagreement theory and ambiguity theory that disagreement and uncertainty sentiments are both positively related to trading volumes. These significant findings are in line with the notion that one piece of news may be interpreted differently among investors, with optimistic investors interpret uncertainty more positively while pessimistic investors interpret it more negatively. Their trades, thus, reflecting their expectations.

### *4.2. Disagreement and uncertainty sentiments with stock price volatility*

Although our climate-related disagreement and uncertainty sentiments are positively related, higher volumes may not lead to higher stock price volatility. As argued in the paper of Siganos et al. (2017), if disagreement only affects individual investors, trading volume will change while prices may not be affected immediately. Therefore, I empirically examine the association between our disagreement and uncertainty sentiments and stock price volatility. Table 3 presents the results of Eq.3 and Eq.4.

As presented in columns 3 and 4 of Table 3, both *DoS_LM* and *UNC_WM* are positively related to future stock price volatility. The estimation coefficients of our disagreement sentiments are significant at the 1% level, suggesting that an increase in disagreement sentiment leads to a daily rise in the volatility of the next day. The parameter coefficient of *DoS_LM* suggests that for every 1 unit increase in disagreement sentiment, stock price volatility will increase approximately 0.02%. These results are aligned with a story where investors interpret the same piece of news differently, thus, having opposing acts that reflect their different expectations. These investors impacted by climate-related sentiments can affect stock prices, thereby creating price volatilities. In column 4 of Table 3, our uncertainty sentiments show similar results as disagreement sentiments. The coefficient of uncertainty sentiments is highly statistically significant, at 0.025. It indicates that each unit increase in *UNC_LM* is associated with a roughly 0.0252% increase in stock price volatility. Our results align with disagreement theory in the study from Banerjee and Kremer (2010), which suggests that when the same public information is available, more extensive diverging views in investors' opinions will result in greater extensive changes in absolute prices. When news conveys uncertain or conflicted information regarding climate change, investors affected by sentiments can influence stock price movements, thus, lead to higher stock volatility. This result also gives an insight that climate change represented in daily news may pose a potential systematic risk to the stock market, leading to stock price fluctuations.

**Table 3: Model of daily stock volatility with disagreement and uncertainty sentiment.**

This table reports results from the following predictive regression:

$$Vs_{t+i}^{(d)} = \alpha + \beta_1 DoS_t + \beta^{(d)} + Vs_t^{(d)} + \beta^{(w)} Vs_t^{(w)} + \beta^{(m)} Vs_t^{(m)} + \beta_3 Control_t + \varepsilon_{t+i}$$

and

$$Vs_{t+i}^{(d)} = \alpha + \beta_1 UNC_t + \beta^{(d)} + Vs_t^{(d)} + \beta^{(w)} Vs_t^{(w)} + \beta^{(m)} Vs_t^{(m)} + \beta_3 Control_t + \varepsilon_{t+i}$$

Where $Vs_{t+i}^{(d)}$ is a simple measure of daily volatility is defined as the first logarithmic difference between the high and low prices $Vs_t^{(w)} = \frac{1}{5}\sum_{i=1}^{5} Vs_{t-i+1}^{(d)}$ and $Vs_t^{(w)} = \frac{1}{5}\sum_{i=1}^{5} Vs_{t-i+1}^{(d)}$ are the weekly and monthly averages of daily log realized volatilities, respectively. Panel A and B report results for two disagreement proxies: DoS_LM and DoS_WM. Robust t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively. The data is in daily frequency, and the sample period is from January 2008 to December 2019.

| | *Dependent: Volatility (t+1)* | | | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| DoS_LM | 0.0266*** | | 0.0202*** | |
| | (7.129) | | (4.642) | |
| UNC_LM | | 0.0345*** | | 0.0251*** |
| | | (7.689) | | (4.840) |
| Vs_s | 0.777*** | 0.777*** | 0.805*** | 0.805*** |
| | (737.7) | (737.7) | (688.9) | (688.9) |
| Vs_w | -1.057*** | -1.057*** | -1.115*** | -1.115*** |
| | (-673.9) | (-673.9) | (-630.4) | (-630.4) |
| Vs_m | -0.0862*** | -0.0862*** | -0.121*** | -0.121*** |
| | (-69.18) | (-69.17) | (-84.19) | (-84.19) |
| Constant | 1.375*** | 1.376*** | 2.722*** | 2.722*** |
| | (253.9) | (264.2) | (45.59) | (45.59) |
| Controls included | No | Yes | No | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 2,730,413 | 2,730,413 | 2,098,786 | 2,098,786 |
| R-squared | 0.276 | 0.276 | 0.316 | 0.316 |
| Number of Ticker | 1,155 | 1,155 | 956 | 956 |

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

### *4.3. Disagreement and uncertainty sentiments with abnormal stock returns*

In order to examine disagreement and uncertainty sentiment at the aggregate level, I examine the association between disagreement and uncertainty sentiments and firm-level stock returns.

Table 4 shows the predictive regression results of Eq.5 and Eq.6, presenting the relationship between climate-related disagreement and uncertainty sentiments and firms' stock abnormal returns over several windows. Columns 1 to 4 of Panel A of Table 4 show the outcome for the regression of abnormal return FF3 on disagreement, while columns 5 to 8 of the same panel show outcome for the regression on uncertainty. I observe a negative relationship between *DoS_LM* and cumulative abnormal return of both intervals [-1 +1] and [+1 +5]. Columns 3 and 4 of Panel A Table 4 indicate that the coefficient estimation of *DoS_LM* in the model of FF3 [-1 1] and [+1 +5] are -0.0238 and -0.0262, respectively, indicating that abnormal return three days around the date of news and five days after the news is significantly reduced by an average of 0.025% because of divergence of sentiments regarding climate change. These coefficients are statistically significant at the 1% level. This result supports the disagreement theory that when investors interpret news differently, changes in absolute prices are driven higher, thus reducing abnormal returns earned by investors.

Interestingly, from columns 5 to 8 of Panel A, the estimated coefficient of uncertainty sentiment is also highly significant but positively signed. In columns 7 and 8 of Panel A, Table 4, the coefficient estimation of *UNC_LM* in the model of *FF3[-1 +1]* and *FF3[+1 +5]* are 0.0218 and 0.0383, respectively. This result demonstrates that when uncertainty sentiment increases by one unit, abnormal return of 3 days interval [-1 +1] will increase by 0.0218%, and abnormal return of 5 days interval [-1 +5] will increase by 0.038%. This finding is in line with the argument that uncertainty can drive higher stock returns following good news and lower stock returns following bad news (Zhang, 2006) and the argument that economic risks of climate change are often underestimated (Stern, 2013). When the market presents higher information uncertainty, especially about topics that are hard to measure, such as climate change, there is more room for psychological biases. Therefore, during a period of higher climate uncertainty, the misevaluation effects should be most substantial when investors are uncertain about whether the information is good or bad. Investors tend to be overconfident when it is hard to value firms' businesses (Daniel et al., 2001). Therefore, when there is high climate-related uncertainty, investors misprice financial assets, leading to higher stock returns.

Panel B of Table 7 reports the predictive regression results for the same equations but with abnormal returns from the CAPM model (*CAR_CAPM [-1 +1]* and *CAR_CAPM [+1 +5]*) as dependent variables. The results remain the same: the coefficient estimates for *DoS_LM* are negative, and those for *UNC_LM* are positive. In the 3 days window, *DoS_LM* and *UNC_LM* are associated with -0.0182 (t-stat -10.51) and 0.01 (t-stat 4.95), respectively. In the 5 days window, *DoS_LM* and *UNC_LM* are associated with -0.0257 (t-stat -12.1) and -0.0138 (t-stat 5.56), respectively.

In summary, I find a negative predictive relation between climate-related disagreement with stock return and positive predictive relation between uncertainty sentiments with a stock return over a short-term horizon. These findings are in line with disagreement and ambiguity theories which indicate that climate-related disagreement and uncertainty impact stock return differently. It justifies our rationale for studying disagreement and uncertainty sentiments separately.

**Table 4: Predictability of cumulative abnormal return with change in investor disagreement with the lagged return**

This table report results from the following predictive regression:

$CAR_{[i;j]} = \alpha + \beta_1 DoS_{t-1} + \beta_2 Return_{t-1} + \beta_3 Control_t + \varepsilon_t$ and $CAR_{[i;j]} = \alpha + \beta_1 UNC_{t-1} + \beta_2 Return_{t-1} + \beta_3 Control_t + \varepsilon_t$

where $CAR_{[i;j]}$ is a cumulative abnormal return calculated from Fama French 3 factors (Panel A) and CAPM model (Panel B), I report results for regression of CAR 3 days interval [-1 +1] and five days interval [-1 -5]. $DoS_LM_{t-1}$and $UNC\_LM_{t-1}$ are our disagreement and uncertainty sentiment variables classified using Loughran and McDonald's lexicon one day before the news date because I account for the delayed effect of the news on stock returns. Robust *t-statistics* are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively. The data is in daily frequency, and the sample period is from January 2008 to December 2019.

*Panel A: Fama French 3 factors model*

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | *FF3 [-1 +1]* | *FF3 [+1 +5]* | *FF3 [-1 +1]* | *FF3 [+1 +5]* | *FF3 [-1 +1]* | *FF3 [+1 +5]* | *FF3 [-1 +1]* | *FF3 [+1 +5]* |
| DoS_LM | -0.0280*** | -0.0223*** | -0.0238*** | -0.0262*** | | | | |
| | (-18.34) | (-12.18) | (-11.88) | (-10.56) | | | | |
| UNC_LM | | | | | 0.0117*** | 0.0381*** | 0.0218*** | 0.0383*** |
| | | | | | (6.364) | (17.24) | (9.304) | (13.19) |
| Return (t-1) | 0.0286*** | -0.00188*** | 0.0266*** | -0.00198*** | 0.0286*** | -0.00189*** | 0.0266*** | -0.00200*** |
| | (78.59) | (-4.293) | (57.34) | (-3.446) | (78.57) | (-4.336) | (57.31) | (-3.487) |
| Constant | -0.459*** | -0.587*** | -0.416*** | -0.744*** | -0.483*** | -0.620*** | -0.442*** | -0.779*** |
| | (-92.26) | (-98.18) | (-14.62) | (-21.09) | (-97.42) | (-104.1) | (-15.52) | (-22.09) |
| Controls included | No | No | No | No | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,242,813 | 2,242,813 | 1,366,823 | 1,366,823 | 2,242,813 | 2,242,813 | 1,366,823 | 1,366,823 |
| Adjusted R-squared | 0.009 | 0.006 | 0.075 | 0.006 | 0.009 | 0.006 | 0.075 | 0.006 |
| Number of Ticker | 1,165 | 1,165 | 942 | 942 | 1,165 | 1,165 | 942 | 942 |

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

*Panel B: CAPM model*

| VARIABLES | (1) *CAPM [-1 +1]* | (2) *CAPM [+1 +5]* | (3) *CAPM [-1 +1]* | (4) *CAPM [+1 +5]* | (5) *CAPM [-1 +1]* | (6) *CAPM [+1 +5]* | (7) *CAPM [-1 +1]* | (8) *CAPM [+1 +5]* |
|---|---|---|---|---|---|---|---|---|
| DoS_LM | -0.0216*** | -0.0248*** | | | -0.0182*** | -0.0257*** | | |
| | (-15.07) | (-14.94) | | | (-10.51) | (-12.10) | | |
| UNC_LM | | | 0.000950** | 0.0107*** | | | 0.0100*** | 0.0138*** |
| | | | -2.549 | (5.311) | | | (4.948) | (5.559) |
| Return (t-1) | 0.0197*** | -0.00505*** | 0.0197*** | -0.00505*** | 0.0196*** | -0.00469*** | 0.0196*** | -0.00470*** |
| | (57.52) | (-12.73) | (57.51) | (-12.74) | (48.80) | (-9.554) | (48.78) | (-9.565) |
| Constant | -0.458*** | -0.483*** | -0.472*** | -0.504*** | -0.549*** | -0.800*** | -0.565*** | -0.823*** |
| | (-97.83) | (-88.99) | (-101.1) | (-93.26) | (-22.24) | (-26.55) | (-22.91) | (-27.31) |
| Controls included | No | No | No | No | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,242,813 | 2,242,813 | 2,242,813 | 2,242,813 | 1,366,823 | 1,366,823 | 1,366,823 | 1,366,823 |
| Adjusted R-squared[7] | 0.008 | 0.006 | 0.008 | 0.006 | 0.073 | 0.009 | 0.073 | 0.009 |
| Number of Ticker | 1,165 | 1,165 | 1,165 | 1,165 | 942 | 942 | 942 | 942 |

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

[7] Although the adjusted R-squared in the model of abnormal returns are smaller than 1%, it can be argued that the models cannot include all relevant predictors to explain the outcome of abnormal return, especially in the area of social or behavioural science in this paper (Neter et al., 1996). Even when small, the adjusted r-squared are significantly different from 0, indicating that our regression models have statistically significant explanatory power.

## 5. Robustness tests

In order to ensure that our sample composition does not influence our findings, I perform several robustness tests.

### *5.1. Controlling for alternative volatilities and sentiment level*

The first test examines whether our disagreement and uncertainty sentiments' effect on volatility will be changed when the level of sentiment is in place. Relatedly, sentiment level has been approved to be a solid element to move volatility and trading volume. Siganos et al. (2014) show that investors' pessimism induces an increase in both stock volatility and trading volume. This issue is because temporary pessimism results in more trades by investors to overcome their negative sentiments. Chang et al. (2008) report that high transaction volumes are caused by cloudy weather, while Coval and Shumway (2005) find that traders who make losses early in a day are likely to take a higher risk later that day. Therefore, I would like to test if the impact of our climate-related disagreement and uncertainty sentiments remains after controlling for the level of sentiments.

**Table 5a: Trading volume and Volatility regression with sentiment level**

This table shows whether *DoS* and *UNC* sentiments are related to trading volume and future stock price volatility after controlling for the level of sentiment. Trading volume is the average daily trading volume for day *t* collected from DataStream. The stock price volatility represents the daily measure of volatility at day t+1, as estimated using the first logarithmic difference between the high and low prices. Robust t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively.

| | *ΔVolume (t)* | | *Volatility (t+1)* | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| DoS_LM | 19.64*** | | 0.0248*** | |
| | (3.533) | | (6.547) | |
| UNC_LM | | 15.78** | | 0.0326*** |
| | | (2.360) | | (7.185) |
| SENT | 88.85 | 113.9 | 0.566*** | 0.575*** |
| | (0.450) | (0.578) | (4.302) | (4.371) |
| Constant | -391.4*** | -386.1*** | 1.384*** | 1.384*** |
| | (-21.56) | (-21.36) | (251.6) | (262.4) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 2,201,103 | 2,201,103 | 2,642,596 | 2,642,596 |
| R-squared | 0.146 | 0.146 | 0.282 | 0.282 |
| Number of Ticker | 1,165 | 1,165 | 1,155 | 1,155 |

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table 5b: Cumulative abnormal return regression with sentiment level**

This table shows whether *DoS* and *UNC* sentiments are related to abnormal stock returns after controlling for the level of sentiment. Cumulative abnormal returns are calculated based on Fama French 3 factors model and CAPM model. I present results for 3 days interval [-1 +1] and 5 days interval [-1 -5]. All regressions include company fixed effects. Robust t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively.

*Panel A: model with DoS_LM*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | *FF3 [-1 +1]* | *CAPM [-1 +1]* | *FF3 [+1 +5]* | *CAPM [+1 +5]* |
| DoS_LM | -0.0338*** | -0.0268*** | -0.0267*** | -0.0269*** |
| | (-21.54) | (-18.06) | (-14.20) | (-15.77) |
| Return (t-1) | 0.0291*** | 0.0201*** | -0.00195*** | -0.00517*** |
| | (78.27) | (57.01) | (-4.379) | (-12.80) |
| SENT | 1.843*** | 1.414*** | 2.162*** | 2.025*** |
| | (33.04) | (26.83) | (32.45) | (33.50) |
| Constant | -0.473*** | -0.465*** | -0.586*** | -0.484*** |
| | (-92.70) | (-96.48) | (-96.18) | (-87.53) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 2,157,470 | 2,157,470 | 2,157,470 | 2,157,470 |
| R-squared | 0.010 | 0.009 | 0.006 | 0.007 |
| Number of Ticker | 1,165 | 1,165 | 1,165 | 1,165 |

*Panel B: model with UNC_LM*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | *FF3 [-1 +1]* | *CAPM [-1 +1]* | *FF3 [+1 +5]* | *CAPM [+1 +5]* |
| UNC_LM | 0.00634*** | 0.0419*** | 0.00152 | 0.0199*** |
| | (3.347) | (18.51) | (0.846) | (9.709) |
| Return (t-1) | 0.0291*** | -0.00196*** | 0.0201*** | -0.00517*** |
| | (78.26) | (-4.411) | (57.01) | (-12.82) |
| SENT | 1.788*** | 2.121*** | 1.370*** | 1.982*** |
| | (32.09) | (31.86) | (26.02) | (32.83) |
| Constant | -0.498*** | -0.624*** | -0.482*** | -0.511*** |
| | (-97.92) | (-102.7) | (-100.3) | (-92.73) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 2,157,470 | 2,157,470 | 2,157,470 | 2,157,470 |
| R-squared | 0.009 | 0.007 | 0.008 | 0.007 |
| Number of Ticker | 1,165 | 1,165 | 1,165 | 1,165 |

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Tables 5a and 5b, I include our disagreement and uncertainty sentiment from both Loughran and McDonald's classification with the level of sentiment in the U.K obtained from Bloomberg in our baseline model specification. The results in table 5b show that the influence of disagreement and uncertainty variables on both stock price volatility and trading volume holds positive after controlling for sentiment level. Coefficients for both *DoS_LM* and *UNC_LM* variables are the same as reported in Tables 2 and 3, all statically significant at the 5% level and higher. In this test, disagreement and uncertainty sentiments and level of sentiment seem to be equally important, and both have a positive effect in predicting future stock price volatility. This result is in line with the finding of Siganos et al. (2017) that highlights the importance of examining divergence of sentiment and uncertainty beyond examining sentiment levels. In table 5b, when controlling for level of sentiment, the effect of *DoS_LM* and *UNC_LM* on abnormal stock returns also remain the same as the baseline models.

**Table 6a: Trading volume and Volatility regression with alternative volatilities**

This table shows whether *DoS* and *UNC* sentiments are related to stock price volatility and trading volume after controlling for other alternative sentiment measures: implied volatility for FTSE100 index: VIX; change in FTSE100 VIX (VIXC); and market state dummy variable, which is UP if lagged return of FTSE100 index in the last 250 trading days is non-negative and DOWN otherwise. All regressions include time and firm fixed effects. Robust t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively.

| | *ΔVolume (t)* | | *Volatility (t+1)* | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| DoS_LM | 15.99*** | | 0.0279*** | |
| | (2.849) | | (7.339) | |
| UNC_LM | | 15.94** | | 0.0365*** |
| | | (2.358) | | (8.053) |
| VIX | 655.9*** | 660.9*** | -0.0595 | -0.0570 |
| | (10.42) | (10.50) | (-1.431) | (-1.372) |
| VIXC | 17.17*** | 17.54*** | 0.00785*** | 0.00850*** |
| | (5.599) | (5.717) | (3.804) | (4.114) |
| StateSign | -12.61** | -12.31** | -0.0280*** | -0.0275*** |
| | (-2.096) | (-2.046) | (-8.212) | (-8.083) |
| Constant | -406.4*** | -403.5*** | 1.397*** | 1.396*** |
| | (-21.21) | (-21.15) | (249.1) | (258.0) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 2,193,076 | 2,193,076 | 2,626,179 | 2,626,179 |
| R-squared | 0.144 | 0.144 | 0.282 | 0.282 |
| Number of Ticker | 1,165 | 1,165 | 1,155 | 1,155 |

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table 6b: Cumulative abnormal return regression with alternative volatilities**

This table shows whether *DoS* and *UNC* sentiments are related to stock returns after controlling for other alternative sentiment measures: implied volatility for FTSE100 index: VIX; change in FTSE100 VIX (VIXC); and market state dummy variable which is UP if lagged return of FTSE100 index in the last 250 trading days is non-negative and DOWN otherwise. All regressions include time and firm fixed effects. Robust t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively.

*Panel A: model with DoS_LM*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | *FF3 [-1 +1]* | *CAPM [-1 +1]* | *FF3 [+1 +5]* | *CAPM [+1 +5]* |
| DoS_LM | -0.0333*** | -0.0269*** | -0.0264*** | -0.0255*** |
| | (-21.02) | (-17.90) | (-13.83) | (-14.62) |
| VIX_FTSE100 | -3.629*** | -3.342*** | -0.137*** | 0.269*** |
| | (-217.4) | (-211.4) | (-6.820) | (14.67) |
| VIXC_FTSE100 | -0.0176*** | -0.0128*** | -0.00986*** | -0.00929*** |
| | (-20.90) | (-16.06) | (-9.722) | (-10.06) |
| StateSign | 0.0698*** | 0.0673*** | 0.000381 | 0.0216*** |
| | (41.97) | (42.69) | (0.190) | (11.81) |
| Constant | -0.386*** | -0.386*** | -0.607*** | -0.492*** |
| | (-72.82) | (-76.85) | (-94.94) | (-84.45) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 2,148,723 | 2,148,723 | 2,148,723 | 2,148,723 |
| R-squared | 0.032 | 0.030 | 0.007 | 0.007 |
| Number of Ticker | 1,165 | 1,165 | 1,165 | 1,165 |

*Panel B: model with UNC_LM*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| VARIABLES | *FF3 [-1 +1]* | *CAPM [-1 +1]* | *FF3 [+1 +5]* | *CAPM [+1 +5]* |
| UNC_LM | 0.00752*** | 0.0383*** | 0.00507*** | 0.0130*** |
| | (3.987) | (16.84) | (2.839) | (6.282) |
| VIX_FTSE100 | -3.629*** | -0.134*** | -3.343*** | 0.269*** |
| | (-217.3) | (-6.652) | (-211.4) | (14.71) |
| VIXC_FTSE100 | -0.0173*** | -0.00978*** | -0.0125*** | -0.00908*** |
| | (-20.51) | (-9.646) | (-15.65) | (-9.835) |
| StateSign | 0.0697*** | 0.000658 | 0.0670*** | 0.0216*** |
| | (41.90) | (0.328) | (42.55) | (11.81) |
| Constant | -0.412*** | -0.642*** | -0.401*** | -0.515*** |
| | (-78.07) | (-101.0) | (-80.38) | (-88.89) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 2,148,723 | 2,148,723 | 2,148,723 | 2,148,723 |
| R-squared | 0.031 | 0.007 | 0.030 | 0.007 |
| Number of Ticker | 1,165 | 1,165 | 1,165 | 1,165 |

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Next step, I examine whether our disagreement and uncertainty sentiments' effect on stock price volatility and trading volumes stay robust when I include other alternative sentiment measures. Following Sun et al. (2016), I contemplate three market-based sentiment measures: FTSE volatility index (*VIX_FTSE100*), change in FTSE100 VIX *(VIXC_FTSE100),* and market state (*StateSign*) as defined by dummy variables based on the sign of lagged 1-year market return (UP if lagged return of FTSE100 in the last 250 trading days is non-negative and DOWN otherwise). Table 6a shows the results of the three alternative sentiment measures in the model with stock trading volume and stock volatility as dependent variables. The estimated coefficients of *DoS_LM* and *UNC_LM* remain positively significant with the inclusion of alternative sentiment measures. However, in terms of adjusted $R^2$, the alternative measures used in our test proved to be less valuable. The adjusted $R^2$ in the model of trading volume decreases from around 14.6% in table 2 to 14.4% in columns 1 and 2 table 6a. And the adjusted $R^2$ decreases from around 31.6% in Table 3 to 28.2% in columns 3 and 4 in Table 6a in the trading volume model. It provides an insight that the disagreement and uncertainty sentiment from climate change news is better than other sentiment proxies in explaining increases in trading volume and stock volatility. Throughout the test, both of our climate-related uncertainty and disagreement sentiments hold their highly significant effects in the trading volume and volatility model.

We also include the three alternative sentiment measures in the regression model of abnormal returns in table 6b. The results show that with the inclusion of alternative sentiment measures, the effect of disagreement and uncertainty sentiments on abnormal stock returns remain highly significant (at the 1% level). Interestingly, the outcome in column 3 Panel A and column 2 Panel B show that the market state dummy variable does not have any explanatory power in some speciation. Volatility index FTSE100 and change in FTSE100 VIX (VIXC) index show a continuous, significant predictability power towards stock price volatility when including in our regression model.

### *5.2. Subsample tests*

Seasonality also sometimes poses a vital role in any stock price anomaly. In literature, it is shown that individuals generate relatively more trades during the beginning of the week (Lakonishok and Maberly, 1990, Venezia and Shapira, 2007). For example, Lakonishok and Maberly (1990) show that Monday and Tuesday are active trading days for individuals. Therefore, to ease the seasonality concern within our research, I first exclude Monday and Tuesday in our subsample.

In Tables 7a and 7b, outcomes of our baseline regression models are reported for the subsample that excludes Monday and Tuesday. Again, it can be observed that all of our disagreement and uncertainty sentiments remain significant throughout the week.

**Table 7a: Cumulative abnormal returns when excluding Monday and Tuesday in the subsample.**

This table shows whether *DoS* and *UNC* sentiments are related to trading volume and stock volatility when excluding Monday and Tuesday in the subsample. All regressions include time and firm fixed effects. Robust t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively.

| | *ΔVolume (t)* | | *Volatility (t+1)* | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| | | | | |
| DoS_LM | 15.69* | | 0.0176*** | |
| | (1.878) | | (3.464) | |
| UNC_LM | | 21.14** | | 0.0273*** |
| | | (2.162) | | (4.581) |
| | | | | |
| Constant | -663.8*** | -664.6*** | 2.437*** | 2.434*** |
| | (-5.260) | (-5.267) | (34.58) | (34.54) |
| | | | | |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| | | | | |
| Observations | 1,058,621 | 1,058,621 | 1,290,114 | 1,290,114 |
| R-squared | 0.135 | 0.135 | 0.427 | 0.427 |
| Number of Tickers | 942 | 942 | 956 | 956 |

**Table 7b: Cumulative abnormal returns when excluding Monday and Tuesday in the subsample.**

This table shows whether *DoS* and *UNC* sentiments relate to stock returns when excluding Monday and Tuesday in the subsample. All regressions include time and firm fixed effects. Robust t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively.

| *Panel A: model with DoS_LM* | *Excluding Monday and Tuesday* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| VARIABLES | *FF3 [-1 +1]* | *CAPM [-1 +1]* | *FF3 [+1 +5]* | *CAPM [+1 +5]* |
| | | | | |
| DoS_LM | -0.0342*** | -0.0251*** | -0.0302*** | -0.0321*** |
| | (-15.28) | (-12.85) | (-11.50) | (-14.35) |
| Return (t-1) | 0.0350*** | 0.0266*** | 0.00185*** | -0.00173*** |
| | (65.50) | (57.02) | (2.940) | (-3.247) |
| | | | | |
| Constant | -0.413*** | -0.592*** | -0.700*** | -0.711*** |
| | (-12.58) | (-20.66) | (-18.14) | (-21.68) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| | | | | |
| Observations | 1,058,872 | 1,058,872 | 1,058,872 | 1,058,872 |
| R-squared | 0.075 | 0.072 | 0.007 | 0.009 |
| Number of Tickers | 942 | 942 | 942 | 942 |

*Panel B: model with UNC_LM*

| VARIABLES | (1)<br>*FF3 [-1 +1]* | (2)<br>*CAPM [-1 +1]* | (3)<br>*FF3 [+1 +5]* | (4)<br>*CAPM [+1 +5]* |
|---|---|---|---|---|
| UNC_LM | 0.0202*** | 0.0397*** | 0.0184*** | 0.0248*** |
| | (7.740) | (12.95) | (8.065) | (9.517) |
| Return (t-1) | -0.00175*** | 0.00181*** | 0.0266*** | 0.0350*** |
| | (-3.269) | (2.888) | (56.99) | (65.47) |
| Constant | -0.741*** | -0.737*** | -0.617*** | -0.446*** |
| | (-22.60) | (-19.12) | (-21.52) | (-13.59) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 1,058,872 | 1,058,872 | 1,058,872 | 1,058,872 |
| R-squared | 0.009 | 0.007 | 0.071 | 0.075 |
| Number of Tickers | 942 | 942 | 942 | 942 |

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Besides, following Fama and French (1992), I exclude banks and financial institutions because their financial data and leverage ratios have different meanings than non-financial firms. I run our main regressions using subsample excluding financial firms and report results in table 8a and 8b. The outcomes indicate that financial firms do not drive our results.

**Table 8a: Trading volume and Volatility regression when excluding financial firms in the subsample.**

This table shows whether *DoS* and *UNC* sentiments relate to stock trading volume and stock volatility when excluding financial firms in the subsample. All regressions include time and firm fixed effects. Robust t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively.

| | *ΔVolume (t)* | | *Volatility (t+1)* | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| DoS_LM | 19.19*** | | 0.0211*** | |
| | (2.634) | | (4.808) | |
| UNC_LM | | 16.41* | | 0.0272*** |
| | | (1.890) | | (5.194) |
| Constant | -551.5*** | -548.0*** | 2.694*** | 2.693*** |
| | (-5.023) | (-4.991) | (44.87) | (44.86) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 1,389,530 | 1,389,530 | 2,057,991 | 2,057,991 |
| R-squared | 0.147 | 0.147 | 0.321 | 0.321 |
| Number of Tickers | 922 | 922 | 936 | 936 |

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

**Table 8b: Cumulative abnormal return regressions when excluding financial firms in the subsample.**

This table shows whether *DoS* and *UNC* sentiments relate to stock returns when excluding financial firms in the subsample. All regressions include time and firm fixed effects. Robust t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively.

*Panel A: model with DoS_LM*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *FF3 [-1 +1]* | *CAPM [-1 +1]* | *FF3 [+1 +5]* | *CAPM [+1 +5]* |
| DoS_LM | -0.0260*** | -0.0266*** | -0.0181*** | -0.0238*** |
| | (-12.12) | (-10.58) | (-10.31) | (-11.73) |
| Return (t-1) | -0.00479*** | -0.00210*** | 0.0198*** | 0.0267*** |
| | (-9.621) | (-3.600) | (48.45) | (56.79) |
| Constant | -0.832*** | -0.769*** | -0.574*** | -0.437*** |
| | (-27.29) | (-21.57) | (-22.99) | (-15.17) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 1,342,956 | 1,342,956 | 1,342,956 | 1,342,956 |
| R-squared | 0.010 | 0.006 | 0.073 | 0.075 |
| Number of Tickers | 922 | 922 | 922 | 922 |

*Panel B: model with UNC_LM*

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *FF3 [-1 +1]* | *CAPM [-1 +1]* | *FF3 [+1 +5]* | *CAPM [+1 +5]* |
| UNC_LM | 0.0139*** | 0.0386*** | 0.0102*** | 0.0220*** |
| | (5.558) | (13.15) | (4.951) | (9.292) |
| Return (t-1) | -0.00480*** | -0.00212*** | 0.0197*** | 0.0267*** |
| | (-9.632) | (-3.642) | (48.44) | (56.76) |
| Constant | -0.855*** | -0.804*** | -0.590*** | -0.462*** |
| | (-28.06) | (-22.56) | (-23.65) | (-16.06) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 1,342,956 | 1,342,956 | 1,342,956 | 1,342,956 |
| R-squared | 0.009 | 0.007 | 0.073 | 0.075 |
| Number of Tickers | 922 | 922 | 922 | 922 |

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We also test whether the relations between our disagreement and uncertainty sentiments and stock price volatility and trading volume differ in different market conditions of negative and positive marker return. Therefore, I run our baseline regression model separately for days with negative market returns compared to those with a positive market return. Table 9 presents that both disagreement and uncertainty sentiments are significantly and positively associated with stock trading volume and stock volatility regardless of the direction of the stock market return. The relations are all significant at 1% in all cases.

**Table 9: Trading volume and Volatility regression in different market return circumstances.**

This table shows whether *DoS* and *UNC* sentiments relate to stock trading volume and stock volatility in different market directions. Panel A shows results for days with a positive market return. Panel B shows results for days with negative market returns. All regressions include time and firm fixed effects. Robust t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively.

*Panel A: Positive market return*

| | *ΔVolume (t)* | | *Volatility (t+1)* | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| DoS_LM | 21.23* | | 0.0231*** | |
| | (1.807) | | (3.872) | |
| UNC_LM | | 20.09* | | 0.0278*** |
| | | (1.781) | | (3.658) |
| Constant | -447.4*** | -436.4*** | 2.932*** | 2.930*** |
| | (-3.256) | (-3.176) | (35.54) | (35.49) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Company FE | Yes | Yes | Yes | Yes |
| Observations | 763,264 | 763,264 | 1,110,007 | 1,110,007 |
| R-squared | 0.099 | 0.099 | 0.318 | 0.318 |
| Number of Tickers | 942 | 942 | 955 | 955 |

*Panel B: Negative market return*

| | *ΔVolume (t; t-1)* | | *Volatility (t+1)* | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| DoS_LM | 20.42* | | 0.0179*** | |
| | (1.844) | | (2.799) | |
| UNC_LM | | 25.11** | | 0.0205*** |
| | | -2.498 | | (2.852) |
| Constant | -485.2*** | -489.5*** | 2.491*** | 2.495*** |
| | (-2.980) | (-3.008) | (28.54) | (28.61) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Company FE | Yes | Yes | Yes | Yes |
| Observations | 650,954 | 650,954 | 988,153 | 988,153 |
| R-squared | 0.193 | 0.193 | 0.315 | 0.315 |
| Number of Tickers | 942 | 942 | 956 | 956 |

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Overall, I can conclude that our disagreement and uncertainty sentiments are pervasive. The sentiment effects in our research are proved to be a widespread phenomenon and rendered by the primary analysis when excluding active trading days or financial firms and in both positive and negative market returns circumstances.

### 5.3. *Quasi-experimental design test – Difference in difference model*

Besides robustness tests performed above, I suspect there might be selection bias in the industry classification. Therefore, companies in the treatment and control groups could not be comparable in observable and unobservable characteristics. I explore this hypothesis in this section.

We aim to design a quasi-experimental approach that compares the changes in outcomes over time between companies in environmentally sensitive industries (the treatment group) and companies that are not (the control group) before and after 2016. I chose 2016 because the Paris Agreement - a legally binding international treaty on climate change – was entered into force this year. The sample period runs from the financial year 2013 to the financial year 2019 (excluding the financial year 2016) to get rid of confusing effects in the year of implementation (Mao & Zhang, 2018). *POST* was set to 1 if it is financial years 2017, 2018, and 2019, and zero otherwise. *TREAT* variable is one if a company operates in environmentally sensitive industries (Material, Utilities, Energy, and Real Estate)

To further mitigate exogenous shock, I deploy PSM match to match treatment group with control group based on firm-level data: Size, ESG score, and ROA. Appendix C provides more details on our PSM matching method.

After matching, I continued to use the difference-in-differences framework for our analysis with matched treatment and control groups. DiD analysis can test the consequences of the Paris Agreement 2016 for the companies in our treatment group (the company operates in environmentally sensitive industries (Material, Utilities, Energy, and Real Estate). Given that the study examines the difference over time between two groups, the DID approach could constitute the omitted factors that impact the two groups alike, and it also rules out omitted trends that correlate with stock volatility, trading volume, and abnormal return in the treatment and control groups. I examine the effects of exogenous shock on treatment and control group by running the following regression:

$$Y_{it} = \alpha_i + \alpha_i \times \alpha_t + \alpha_s \times \alpha_t + \beta_1 TREAT_i + \beta_2 POST_t + \beta_3 TREAT_i \times POST_t + \beta_4 Control_t + \varepsilon_{t+1}$$

In which, *i* indexes firms, t indexes years, and s indexes 2-digit ICB industries; y is the outcome variable of interest (e.g., Trading volumes, volatility, and abnormal return); $\alpha_i$ are firm fixed effects; $\alpha_i \times \alpha_t$ are firm by year fixed effects; $\alpha_s \times \alpha_t$ are industry by year fixed effects; *TREAT* is a dummy variable ("treatment dummy") that equals one if firm *i* company operates in an environmentally sensitive industry (Material, Utilities, Energy, and Real Estate and zero otherwise). *POST* is a dummy variable for the year before and after 2016 (1 for 2017, 2018, and 2019 and zero for 2013, 2014, and 2015).

**Table 10: Trading volume and volatility DID regressions.**

This table compares DID models between the original sample and PSM sample of stock trading volume and stock volatility. *POST* is one year after 2016 (Paris Agreement), *TREAT* is 1 for Material, Utilities, Energy, and Real Estate company. Robust t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively.

| | *DID with the original sample* | | *DID with PSM sample* | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| VARIABLES | *ΔVolume (t)* | *Volatility (t+1)* | *ΔVolume (t)* | *Volatility (t+1)* |
| TREAT | 44.28 | 0.00205** | 20.68 | 0.00259*** |
| | (1.325) | (2.482) | (0.246) | (2.748) |
| POST | -149.2*** | 0.000687*** | -238.0** | 0.00102*** |
| | (-2.999) | (3.006) | (-2.327) | (2.641) |
| TREAT×POST | -94.48** | -0.000112 | 29.74 | -0.000279 |
| | (-2.252) | (-0.571) | (0.159) | (-0.958) |
| Constant | -114.2 | 0.00200 | -286.2 | -0.00343** |
| | (-1.294) | (1.495) | (-0.921) | (-2.098) |
| Controls included | Yes | Yes | Yes | Yes |
| Year × Industry FE | Yes | Yes | Yes | Yes |
| Year × Country FE | Yes | Yes | Yes | Yes |
| Observations | 1,102,072 | 790,214 | 618,147 | 435,039 |
| R-squared | 0.14 | 0.12 | 0.256 | 0.276 |
| Number of Ticker | 919 | 893 | 807 | 762 |

z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tables 10 and 11 present the results from our model specifications. From columns 3 and 4 of Table 10, I observe that the interaction terms TREAT×POST in both models are insignificant. It indicates that expected mean changes in volatility and trading volume from before to after the Paris Agreement event were not different in the two groups (environmentally sensitive and non-sensitive industries). Results from table 11 also show incognizant interaction term TREAT×POST in models of abnormal returns. It indicates that firms' abnormal returns did not change because of firms' industries when Paris Agreement entered force.

Interestingly, when comparing the PSM data sample with the original sample, the results of DID with the PSM sample report a significantly lower estimated coefficient. Therefore, our results are sensitive to probability score matching at the baseline, perhaps providing evidence of baseline selection bias reduced by matching. Thus, I conclude that exogenous shocks do not affect companies in environmentally sensitive industries and non-sensitive industries differently.

**Table 11: Cumulative abnormal return DID regressions.**

This table compares DID models between the original sample and the PSM sample of stock returns. Panel A reports regression of abnormal return measured by *POST* is one for the years after 2016 (Paris Agreement), *TREAT* is 1 for Material, Utilities, Energy, and Real Estate company. Robust t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively.

*Panel A: FF3 model*

| | *DID with the original sample* | | *DID with PSM sample* | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| VARIABLES | *FF3 [-1 +1]* | *FF3 [+1 +5]* | *FF3 [-1 +1]* | *FF3 [+1 +5]* |
| TREAT | -0.105** | -0.117** | -0.0575* | -0.0355 |
| | (-2.035) | (-2.043) | (-1.836) | (-0.978) |
| POST | -0.0791*** | -0.0252 | -0.00576 | 0.0860*** |
| | (-3.057) | (-0.900) | (-0.608) | (8.371) |
| TREAT×POST | 0.0883* | 0.116** | 0.0122 | 0.00607 |
| | (1.756) | (2.039) | (1.029) | (0.474) |
| Constant | -0.108 | -0.159 | -0.147*** | -0.267*** |
| | (-0.949) | (-1.260) | (-2.752) | (-4.386) |
| Controls included | Yes | Yes | Yes | Yes |
| Year × Industry FE | Yes | Yes | Yes | Yes |
| Year × Country FE | Yes | Yes | Yes | Yes |
| Observations | 591,483 | 591,483 | 325,664 | 325,664 |
| R-squared | 0.063 | 0.007 | 0.075 | 0.009 |
| Number of Ticker | 893 | 893 | 762 | 762 |

z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

*Panel B: CAPM model*

| | *DID with the original sample* | | *PSM matching data set* | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| VARIABLES | *CAPM [-1 +1]* | *CAPM [+1 +5]* | *CAPM [-1 +1]* | *CAPM [+1 +5]* |
| TREAT | -0.0997* | -0.0994* | -0.0370 | -0.0792** |
| | (-1.853) | (-1.694) | (-1.116) | (-2.325) |
| POST | -0.0862*** | -0.0108 | 0.00515 | 0.0478*** |
| | (-3.310) | (-0.396) | (0.595) | (4.475) |
| TREAT×POST | 0.100** | 0.103* | 0.00808 | 0.0434 |
| | (2.001) | (1.886) | (0.749) | (0.25) |
| Constant | -0.115 | -0.200 | -0.171*** | -0.162*** |
| | (-0.899) | (-1.420) | (-3.122) | (-2.783) |
| Controls included | Yes | Yes | Yes | Yes |
| Year × Industry FE | Yes | Yes | Yes | Yes |
| Year × Country FE | Yes | Yes | Yes | Yes |
| Observations | 591,483 | 591,483 | 325,664 | 325,664 |
| R-Squared | 0.053 | 0.006 | 0.027 | 0.009 |
| Number of Ticker | 893 | 893 | 762 | 762 |

z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

## 6. Further analysis

### *6.1 Corporate sustainability responsibilities, disagreement and uncertainty sentiments, and stock performance.*

We further analyze how disagreement and uncertainty sentiments in climate change news affect firms' stock performances of green firms compared to non-green firms.

The growing global concern over climate change and corporate sustainability has recently sparked a new trend to mitigate climate risk in investment portfolios. I expect that some investors concentrate on disinvestment to mitigate risks. As a result, firms in environmentally sensitive industries are more likely to be excluded, short sold, or reduced weights in investors' portfolios in the existence of climate risks[8]. Consequently, I posit that firms that operate in environmentally sensitive industries are more likely to face higher risks and be more volatile when there is a higher level of disagreement and uncertainty in climate change news.

In addition to industry classification, I also expect that information on firms' environmental engagements also distinguishes green firms from non-green firms. Regarding stakeholder theory, literature shows that sustainability performance and disclosure contribute to higher market confidence, thereby lowering stock price volatility. Our analysis relates to Dhaliwal et al. (2012), which suggests that the higher sustainability engagement level of the company leads to higher efficiency in controlling and refining long-term risk management. Such evidence for this notion is found in the study of Harjoto and Jo (2015), in which the legalized CSR disclosure based on requirements from the government will benefit the market since the information will be less costly to obtain and likely to be more genuine.

Apart from environmental performance, arguments on sustainability information are divided into two directions based on how investors interpret disclosed information. First of all, the optimistic perspective believes sustainability information can maximize the company's value in the future by showing the firm's wealth creation, although it might not affect the current value. In addition, the companies' commitment to a sustainable business promises an increase in long-term performance, enhances market participants' confidence, and reduces price volatility (Dhaliwal et al., 2012). On the other hand, sustainability disclosure may increase information asymmetry, which leads to dispersed opinions on published information (Harjoto and Jo, 2015). With different interpretations of the same

[8] See, e.g., ANDERSSON, M., BOLTON, P. & SAMAMA, F. 2016. Hedging Climate Risk. *Financial Analysts Journal,* 72**,** 13-32. ENGLE, R. F., GIGLIO, S., KELLY, B., LEE, H. & STROEBEL, J. 2020. Hedging Climate Change News. *The Review of Financial Studies,* 33**,** 1184-1216, ANDERSSON, M., BOLTON, P. & SAMAMA, F. 2016. Hedging Climate Risk. *Financial Analysts Journal,* 72**,** 13-32. for discussion on hedging climate risks for portfolio strategies.

piece of news, the stock will be evaluated differently, leading to higher stock price volatility and stock price bubbles (Jo and Na, 2012, Orlitzky and Shen, 2013).

To test our expectation that firms that have better environmental performance would have their stocks prices less volatile and higher trading volumes, I construct three analyses regarding environmental disclosure and industrial affiliation: (i) environmentally sensitive industries, (ii) environmental engagements, (iii) environmental performance.

### *6.1.1 Environmental sensitive industries*

Following Jia and Li (2020), I group companies into environmentally sensitive industries if they operate in Basic Materials, Energy, Industrials, and Utilities. I also include firms in Real Estates as physical climate changes may also harm their businesses. Other companies which do not fall into these categories will be grouped into environmentally non-sensitive industries.

**Table 12: Models of trading volume changes and stock price volatility and climate-related sentiments with sectoral analysis**

This table shows whether the impact of *DoS* and *UNC* sentiments on trading volume and stock price volatility is exacerbated for environmentally sensitive industries. *SENSI* denotes 1 for firms in Basic Materials, Energy, Industrials, Utilities, and Real Estates industries, and zero otherwise, Robust t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively.

| | *ΔVolume (t)* | | *Volatility (t+1)* | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| DoS_LM | 2.623 | | -0.0216*** | |
| | (0.262) | | (-3.494) | |
| DoS_LM×SENSI | 31.96** | | 0.0440*** | |
| | (2.283) | | (5.108) | |
| UNC_LM | | 24.05** | | -0.0303*** |
| | | (2.022) | | (-4.111) |
| UNC_LM×SENSI | | 13.97 | | 0.0682*** |
| | | (0.840) | | (6.659) |
| SENSI | -74.61 | -36.84 | 0.969 | 0.960 |
| | (-0.407) | (-0.201) | (0.808) | (0.801) |
| Constant | -540.5*** | -539.7*** | 2.343*** | 2.340*** |
| | (-4.994) | (-4.986) | (38.24) | (38.19) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 1,414,218 | 1,414,218 | 2,098,786 | 2,098,786 |
| R-squared | 0.147 | 0.147 | 0.317 | 0.317 |
| Number of Tickers | 942 | 942 | 956 | 956 |

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12 shows the coefficient on the interactive term *DoS_LM×SENSI* and *UNC_LM×SENSI* are positive and significant in the regression model of stock volatility, indicating that stocks of companies in environmentally sensitive industries are more volatile when facing disagreement and uncertainty regarding climate change. In the regression of trading volume changes, the estimated coefficient of the interactive term *DoS_LM×SENSI* is significant and positive, suggesting that investors generate more trades for firms that are sensitive to the environment. The interaction term *UNC_LM×SENSI* in the trading volume model is insignificant but remains positive.

#### *6.1.2 Sustainability performance and sustainability discloser*

In the last decade, the U.K government has been integrating several initiatives into reporting procedures in order to promote the disclosure of sustainability materials. I propose to explore further if companies' ESG data can mitigate the risk posed in climate change news. Regarding stock performance, Ashwin Kumar et al. (2016) indicate that ESG firms listed on Dow Jones Sustainability Index experienced lower stock volatility compared to their peer operating in the same industry. Furthermore, companies with higher ESG practices also generate higher returns (Ashwin Kumar et al., 2016). Thus, this study extends the existing literature on ESG issues by presenting the effect of uncertainty and disagreement sentiments on stock performance, considering the effect of ESG performance and disclosure. I collect ESG scores from DataStream and disclosure data from Bloomberg.

Columns 1 and 2 of Panel A, Table 13 show positive and significant interaction terms *DoS_LM×ESG* and *UNC_LM×ESG* with ESG performance score in trading volume changes regression. One possible explanation is that when firms have strong ESG performances, investors trade these stocks with confidence. Thereby, when investors face uncertainty or diverging opinions in climate change news, they seek to generate trades for firms with higher ESG scores to hedge against climate risks. This result is aligned with the work of Dhaliwal et al. (2011, 2012), which suggests that the higher sustainability engagement level of the company leads to higher efficiency in controlling and refining long-term risk management. Therefore, firms' commitment to sustainability increases market confidence, increasing firms' value.

On the other hand, I do not find any significant moderating effect of ESG on the relationships between disagreement and uncertainty and firms' stock volatility. However, both interaction terms *DoS_LM×ESG* and *UNC_LM×ESG* are negatively signed. Thus, it implies that ESG scores may reduce the negative effect of climate-related disagreement and uncertainty.

**Table 13: Models of trading volume changes and stock price volatility and climate-related sentiments with ESG performance**

This table shows whether the impact of *DoS* and *UNC* sentiments on trading volume and stock price volatility is affected by firms' sustainability performance. *ESG* is firms' ESG performance scores, and *ESG_RS* is a dummy variable that denotes 1 for firms with their ESG reporting score available and zero otherwise. Robust t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively.

*Panel A: ESG score*

| | *ΔVolume (t)* | | *Volatility (t+1)* | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| DoS_LM | -0.00417 | | 0.0208*** | |
| | (-0.000514) | | (4.316) | |
| DoS_LM×ESG | 1.471*** | | -0.000143 | |
| | (4.981) | | (-0.741) | |
| UNC_LM | | 3.875 | | 0.0247*** |
| | | (0.401) | | (4.286) |
| UNC_LM×ESG | | 1.024*** | | -5.11e-05 |
| | | (2.930) | | (-0.224) |
| ESG | 2.972*** | 3.735*** | 0.00559*** | 0.00548*** |
| | (3.046) | (3.869) | (9.935) | (9.845) |
| Constant | -555.2*** | -561.5*** | 2.680*** | 2.680*** |
| | (-5.043) | (-5.101) | (44.70) | (44.72) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 1,409,156 | 1,409,156 | 2,093,732 | 2,093,732 |
| R-squared | 0.147 | 0.147 | 0.316 | 0.316 |

*Panel B: ESG reporting score*

| | *ΔVolume (t)* | | *Volatility (t+1)* | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| DoS_LM | 23.38** | | 0.0394*** | |
| | (2.479) | | (7.303) | |
| DoS_LM×ESG_RS | -10.47 | | -0.0604*** | |
| | (-0.654) | | (-6.669) | |
| UNC_LM | | 10.57 | | 0.0468*** |
| | | (0.977) | | (7.511) |
| UNC_LM×ESG_RS | | 15.04 | | -0.0797*** |
| | | (0.752) | | (-7.120) |
| ESG_RS | 14.57 | -8.223 | -0.0391*** | -0.0387*** |
| | (0.551) | (-0.318) | (-2.649) | (-2.693) |
| Constant | -16.10 | -0.735 | 2.751*** | 2.755*** |
| | (-0.140) | (-0.00642) | (45.75) | (45.85) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Observations | 1,414,218 | 1,414,218 | 2,098,786 | 2,098,786 |
| R-squared | 0.002 | 0.002 | 0.316 | 0.316 |

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Results are shown in Panel B table 13; unlike ESG performance, ESG reporting score significantly interacts with disagreement and uncertainty sentiments in the regression models of stock volatility. For example, in column 3 4 Panel B table 13, the negative signs of interaction terms *DoS_LM×ESG* and *UNC_LM×ESG* indicate that during the time of high climate-related disagreement and uncertainty sentiments, companies with higher ESG reporting scores experience lower stock price risk. It suggests that extensive disclosure is likely to reduce the risk increase associated with climate-related disagreement and uncertainty.

Overall, I find strong evidence that firms with higher ESG performance scores have their trading volumes higher than other firms when there are high climate-related disagreements and uncertainty. On the other hand, more extensive ESG disclosures tend to reduce information asymmetry, leading to a lower effect of disagreement and uncertainty sentiments on stock volatility. Our findings support the literature on the benefit of corporate sustainability engagements. It shows that firms that are sensitive to climate change news (e.g., those operating in environmentally sensitive industries, lower ESG scores, or do not disclose sustainability information) experience significantly higher stock volatility than other firms when there is an increase in the level of disagreement and uncertainty sentiments.

### *6.2 Climate change topics*

Motivated by the suggestion for future research from Engle et al. (2020), I also classified climate change news into separated topics to observe whether disagreement and uncertainty relating to different topics have a different impact on firms' stock trading volume and volatility. The climate change news topics are classified using corpus analysis and comparison tool – WMatrix – developed by Lancaster University (Rayson, 2008). In general, the program chooses the appropriate semantic category by taking in Part of Speech (POS)-tagging information, then considers the general likelihood in accordance with the frequency in English corpus widely, and the area of the discourses as identified by a longer text (for example, a temperature condition would prompt a reading of 'hot' as a weather level instead of the spiciness). For the purpose of this research, I categorize topics in news into physical climate (*PHY)*, social climate (*SOC)* and climate policy (*POL)*.

We interact climate-related news topics: *PHY, SOC,* and *POL* with disagreement and uncertainty sentiments. As shown in column 3 of Panel A, Table 14, the coefficient estimation on the interaction term *DoS_LM×ENV* is significantly positive, suggesting that firms' stock prices fluctuate when disagreement sentiment is related to physical climate change, even more, leading to higher volatility. This result aligns with studies in the relationship between physical climate risk and the stock market (Kruttli et al., 2019, Griffin et al., 2019). For example, Griffin et al. (2019) find that equity volatility increases following extreme high-temperature events, especially with unforeseen uncertainties about physical climate risk.

**Table 14: Models of trading volume changes and stock price volatility and climate-related sentiments with climate change topics**

This table shows whether the impact of *DoS* and *UNC* sentiments on trading volume and stock price volatility is affected by firms' sustainability performance. *ESG* is firms' ESG performance scores, and *ESG_RS* is a dummy variable that denotes 1 for firms with their ESG reporting score available and zero otherwise. Robust t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively.

*Panel A: Environment topic*

| | *ΔVolume (t)* | | *Volatility (t+1)* | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| DoS_LM | 0.491 | | 0.0221* | |
| | (0.0245) | | (1.909) | |
| DoS_LM×ENV | 14.66 | | 0.0154** | |
| | (1.118) | | (2.014) | |
| UNC_LM | | 30.76 | | -0.00160 |
| | | (1.514) | | (-0.133) |
| UNC_LM×ENV | | -11.19 | | 0.00416 |
| | | (-0.849) | | (0.535) |
| ENV | 0.992 | 26.42 | 0.0105 | -0.00974 |
| | (0.0536) | (1.581) | (0.989) | (-1.012) |
| Constant | 32.85 | 2.755 | 2.327*** | 2.353*** |
| | (0.274) | (0.0231) | (36.97) | (37.63) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Company FE | Yes | Yes | Yes | Yes |
| Observations | 1,414,218 | 1,414,218 | 2,098,786 | 2,098,786 |
| R-squared | 0.002 | 0.002 | 0.317 | 0.317 |
| Number of Tickers | 942 | 942 | 956 | 956 |

*Panel B: Social topic*

| | *ΔVolume (t)* | | *Volatility (t+1)* | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| DoS_LM | 44.16 | | -0.0424** | |
| | (1.509) | | (-2.460) | |
| DoS_LM×SOC | -4.713 | | 0.00879*** | |
| | (-0.824) | | (2.576) | |
| UNC_LM | | -23.98 | | -0.0295 |
| | | (-0.785) | | (-1.610) |
| UNC_LM×SOC | | 8.521 | | 0.00734* |
| | | (1.339) | | (1.918) |
| SOC | 28.85** | 8.972 | -0.0200*** | -0.0165** |
| | (2.368) | (0.749) | (-2.867) | (-2.378) |
| Constant | -99.46 | -4.505 | 2.434*** | 2.416*** |
| | (-0.768) | (-0.0349) | (35.26) | (35.07) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Company FE | Yes | Yes | Yes | Yes |
| Observations | 1,414,218 | 1,414,218 | 2,098,786 | 2,098,786 |
| R-squared | 0.002 | 0.002 | 0.317 | 0.317 |
| Number of Tickers | 942 | 942 | 956 | 956 |

| *Panel C: Government and policy topic* | *Volume (t+1)* | | *Volatility (t+1)* | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| DoS_LM | 34.50* | | 0.00448 | |
| | (1.898) | | (0.418) | |
| DoS_LM×POL | -5.412 | | -0.00154 | |
| | (-0.857) | | (-0.402) | |
| UNC_LM | | -10.08 | | 0.00350 |
| | | (-0.468) | | (0.270) |
| UNC_LM×POL | | 12.48 | | 0.000269 |
| | | (1.350) | | (0.0492) |
| POL | 24.78** | 6.975 | 0.00193 | -0.000303 |
| | (2.018) | (0.588) | (0.272) | (-0.0444) |
| Constant | -26.84 | 17.33 | 2.338*** | 2.342*** |
| | (-0.223) | (0.144) | (36.78) | (37.01) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Company FE | Yes | Yes | Yes | Yes |
| Observations | 1,414,218 | 1,414,218 | 2,098,786 | 2,098,786 |
| R-squared | 0.002 | 0.002 | 0.317 | 0.317 |
| Number of Tickers | 942 | 942 | 956 | 956 |

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As presented in columns 3 and 4 of Panel B table 14, social climate topics in the news positively interact with both disagreement and uncertainty sentiments in the regression models of stock volatility. These results imply that stock prices are more volatile when climate-related disagreement and uncertainty sentiments are associated with social topics. This finding contributes to the literature in social and environmental accounting literature and stakeholder engagement stream (King and Soule, 2007, Bolton and Landells, 2015, Gomez-Carrasco and Michelon, 2017, Kumar et al., 2016). Differentiating from prior researches, I account our analysis on the broader cover of all potential social activities regarding climate change conveyed in the news, rather than studying individual events. A possible explanation is that social activity regarding climate change enhances investors' beliefs and awareness about the level of environmental preferences in the economy. Furthermore, climate-related social activities may lead to higher investors' anticipation about strengthening environmental supervision and implementing new legislative initiatives.

On the other hand, I find no significant interaction terms between sentiments and climate policy topics (*DoS_LM×POL* and *UNC_LM×POL*).

### 6.3 Stock returns, news sentiment, and noise trading

#### 6.3.1. January effect

Behavioural finance provides evidence that individual investors are more sensitive to sentiments than institutional investors (e.g., Baker and Wurgler, 2007 ). In addition, some previous studies find that sentiments exhibit either monthly or weekly seasonality (Cooper et al., 2005, Da et al., 2015). Therefore, I explore further based on preliminary evidence that individual investors trade more at the beginning of the year – January effect.

Table 15 shows the results when I regress our abnormal return model separately for January and the rest of the month. In Panel A, I observe consistent results for both January and other months. The coefficient for the divergence of sentiment in regression of abnormal return within the interval [+1 +5] is negative, and that for uncertainty, sentiment is positive. This result is consistent with our baseline model results.

However, for the regression of abnormal return within the interval [-1 +1], the effects of disagreement and uncertainty sentiments in climate change news on abnormal stock returns in January are opposite to those in the rest of the year. In January, disagreement sentiment significantly increases abnormal stock return. However, there appears to be some evidence of reversal after a short period. This shows strong evidence that disagreement and uncertainty in climate change news create price bubbles in times of higher trade (e.g., January). After a short time, prices are driven back to their fundamental value, leading to lower returns (abnormal return within the interval [-1 +1] increases but quickly reverse to negative within the interval [+1 +5]). This suggests the existence of noise traders, which affect short-term abnormal returns. This is in line with the claim of Yu and Yuan (2011) that noise traders are more likely to trade in the market during the high sentiment period, leading to short-sale constraints. In line with this theoretical framework, Yu (2011) and Hong and Sraer (2016) report that investors' disagreement results in overpricing during the period of short-sale impediments. Also, individual investors are generally hesitant to short stocks when they have limited knowledge or behavioural biases (Barber and Odean, 2008). Thereby, the short-sale constraint is generally more assertive during high sentiment periods because of the increased tendency to avoid short selling of stocks resulting from the increased number of individual investors. Nevertheless, in line with the argument of Shleifer and Vishny (1997), our results show that although stocks are overvalued, the stock price continues to accelerate for a short time before falling back to its fundamental values.

**Table 15: Model of cumulative abnormal returns and disagreement and uncertainty sentiments during different months.**

This table shows whether *DoS* and *UNC* sentiments relate to stock returns when dividing out samples into two subsamples: (i) January and (ii) February to December. All regressions include time and firm fixed effects. I report standard errors clustered by date, as shown in parentheses. ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10, 5, and 1% levels, respectively.

| *Panel A* | *Dependent: CAPM[+1 +5]* | | | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| | *Jan* | *Feb-Dec* | *Jan* | *Feb-Dec* |
| DoS_LM | -0.0324*** | -0.0269*** | | |
| | (-4.281) | (-10.23) | | |
| UNC_LM | | | 0.0447*** | 0.0413*** |
| | | | (3.774) | (13.77) |
| Constant | -0.504*** | -0.816*** | -0.568*** | -0.853*** |
| | (-3.948) | (-22.04) | (-4.453) | (-23.04) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Company FE | Yes | Yes | Yes | Yes |
| Observations | 109,843 | 1,256,980 | 109,843 | 1,256,980 |
| R-squared | 0.049 | 0.008 | 0.049 | 0.008 |
| Number of Tickers | 917 | 942 | 917 | 942 |

| *Panel B* | *Dependent: CAPM[-1 +1]* | | | |
|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) |
| | *Jan* | *Feb-Dec* | *Jan* | *Feb-Dec* |
| DoS_LM | 0.0570*** | -0.0309*** | | |
| | (9.548) | (-14.55) | | |
| UNC_LM | | | -0.203*** | 0.0328*** |
| | | | (-21.77) | (13.50) |
| Constant | 0.199** | -0.448*** | 0.388*** | -0.484*** |
| | (1.976) | (-14.95) | (3.862) | (-16.13) |
| Controls included | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes |
| Company FE | Yes | Yes | Yes | Yes |
| Observations | 109,843 | 1,256,980 | 109,843 | 1,256,980 |
| R-squared | 0.107 | 0.076 | 0.110 | 0.076 |
| Number of Tickers | 917 | 942 | 917 | 942 |

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

### 6.3.2. *Noise trading and liquidity*

A natural explanation for the relationship between stock return and disagreement and uncertainty is that it results from the actions of noise traders who are more likely to be disposed of by movements in sentiments. Following the argument in behavioural economics, I investigate further whether disagreement and uncertainty variables can capture noise's trading effect in the stock market.

Firstly, I investigate alternative explanations on noise trading by performing our regression specification with the inclusion of trading volume. I argue that if the noise trading hypothesis is correct, one should assume that ambiguity sentiment's predictive power will appear mostly in days when trading volume is high. Trading volume has been considered a noise trading indicator in several papers, such as Barber and Odean (2008). I follow Sun et al. (2016) and consider the following regression for testing the noise trading hypothesis:

$$CAR = \alpha + \beta_1 DoS_t + \beta_2 HighVol_t + \beta_3 AMB_t HighVol_t + \varepsilon_{t+1}, \qquad \textit{(Equation 7)}$$

$$CAR = \alpha + \beta_1 UNC_t + \beta_2 HighVol_t + \beta_3 AMB_t HighVol_t + \varepsilon_{t+1}, \qquad \textit{(Equation 8)}$$

In which $DoS_t$ and $UNC_t$ denotes the sentiment variables used in our research: disagreement and uncertainty, obtained from LM (Loughran and McDonalds) and WM (WMatrix); *HighVol* is a dummy variable that takes the value of 1 when trading volume is above the sample mean and zero otherwise. As suggested in Andersen (1996), to avoid long-run trends in raw trading volume, I log transform the stock trading volume of all included companies, then subtracting the moving average of 500 days to detrend the raw volume.

This regression model includes both disagreement and uncertainty sentiment variables and dummy variables, High Volume, and an interaction term between them. I wish to obtain the interaction of our ambiguity index with days with high trading volume. As observed from Table 16, it is confirmed that the noise trading hypothesis holds true since, in all cases, the coefficient estimate of the interaction term is significant and positive. The interaction term coefficient estimates *DoS_LM×HighVol* and *UNC_LM×HighVol* in the model of sentiments from Loughran and McDonalds, *DoS_LM,* and *UNC_LM*, are both significant at the 1% respectively. Interestingly, the results also show that the estimated coefficients of our disagreement and uncertainty sentiments rendered the primary analysis, thus, showing the consistency between this model and our baseline models earlier.

**Table 16: Model of cumulative abnormal returns and disagreement and uncertainty sentiment with the moderating effect of the market trading volume.**

This table examines the moderating effect of the day with high market trading volume on the relationship between disagreement and uncertainty sentiment, and abnormal returns. HighVol is a dummy variable that takes 1 when trading volume is above the sample mean and zero otherwise. All regressions include company fixed effects. I report standard errors clustered by date, as shown in parentheses. ∗, ∗∗, and ∗∗∗ indicate statistical significance at the 10, 5, and 1% levels, respectively.

| | *Dependent: CAPM[-1 -1]* | |
|---|---|---|
| VARIABLES | (1) | (2) |
| DoS_LM | -0.0203*** | |
| | (-10.12) | |
| DoS_LM×HighVol | 0.00786** | |
| | (2.021) | |
| UNC_LM | | 0.0170*** |
| | | (6.382) |
| UNC_LM×HighVol | | 0.0200*** |
| | | (3.726) |
| HighVol | 0.00233 | -0.00718 |
| | (0.443) | (-1.248) |
| Constant | -0.554*** | -0.443*** |
| | (-22.25) | (-15.41) |
| Controls included | Yes | Yes |
| Time FE | Yes | Yes |
| Company FE | Yes | Yes |
| Observations | 1,366,823 | 1,366,823 |
| R-squared | 0.073 | 0.075 |
| Number of Tickers | 942 | 942 |

t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Next, I follow Sun et al. (2016) to further investigate noise trading by studying liquidity level during the time of disagreement and uncertainty news a released. I calculate a well-known illiquidity measure – Amihud illiquidity – with the following formula:

$$AIL\_(n) = \sum_{i=1}^{n} \frac{|r_i|}{DVol_i}$$

In which $|r_i|$ is the absolute return in local currency of firm at day t, $DVol_i$ is the dollar value of average trading volume on the same day. I take n = 10, 20, and 50 and run the following regression:

$$AIL\_(n) = \alpha + \beta_1 DoS_t + \beta_2 Control_t + \varepsilon_t \qquad \textit{(Equation 9)}$$

$$AIL\_(n) = \alpha + \beta_1 UNC_t + \beta_2 Control_t + \varepsilon_t \qquad \textit{(Equation 10)}$$

**Table 17: Stock liquidity model.**

This table report results from equation 9. Panel A reports the result for disagreement sentiment – *DoS_LM*; panel B reports the result for uncertainty sentiment – *UNC_LM*. Robust t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively. The data is in daily frequency, and the sample period is from January 2008 to December 2019.

| | α | *β1* | *β2* | *R2 (%)* |
|---|---|---|---|---|
| *Panel A: Predictive regression for DoS_LM* | | | | |
| *AIL_10* | 0.00102 | 0.00160*** | Included | 2.65 |
| | (0.902) | (3.622) | | |
| *AIL_20* | -0.000609 | 0.000701** | Included | 2.71 |
| | (-0.786) | (2.319) | | |
| *AIL_50* | -0.000122 | -0.000310* | Included | |
| | (-0.280) | (-1.822) | | 1.82 |
| *Panel B: Predictive regression for UNC_LM* | | | | |
| *AIL_10* | 0.000264 | 0.00289*** | Included | 2.52 |
| | (0.235) | (5.511) | | |
| *AIL_20* | -3.81e-05 | 0.000247** | Included | 2.13 |
| | (-0.0498) | (2.690) | | |
| *AIL_50* | -0.000440 | -3.55e-05 | Included | 1.85 |
| | (-1.020) | (-0.176) | | |

**Table 18**

This table report results from equation 10. However, I use *DoS_LM* and *UNC_LM* with a lag of five and ten days. Robust t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively. The data is in daily frequency, and the sample period is from January 2008 to December.

| | *DoS_LM (t-5)* | *DoS_LM (t-10)* | *UNC_LM (t-5)* | *UNC_LM (t-10)* |
|---|---|---|---|---|
| *AIL_10* | -0.00120* | -0.00322*** | -0.00199*** | -0.00106 |
| | (-1.901) | (-4.376) | (-3.658) | (-1.351) |
| *AIL_20* | -0.000430 | -0.00185*** | 0.000506 | -0.000468 |
| | (-1.064) | (-3.943) | (1.457) | (-0.920) |
| *AIL_50* | -0.000534** | -0.000461* | 0.000215 | 0.000516* |
| | (-2.361) | (-1.752) | (1.106) | (1.719) |

Table 17 shows the results for the regression above. It demonstrates that the release of news that conveys disagreement and uncertainty about climate change induces a decrease in stock liquidity. However, as shown in table 18, the higher level of disagreement and uncertainty sentiments from the previous five days and ten days, the higher liquidity for sticks. It illustrates the notion that price can be pushed away from its fundamental values due to noise trading from news, but informed traders will eventually take the liquidity back.

Overall, I conclude that noise trading can be one underlying factor for short-term abnormal returns predictability of our disagreement and uncertainty sentiments.

## 7. Summary of the chapter

We introduce a novel and extensive dataset consisting of daily sentiment variables on climate change news, firm-level data, and economic data over twelve years. I use a well-known sentiment classification technique from a commonly used dictionary – Loughran and McDonald –to identify important stock performance drivers. Our empirical results have shown convincing evidence that disagreement and uncertainty sentiments in climate change news strongly affect stock price volatility, trading volumes, and abnormal returns.

First, our research reports that climate-related disagreement and uncertainty sentiments are positively associated with daily trading volume changes and future volatility when controlling for a large set of firm-level and economic variables. These results are in line with disagreement theory and ambiguity theory that when investors interpret the same piece of news differently, they trade in accordance with their diverged beliefs, thus leading to higher stock trading volumes and volatility.

Second, I also document that climate-related disagreement sentiment decreases abnormal stock returns while uncertainty sentiment increases abnormal returns. These different reactions of abnormal returns to disagreement and uncertainty sentiments clarify our rationale to study disagreement and uncertainty separately. I argue that these two sentiments have different impacts on stock markets and should be studied thoroughly, especially when one studies the impact of climate change. Researches in climate communication suggest that extreme weather or climate change highlighted in media will help elicit public concern and promote protective actions. One could claim that it is unavoidable that there will be disagreement where scientific uncertainty exists. However, these two do not amount to the same scale (D'Amico & Orphanides, 2008; Glas & Hartmann, 2016; Rich & Tracy, 2010, 2018). There may be disagreement among people regarding the origins and extent of subjects where uncertainty occurs.

Third, I show evidence that firms sensitive to climate change news (e.g., those operating in environmentally sensitive industries, have lower ESG scores, or do not disclose sustainability information) experience significantly higher stock volatility than other firms when disagreement and uncertainty sentiments in climate news increase. Also, firms' stock volatility is influenced more when the disagreement and uncertainty sentiments are associated with the news's physical climate and social climate topics.

Regarding why news disagreement and uncertainty sentiments can lead to positive abnormal stock returns while increasing the stock volatility, there are two potential reasons.

Firstly, there could be noise traders or sentiment traders who actively trade in the stock market, especially in active trading months (e.g., January). When climate change news is first released, it will be interpreted differently between optimistic and pessimistic traders. Diverging opinions of investors lead to widespread stock price, resulting in higher stock price volatility. Additionally, price is also pushed far away from its fundamental value, creating high returns for stock at the beginning. After a short time, rational and informed traders will eventually step in, and prices are set up back to fair value.

Our findings have important implications for asset pricing literature. While prior studies have documented the impact of investor sentiments (positive and negative) on asset prices, especially for small stocks, it has not been a consensus that disagreement and uncertainty sentiments also play an equally important part in sentiments in the stock market. I provide strong evidence that stock performance can be predicted by disagreement and uncertainty sentiment. Thus, the two sentiments studied in this paper should not be left out in the asset pricing model in the future. Although the stock return is predictable with sentiments from media news, it should be taken with caution since this may result from noise trading on the short-term horizon. When uncertainty sentiment in news increases, prices are pushed to positive and far away from their fundamental value, then reversed to negative not long after that. In this notion, disagreement and uncertainty sentiments can also be used as a hedge target that presents climate change risk to form profitable portfolios.

Furthermore, firms' sustainability performance and disclosure information are found to help to mitigate the effect of disagreement and uncertainty sentiments in climate change news on firms. Therefore, it allows formulating some interesting managerial recommendations. Lastly, climate communication can also be benefited from this paper. As the impact of climate-related sentiments on stock volatility can be exacerbated by physical climate and social climate topics mentioned in the news, news media regarding climate change can improve their communication to reduce ambiguity or uncertainty in climate change news, avoiding denial, avoidance, or disagreement reactions in the market.

Nevertheless, this paper encounters some limitations. Firstly, the dictionary we used for sentiment classifications are either specified for finance (Loughran & McDonald) or general corpus (WMatrix). There is a need for a more complete climate change lexicon in future research. Secondely, divergence of sentiment and uncertainty are relatively hard to quantify, and news arrival is also another obstacle; thus, we can only conduct general tests. Lastly, there are several advanced techniques presented in textual analysis literature and the bag-of-word methods used in this paper is only one of them. The future research can utilize a better methodology to get better prediction.

Appendix A: Table of variables

| VARIABLES | ABBREVIATION | MEASUREMENT | SOURCE |
|---|---|---|---|
| **DEPENDENT VARIABLES** | | | |
| Trading Volume | VO | The average number of shares traded for a stock on a particular day. | DataStream |
| Stock price volatility | Vs | The simple measure of daily volatility is defined as the first logarithmic difference between the high and low prices (Alizadeh et al., 2002, Gallant et al., 1999a): $$V_s = \ln(H_t) - \ln(L_t)$$ For the model of volatility, I employed the HAR model with $$Vs_t^{(w)} = \frac{1}{5}\sum_{i=1}^{5} Vs_{t-i+1}^{(d)}$$ And $$Vs_t^{(m)} = \frac{1}{22}\sum_{i=1}^{22} Vs_{t-i+1}^{(d)}$$ are the weekly and monthly averages of daily log realized volatilities, respectively. | Low and high prices are downloaded from DataStream |

| | | | |
|---|---|---|---|
| Abnormal returns | CAR_CAPM | We consider the FTSE100 index as market returns and 10-year Gilt bond yield for the risk-free rate.<br><br>We estimate the beta within the window of 300 to 50 trading days before the day that climate change news is released.<br><br>$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i \times (R_{m,t} - R_{f,t}) + e_{i,t}$$<br><br>Parameter then used to $\alpha_i$ and $\beta_i$ calculate expected $\hat{R}_{it}$<br><br>$$\hat{R}_{i,t} - R_{f,t} = \hat{\alpha}_i + \hat{\beta}_i \times (R_{m,t} - R_f) + e_{i,t}$$<br><br>$\hat{R}_{i,t}$ is then used to calculate abnormal returns:<br><br>$$AR_{i,t} = R_{ii} - \hat{R}_{it}$$ | Returns are calculated from daily stock prices downloaded from DataStream.<br><br>FTSE100 index return and 10-year Gilt bond are downloaded from DataStream. |
| | CAR_FF3 | Similar steps to CAR_CAPM but with Fama_French 3 factors model:<br><br>$$R_{i,t} - R_{f,t} = \alpha_i + \beta_1 \left(R_{m,t} - R_{f,t}\right) + \beta_2\, SMB + \beta_3\, HML + e_{i,t}$$<br><br>$$\hat{R}_{i,t} - R_{f,t} = \hat{\alpha}_i + \hat{\beta}_1 \left(R_{m,t} - R_f\right) + \hat{\beta}_2 SMB + \hat{\beta}_3 HML + e_{i,t}$$<br><br>*SMB* and *HML* indexes are Small Minus Big and High Minus Low index | *SMB* and *HML* indexes (2008-2017) Gregory et al. (2013)<br><br>SMB and HML indexes (2018-2019) are calculated by the author, |

| | | | |
|---|---|---|---|
| | | | and data are retrieved from DataStream. |
| Amihud liquidity | AIL_(n) | $$AIL\_(n) = \sum_{i=1}^{n} \frac{\lvert r_i \rvert}{DVol_i}$$ In which $\lvert r_i \rvert$ is the absolute return in local currency of firm at day $t$<br>$DVol_i$ is the dollar value of average trading volume on the same day.<br>We take n = 10, 20 and 50 | Returns are calculated from daily stock prices downloaded from DataStream. |
| **INDEPENDENT VARIABLES** | | | |
| Disagreement sentiment | DoS_LM | $$DoS_t = \left\lvert \frac{x_{p,t} - x_{p,all}}{\sigma_{p,all}} + \frac{x_{n,t} - x_{n,all}}{\sigma_{n,all}} \right\rvert$$ In which:<br>$x_{p,t}$ and $x_{n,t}$ are positive and negative probabilities based on Loughran and McDonald's (2011) classification.<br>$x_{p,all}$ and $x_{n,all}$ are the average percentage of positive and negative probabilities detected during the time frame of the data set.<br>$\sigma_{p,all}$ and $\sigma_{n,all}$ are standard deviation for positive and negative sentiments | News collected from ProQuest. |

| | | | |
|---|---|---|---|
| | DoS_WM | $$DoS_t = \left\| \frac{x_{p,t} - x_{p,all}}{\sigma_{p,all}} + \frac{x_{n,t} - x_{n,all}}{\sigma_{n,all}} \right\|$$ In which: $x_{p,t}$ and $x_{n,t}$ are positive and negative probabilities based on the WMatrix corpus analysis tool. $x_{p,all}$ and $x_{n,all}$ are the average percentage of positive and negative probabilities detected during the time frame of the data set. $\sigma_{p,all}$ and $\sigma_{n,all}$ are standard deviation for positive and negative sentiments | News collected from ProQuest. |
| Uncertainty sentiment | UNC_LM | $$UNC_t = \left\| \frac{x_{u,t} - x_{u,all}}{\sigma_{u,all}} \right\|$$ $x_{u,t}$ is uncertainty probability based on Loughran and McDonald's (2011) classification. $x_{u,all}$ is average percentage uncertainty probability detected during the time frame of the data set $\sigma_{p,all}$ and $\sigma_{n,all}$ are standard deviation for uncertainty probability. | News collected from ProQuest. |

| | | | |
|---|---|---|---|
| | UNC_WM | $$UNC_t = \left\lvert \frac{x_{u,t} - x_{u,all}}{\sigma_{u,all}} \right\rvert$$ $x_{u,t}$ is uncertainty probability based on the WMatrix corpus analysis tool.<br><br>$x_{u,all}$ is average percentage uncertainty probability detected during the time frame of the data set.<br><br>$\sigma_{p,all}$ and $\sigma_{n,all}$ are standard deviation for uncertainty probability. | News collected from ProQuest. |
| **CONTROL VARIABLES** | | | |
| **FIRM FINANCIAL VARIABLES** | | | |
| Book-to-Market | BTM | Book value to the market value of equity | Author's calculation, DataStream |
| Company size | SIZE | The natural logarithm of total assets in local currency. | Author's calculation, DataStream |
| Leverage | LEV | The ratio of long-term debt to total assets. | Author's calculation, DataStream |

| EQUITY MARKET VARIABLES | | | |
|---|---|---|---|
| Dividend-Price Ratio FTSE100 | DP_FTSE100 | Log dividend-price ratio of FTSE100 index | DataStream |
| Dividend-Price Ratio stocks | DP | Log dividend-price ratio of each stock | DataStream |
| Stock return | R | Log return: $R = ln\,(\frac{P_t}{P_{t-1}})$ | Author's calculation, DataStream |
| Equity-Market Return (Fama-French) | MKT | FTSE100 index | DataStream |
| Small-minus-Big (Fama-French) | SMB | Fama French Small minus big factor<br><br>Indexes from 2008-2017 collected from Gregory et al. (2013)<br><br>Indexes for 2018-2019 are calculated by the author, and data are retrieved from DataStream | DataStream (raw data) |

| | | | |
|---|---|---|---|
| High-minus-Low (Fama-French) | HML | Fama French High minus low factor | Indexes from 2008-2017 collected from Gregory et al. (2013)<br><br>Indexes for 2018-2019 are calculated by the author, and data are retrieved from DataStream |
| UK VIX level | VIX | Implied volatility of FTSE100 index VIX | DataStream |
| UK VIX Change | VIX_C | Log change in the index level | DataStream |
| State | State | Dummy variables based on the sign of lagged 1-year market return. UP if the lagged return of FTSE100 in the last 250 trading days is non-negative and DOWN otherwise | Author's calculation, DataStream |
| **BOND MARKET VARIABLES** | | | |
| Relative T-Bill Rate | Rltv_Tb3 | T-Bill Rate (daily yield) minus 12-m moving average yield | Author's calculation, Bloomberg |

| | | | |
|---|---|---|---|
| Relative Bond Yield | Rltv_G10 | The yield of 10-year government bonds minus 12-month MA | Author's calculation, Bloomberg |
| Term spread | TERM | Difference between long-term gov. Bond and T-Bill | Author's calculation, Bloomberg |
| **LIQUIDITY VARIABLES** | | | |
| Turnover Ratio Change FTSE100 | TOC_FTSE100 | Log-change in the turnover ratio (Daily turnover (daily traded volume) divided by total market capitalization) | Author's calculation, DataStream |
| Turnover Ratio Stock | TO | Daily turnover (daily traded volume) divided by total market capitalization for each stock | Author's calculation, DataStream |
| **MACROECONOMIC VARIABLES** | | | |
| Inflation rate | CPIC | Log change in GB CPI month over month | Author's calculation, Bloomberg |
| Expected inflation change | EXPINF_C | The first difference in YOUGOV/CITIGROUP expected inflation | Author's calculation, Bloomberg |

| | | | |
|---|---|---|---|
| Industrial Production Growth MoM | IPIM | Log differences in SA Industrial Production month over month | Author's calculation, Bloomberg |
| Housing start | HSSA | Monthly log-change in new private housing started (seasonal adjusted) | Bloomberg |
| Housing start | HSNSA | Monthly log-change in new private housing started (not seasonally adjusted) | Bloomberg |
| M1 Growth MoM | M1 | Monthly log change in M1 money supply | Author's calculation, Bloomberg |
| Capacity Utilization Level | CAPC | Level of SA capacity utilization (percentage) | Bloomberg |
| Consumer Sentiment | SENT | Monthly log change consumer sentiment | Author's calculation, Bloomberg |
| Consumer Confidence | CONF | Monthly log change consumer confidence | Author's calculation, Bloomberg |
| Employment Growth | EMP | Monthly log-change SA employment number | Author's calculation, Bloomberg. |
| **ENVIRONMENTAL DISCLOSURE DATA** | | | |

| | | | |
|---|---|---|---|
| Environmental sensitive industry | SENSI | Denotes 1 if companies operate in Basic Materials, Energy, Industrials, Utilities and Real Estate and zero otherwise. | DataStream’s industry classification. |
| ESG Disclosure Score | DISC | Proprietary Bloomberg scores are based on the extent of a company's ESG disclosure. The score ranges from 0.1 for companies that disclose a minimum amount of governance data to 100 for those that disclose every data point collected by Bloomberg. | Bloomberg |
| ESG score | ESG | Refinitiv's ESG Score is an overall company score based on the self-reported information in the environmental, social, and corporate governance pillars. | DataStream |

Appendix B: Constructing disagreement and uncertainty sentiments.

We construct the daily disagreement and uncertainty sentiment index based on the aggregated textual tone in climate change news from 1st January 2008 to 31st December 2019. In order to avoid fake news issues, following Tetlock (2007), I specifically download climate change news from trustworthy news outlets, namely: The Financial Times, the Daily Telegraph, The Guardians and The Times, The Wall Street Journal, and The Independent.

We identify climate change news using the advanced search function in ProQuest – a news database – and search for news with keywords: “Climate change” OR “Global warming”. The purpose is to capture climate change-related news but not limiting it to too narrowed topics. A total of 65,957 news articles are collected at first. I then remove the duplicate articles to prevent repeated news. The duplicate articles may affect the accuracy of the sentiment presented in the articles when targeted words appear more than once. As a result, I collect a sample of 52,326 climate-related news. In order to obtain only the informative content from the news, I pre-process our news files. Furthermore, I strip out several words that do not add any value to the information conveyed by the news. These words are defined in several categories, namely: currencies, dates, and numbers, generic, and names, which are defined in Loughran and Mcdonald (2011).

For disagreement sentiment, negative and positive words are classified based on (i) financial lexicon dictionary from (Loughran and Mcdonald, 2011) and (ii) semantic tagging from the WMatrix tool. LM dictionary is a set of well-established and highly influential word lists that better indicate tone in the financial context[9]. In WMatrix semantic tagging tool, climate change news is analyzed using the corpus analysis tool developed by Dr Rayson from Lancaster University Centre for Corpus Research on Language (Rayson, 2008). This tool allows us to categorize the keyness words based on semantic categories. WM dictionary is based on British National Corpus; thus, the classifications of negative and positive words are broader and more general compared to the LM dictionary.

Uncertainty sentiment is also classified based on LM and WM dictionary. Similar to negative and positive sentiments, WM offers a broader range for uncertainty sentiment than the LM dictionary. For instance, the word “uncertainty”, I then have its lexical synonym: “contentious” or “unsure”, which are not included in the LM dictionary.

After the word-classification stage, each positive and negative sentiment are calculated by counting the probability a sentiment occurs within a day worth of news:

[9] See https://www3.nd.edu/~mcdonald/Word_Lists.html.

$$X_{p,t} = \frac{N_{p,t}}{N_{all,t}}$$

and

$$X_{n,t} = \frac{N_{n,t}}{N_{all,t}}$$

In which $X_{p,t}$ and $X_{n,t}$ are positive and negative proportion; $N_{p,t}$ and $N_{n,t}$ are number of positive and negative from the dictionary that appears in the news on day $t$ and $N_{all,t}$ is total informative words appear in that day.

From negative and positive sentiments, I follow the paper of Siganos et al. (2017) in using the divergence of sentiment rather than using solely average of either positive or negative sentiment. However, in their paper, the disagreement is extracted from a subjective source of sentiment - Facebook status. The disadvantage of that research then restricted to the limitation of investors' credit from Facebook users. Not every user is an investor, and not every investor uses Facebook. In order to overcome this limitation, our research use published news as an alternative source which does not only shows the ways investors interpret the news but also, presumably, all investors read the news to collect the necessary information.

Following (Siganos et al., 2017)'s paper, I employ sentiment analysis to calculate the divergence of positive and negative as follow:

$$DoS_t = \left| \frac{x_{p,t} - x_{p,all}}{\sigma_{p,all}} + \frac{x_{n,t} - x_{n,all}}{\sigma_{n,all}} \right|$$

In which, $\frac{x_{p,t} - x_{p,all}}{\sigma_{p,all}}$ and $\frac{x_{n,t} - x_{n,all}}{\sigma_{n,all}}$ are positive and negative sentiments where $x_{p,all}$ and $x_{n,all}$ are the average percentage of positive and negative sentiment detected during the time frame of the data set and $\sigma_{p,all}$ and $\sigma_{n,all}$ are standard deviation for those variables. Similarly, I also calculate the uncertainty sentiment to be the absolute value of change in uncertainty proportion:

$$UNC_t = \left| \frac{x_{u,t} - x_{u,all}}{\sigma_{u,all}} \right|$$

In which, $x_{u,t}$ is the uncertainty proportion calculated as the number of uncertainty words over the total number of words in day *t*, $X_{u,t} = \frac{N_{u,t}}{N_{all,t}}$ ; $x_{u,all}$ is the average percentage of uncertainty that appeared during the dataset and $\sigma_{u,all}$ is the standard deviation of these variables. The absolute value indicates the distance of uncertainty counts on day *t* to the mean uncertainty of the whole sample.

From this step, I have got two sets of sentiment: the divergence of sentiment and uncertainty sentiments from Loughran and McDonald dictionary, and the other is those sentiments from WMatrix. I then denote them to be $DoS\_LM_t$ and $UNC\_LM_t$ (from Loughran and McDonald's method) and $DoS\_WM_t$ and $UNC\_WM_t$ (from WMatrix semantic tagging).

**Figure B1: Bin scatter plot of DoS_LM and DoS_WM**

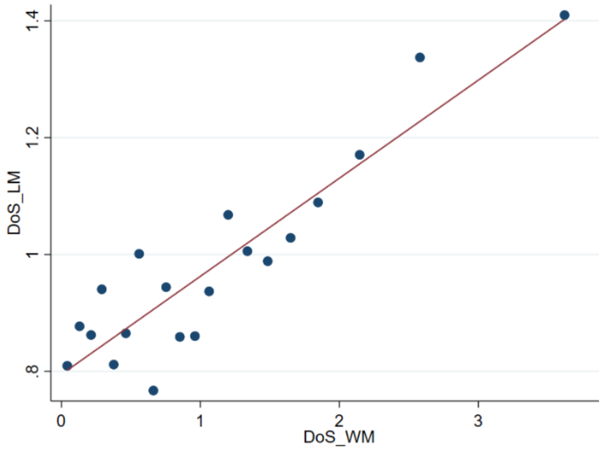
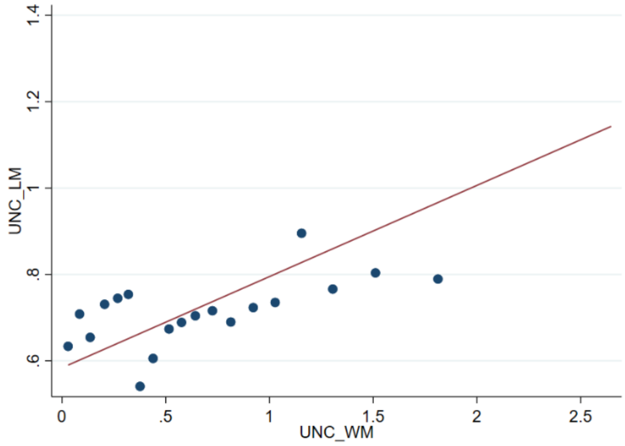



**Figure B2: Bin scatter plot of UNC_LM and UNC_WM**




The above figures show binned scatterplots that demonstrate the correlation between disagreement and uncertainty sentiments from two dictionaries: Loughran and McDonald (LM) and WMtrix (WM). The correlation coefficient between the two disagreement indexes is 0.189, and the correlation coefficient between the two uncertainty indexes is 0.206. Thus, the low correlations are the results of differences in two dictionaries: LM and WM.

In order to cross-validate our disagreement and uncertainty index as an interpretation for the sentiment of our investors, I follow Sun et al. (2016) and run the regressions below:

$$DoS_t = \beta_t + \beta_1 Proxy_t + \varepsilon_t \qquad (a)$$

In which $DoS_t$ is the divergence of sentiment from both dictionaries used throughout our research: Loughran and McDonald and WMatrix measured at month $t$. $Proxy_t$ presents alternative proxies for the sentiment. Since disagreement sentiment is rarely studied, let alone a defined disagreement index, thus I use two proxies for general sentiment, namely: (Baker and Wurgler, 2006)'s sentiment (BW) and consumer sentiment index from the University of Michigan (UM). I consider both BW and its counterparts $BW^{\perp}$ which is orthogonal to macroeconomic set stated in Baker and Wurgler (2006). For uncertainty sentiment, I consider the Economic Policy Uncertainty (EPU) index from (Baker et al., 2016) and the World Uncertainty Index (WUI) generated by the International Monetary Fund, both specified for the U.K, as alternative proxies for the following regression:

$$UNC_t = \beta_t + \beta_1 Proxy_t + \varepsilon_t \qquad (b)$$

We transformed our daily sentiment to monthly frequency because these independent variables are in a monthly format. The sample period ranges from January 2008 to December 2018 since the BW dataset is currently available up to 2018.

**Table B1:**

Panel A reports results from the following regression

$$DoS_t = \beta_t + \beta_1 Proxy_t + \varepsilon_t$$

Where $DoS_t$ Is the divergence of sentiment as the results from Loughran and McDonald (DoS_LM) and WMatrix (DoS_WM). Proxy denotes an alternative proxy for investor sentiment. I consider three proxies: investor sentiment index from (Baker and Wurgler, 2006) (BW), the orthogonal counterpart BW⊥, and the University of Michigan consumer sentiment index (UM). The data set is in monthly frequency, t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively. The sample period is from January 2008 to December 2018.

*Panel A: DoS vs. BW, orthogonal BW, and UM*

| | DoS_LM | | | DoS_WM | | |
|---|---|---|---|---|---|---|
| Sentiment proxy | *β₀* | *β₁* | *Adj*. R2 | *β₀* | *β₁* | *Adj*. R2 |
| *BW* | 1.04222*** | 0.20755*** | 3.20 | 1.216019*** | 0.379907*** | 7.70 |
| | (29.78) | (2.07) | | (30.22) | (3.29) | |
| $BW^{\perp}$ | 1.0186*** | 0.22327*** | 5.80 | 1.162639*** | 0.336738*** | 9.60 |
| | (40.88) | (2.84) | | (40.44) | (3.72) | |
| *UM* | 0.1209 | 1.071462*** | 27.68 | 0.324912*** | 0.977129*** | 16.60 |
| | (0.97) | (7.05) | | (2.06) | (5.08) | |

Panel B reports results from the following regression

$$UNC_t = \beta_t + \beta_1 Proxy_t + \varepsilon_t$$

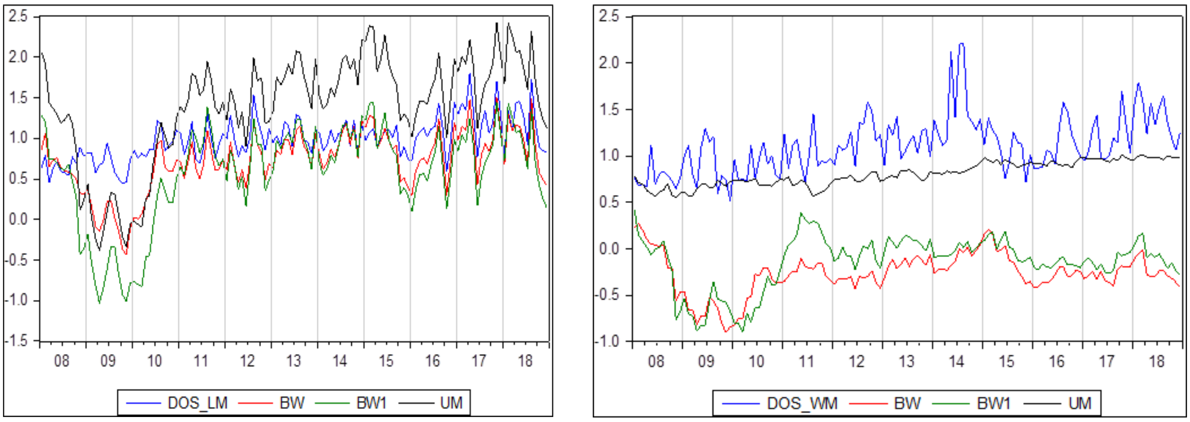
Where $UNC_t$ is the divergence of sentiment as the results from Loughran and McDonald (DoS_LM) and WMatrix (DoS_WM). Proxy denotes an alternative proxy for investor sentiment. I consider two proxies: Baker et al.(2016) Economic Policy Uncertainty (EPU) and the IMF (2020) World Uncertainty Index (WUI). The data set is in monthly frequency, t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and * respectively. The sample period is from January 2008 to December 2019.

*Panel B: UNC vs. EPU, and WUI*

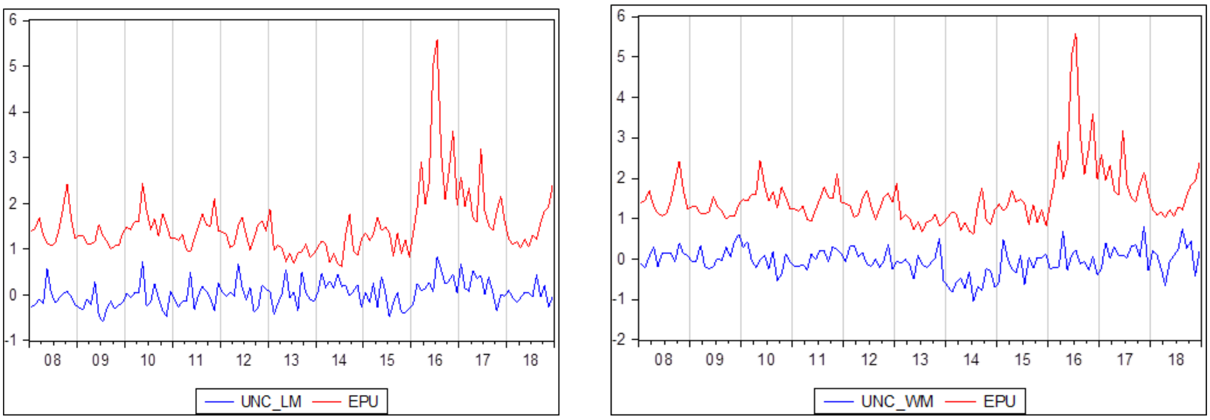
| | UNC_LM | | | UNC_WM | | |
|---|---|---|---|---|---|---|
| Sentiment proxy | *β₀* | *β₁* | *Adj*. R2 | *β₀* | *β₁* | *Adj*. R2 |
| *EPU* | 0.618561*** | 0.085953*** | 7.2 | 0.743037*** | 0.022371 | 0.5 |
| | (13.79) | (3.19) | | (16.32) | (0.82) | |
| *WUI* | 0.523156*** | 0.001064*** | 7.78 | 0.567841*** | 0.000992*** | 7.05 |
| | (7.35) | (3.27) | | (8.11) | (3.12) | |

We can see the results reported in table 1. Our disagreement and uncertainty indexes have positive and significant relationships with all regressors except for *UNC_WM* with *WUI,* in which the relationship is still positive although not significant. In detail, disagreement sentiments from both LM and WM dictionaries are found to have highly significant and positive relationships with both BW (raw and orthogonalized) and UM. Interestingly, visually graph inspection in Figure 3 shows that *DoS_LM* seems to move much closer to *BW* and *UM* while there is a gap between *DoS_WM* moves versus these sentiment benchmarks. This difference can be explained by the differences in how each disagreement index was composed. Loughran and McDonald's' dictionary is more established with several usages among researchers, while WMatrix expresses a more generic collection of words used in the news and at the very early stage of its development. The disagreement index was calculated as the distance between positive and negative sentiment within a day. An increase in sentiment can either rise in both negative and positive sentiment (resulting in smaller disagreement) or raise in negative or positive sentiment while the other remains the same (resulting in more considerable disagreement).

**Figure B3: Movements between BW, UM and DoS_LM and DoS_WM**




***Fi*gure B4: Movement between EPU and UNC_LM and UNC_WM**




Overall, I conclude that the above results support the view that our disagreement and uncertainty index from both dictionaries can capture investors' sentiments.

## Appendix C: PSM matching method

First, to further mitigate exogenous shock, I deploy PSM match to match treatment group with control group based on firm-level data: Size, ESG score, and ROA. Table 1 shows and compares outcomes given by several PSM methods: probit model, logit model, matching one neighbour, matching five neighbours, radius matching, and kernel matching.

**Table C1: Comparing PSM matching methods.**

| Variables | M0 | M1 | M2 | M3 | M4 | M5 | M6 |
|---|---|---|---|---|---|---|---|
| | Original dataset | Probit model | Logit model | Neighbour 1:1 | Neighbour 1:5 | Radius Calliper | Kernel |
| ***C1: T-test or chi-square test P-values*** | | | | | | | |
| SIZE | 11.66 | 0.69 | 0.86 | 0.61 | 0.89 | 0.00 | 0.39 |
| ROA | 6.11 | 0.73 | 0.79 | 0.83 | 0.76 | 0.00 | 0.36 |
| ESG | 4.07 | 0.11 | 0.42 | 0.29 | 0.68 | 0.46 | 0.75 |
| ***C2: The mean difference as a percentage of the average standard deviation*** | | | | | | | |
| SIZE | | 1.50 | 0.70 | 1.90 | 0.50 | -12.80 | -3.20 |
| ROA | | -1.20 | -0.90 | 0.40 | -0.60 | -6.10 | -2.00 |
| ESG | | -6.10 | -3.00 | -4.00 | -1.50 | -2.70 | -1.20 |
| ***C3: Percent reduction bias in means of explanatory variables*** | | | | | | | |
| SIZE | | 95.60 | 98.10 | 94.40 | 98.40 | 62.80 | 90.70 |
| ROA | | 91.00 | 93.00 | 97.00 | 95.10 | 53.80 | 85.00 |
| ESG | | 44.80 | 72.90 | 63.30 | 86.40 | 75.50 | 89.20 |
| ***C4: Comparison of treatment and control variance ratio*** | | | | | | | |
| SIZE | | 1.15 | 1.12 | 1.11 | 1.08 | 1.49 | 1.21 |
| ROA | | 3.07 | 2.88 | 1.08 | 1.30 | 1.46 | 1.33 |
| ESG | | 0.86 | 0.97 | 0.90 | 0.97 | 0.99 | 0.99 |
| ***C5: Comparison of the density estimates of the propensity scores of control units with those of the treated units*** | | | | | | | |
| B | | 7.00 | 3.60 | 4.90 | 2.30 | 15.60 | 4.30 |
| R | | 1.13 | 1.28 | 1.09 | 1.22 | 1.38 | 1.13 |
| Untreated | 5,022 | 3,499 | 3,499 | 3,499 | 3,499 | 3,499 | 3,499 |
| Treated | 1,992 | 1,383 | 1,383 | 1,348 | 1,348 | 1,382 | 1,382 |

We propose the following set of guidelines for selecting the most appropriate application:

**C1.** Measure two-sample t-statistics between the mean of the green bond issuer for each explanatory variable and the mean of the match firms for each explanatory variable.

**C2.** Measure the mean difference as a percentage of the average standard deviation.

**C3.** Measure the reduction bias percentage in the means of the explanatory variables post matching.

**C4.** Use the variance ratio test to compare the treatment and control F-ratio test or F-test. The F-test demonstrates that whether the variance of two populations from which the samples have been drawn is equal or not.

**C5.** Use the Rubins' B (the absolute standardized difference of the means of the linear index of the propensity score in the treated and (matched) non-treated group) and Rubin's R (the ratio of treated to (matched) non-treated variances of the propensity score index). Rubin (2001) recommends that B be less than 25 and that R be between 0.5 and 2 for the samples to be considered sufficiently balanced.

The primary purpose of a matching procedure is to reduce selection bias by increasing the balance between the treatment and control groups. In this respect, one would like to see insignificant differences or larger P – values (criterion 1); low mean differences as a percentage of the average standard deviation (criterion 2); 100% reduction bias in the means of explanatory variables (criterion 3); and insignificant differences when comparing the density estimates of the treatment and control groups (criterion 4 and criterion 5). Therefore, the best matching algorithm for the data is the one that satisfies all five criteria.

After comparing the different PSM models in table 1, I choose the model with one neighbour and calliper of 0.01 (M3). Comparing to the original data set (M0), the t-test of our covariates: Size, ROA, and ESG significantly reduced from 11.66, 6.11, and 4.07 to 0.61, 0.79, and 0.42, respectively.

Figure 1 compares propensity scores between treatment and control groups before and after matching. I can see that after matching, the gap between the two groups is significantly reduced. Figure 2 shows that propensity score is evenly distributed between treated and control groups. Figure 3 demonstrates that selection bias (in terms of measured and tested covariates) is reduced by matching. Standardized % bias across covariates after matching is close to 0.

**Figure 3: Comparing treatment and control groups before and after matching.**

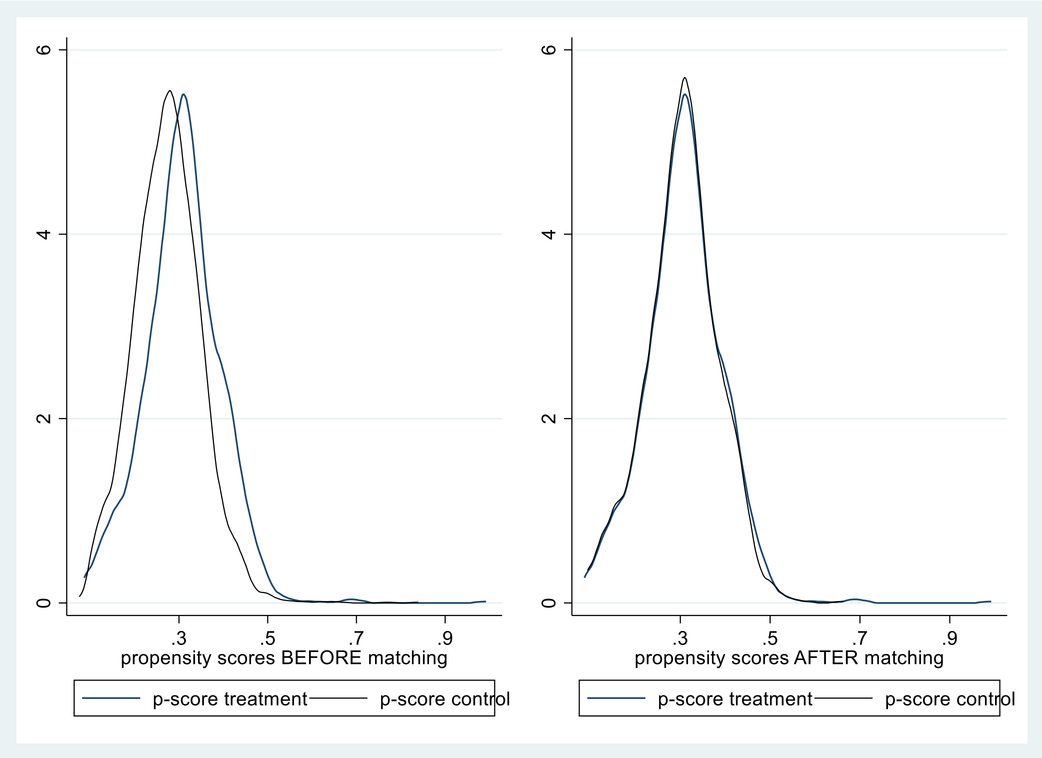
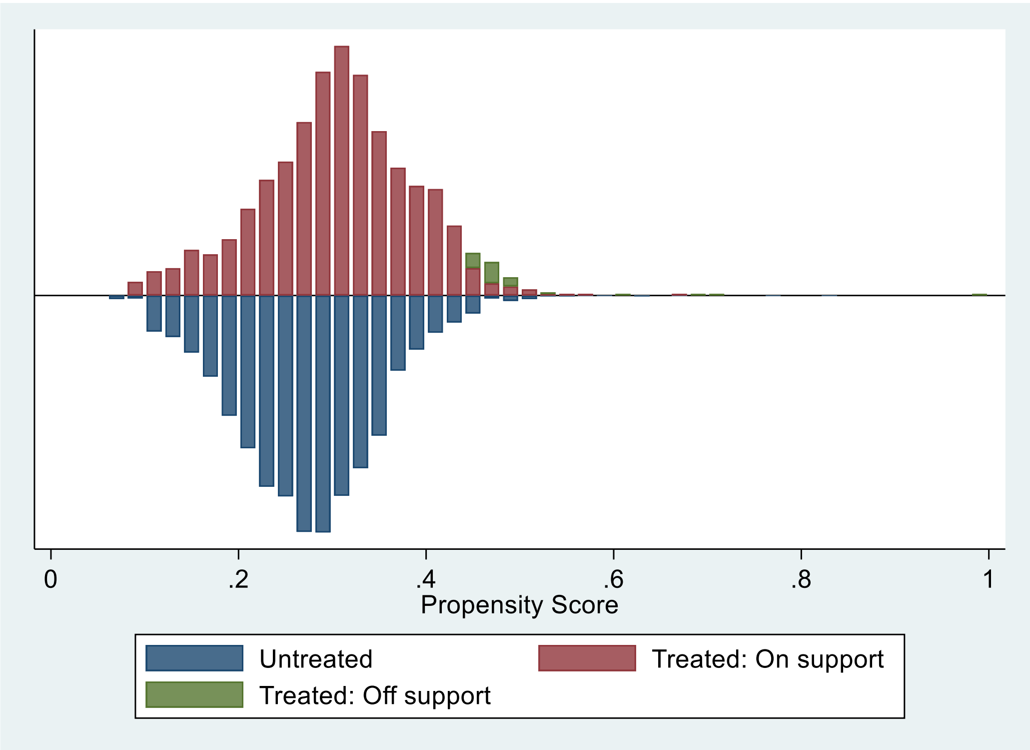



**Figure 4: Histogram of the propensity scores in treatment and control groups.**




In summary, I am able to reduce baseline bias using the PSM technique. I also find common support for the distribution of propensity scores (figure C1).

# Chapter 2:

## HEDGING AGAINST CLIMATE CHANGE UNCERTAINTY.

## 1. Overview of the chapter

Climate change has had a significant impact on global society and economies. Investors have been increasing their environmental sustainability concerns and attempting to mitigate risk and exploit opportunities that climate change presents. As the natures of climate change are non-diversifiable, individual investors are constrained to self-insure against climate change risk. However, despite climate change risk concerns, it is often thought that limiting the investable universe of financial instruments may reduce risk-adjusted returns.

There has been a debate regarding the effect of firms' environmental information. The first view is associated with suggestions from Crane et al. (2013) and Orlitzky (2013), that information asymmetry will be exacerbated by the disclosure of CSR data; thus, there is no difference between corporate social responsibility (CSR) information and other news, like noise. The second view is adopted from stakeholder theory, in which other stakeholders are believed to be able to alter the market expectation, thus driving the firms' activities moving towards sustainable expectations. This perspective is associated with studies of Godfrey (2005) and Jo and Na (2012). This view adopts the stakeholder theory introduced by Freeman (1984), in which influential stakeholders can ensure the delivery of sustainability management, offering shareholders guaranteed protection for their investment.

The debate on whether ESG disclosures can help maximise shareholder value is likely to be the reason to limit large-scale capitals to invest in a low carbon economy. In order to support the international transition to a low carbon economy, it is needed to demonstrate investment portfolios that are constructed in line with investor's return target with a more climate-resilient economy. Therefore, I wish to propose an approach for constructing a climate risk hedge portfolio using publicly traded assets. Our approach follows Engle et al. (2020) and deploys a dynamic hedging approach similar to Black and Scholes (1973) and Merton (1973). In this approach, I construct portfolios whose short-term returns hedge climate change risks and uncertainties over the holding period.

In order to implement a dynamic hedging strategy for climate risk, I first capture climate risk from the news as a hedge target. The rationale for this decision is that when there are new changes in climate change topics or global warming, it is likely that these changes will be covered in newspapers. Information extracted from written or spoken forms is suggested to contribute more independent tests of market efficiency compared to ones using the number-based measure. There is a higher chance for number-based measures to be correlated, resulting in different anomalies for the same empirical regularity (Li, 2006). Therefore, news information provides the specific content important to customers' investment decisions and contributes to the way investors behave and interpret it to form their portfolios. Moreover, compared to traditional investor sentiment, text-based sentiment contains behavioural characteristics and subject judgment of investors and reflects conditions of markets and firm's textual sentiment. Researches in climate communication also warn against fear appeals that climate change highlighted in media may trigger counter-productive responses like denial, avoidance, and disagreement because solutions are uncertain, unknown, or undesirable[10].

Our approach in this paper uses disagreement and uncertainty sentiments extracted from climate change news to be one of our climate-change risks. In order to avoid fake news issues, following Tetlock (2007), I specifically download climate changes news from trustworthy news outlets, namely: The Financial Times, the Daily Telegraph, The Guardians and The Times, The Wall Street Journal, and The Independent, as our climate change news database. These six newspapers are among the most salient media outlets, covering both professional and lay readership and accessible to the investment community. The sentiments are then calculated as the correlation between the textual content of our news database and two fixed text classifications: Loughran and McDonald financial dictionary and WMatrix semantic tagging. I then have two sets of hedge targets: disagreement and uncertainty from LM classification and disagreement and uncertainty from WMatrix semantic tagging.

Besides sentiment indices, I also examine the content of climate change news. This choice comes from the observation that both sentiments and topics are two essential parts conveyed in the news. There is a list of topics often covered by newspapers regarding climate risk discussion, such as extreme weather events (e.g., hurricanes, extreme temperature, wildfires) or physical changes (e.g., rising sea level, glacial melting). Instead of examining individual climate events, news coverage of general physical climate changes can be a valuable resource for all extreme weather over time. Studying physical climate topics in the news will generate a systematic hedge target for our portfolio's formation.

Another measure for climate change risks is the vulnerability to adapt to climate change's adverse effects of the country in which firms operate. National-level exposure, sensitivity, and adaptive capacity can have a threatening remark on organisations' businesses. The impacts of climate change have become more visible. For example, in 2018, the unusually hot weather in Europe caused extreme drought, leading to severe losses for agriculture-related industries (Schiermeier, 2018a), while climate change also become a threat to Australian farmers (Chan, 2019b). In the literature, studies from the macroeconomy aspect recognised that climate change, which causes extreme weather (e.g., rising sea

[10] See, e.g., LAZARUS, R. S. 1999. Hope: An Emotion and a Vital Coping Resource Against Despair. *Social Research,* 66**,** 653-678.; HASTINGS, G., STEAD, M. & WEBB, J. 2004. Fear appeals in social marketing: Strategic and ethical reasons for concern. *Psychology and Marketing,* 21**,** 961-986.

level, drought, and flooding), has an observable adverse effect on economic development. Physical climate change can directly impact firms' intangible assets as well as their operation. For example, firms that are located near coastal areas may have their property and equipment damaged directly by rising sea levels. Business activities and manufacturing activities may have to stop by flooding (e.g., flood affects logistic process) or drought (if water is required for operations. Due to the nature of businesses, agriculture, mining, utility, tourism, and insurance firms can be influenced more profoundly (IPCC, 2014). Thus, a country's vulnerabilities to natural disasters raised by climate change can inflict significant losses to corporate profits. I then use the Notre Dame Global Adaptation vulnerability index as climate change-induced uncertainty for our research.

After identifying various hedge targets, the second step is to construct portfolios that can hedge innovations in our news series. In particular, I seek to systematically explore which stocks tend to rise in value and which stocks fall in value when climate change risks and uncertainties materialised. I implement this characteristic-based approach using firm-level sustainability engagement information. Previous studies use the general ESG scores to examine the relationship between asset returns and environmental activities. However, ESG criteria used to construct ESG scores are different among companies from different industries. Some ESG data items that are more relevant to a company's industry may be irrelevant for the other companies. For example, GHG emission is an essential factor for the transportation or mining industry but not relevant to financial firms. In addition, the majority of ESG disclosed data are voluntary, and there are no uniform standards to ensure comparability of those items across companies. Different ESG score providers also have their approach and ranking, which show low correlation across them. Therefore, ESG data is collected irregularly and meagrely, and the data collection and firm rankings by ESG data providers add more noise to integrating ESG into portfolio construction. Thus, it is critical to use appropriate ESG scales that reflect an accurate cross-sectional comparison between firms' sustainability performance. Differentiating from the paper of Engle et al. (2020), I use both ESG performance scores and ESG reporting scores. The former is collected from REFINITIV ASSET 4, which uses several subcategories and evaluates each firm's score compared to its peer in the same TRBC industry groups. The latter is retrieved from Bloomberg, which ranks the relative performance of companies across four key focus areas of diversity, tenure, overboard, and independence

As far as the authors are aware, this is the first paper that examines the hedging power of a firm's sustainability activities against an extensive set of climate change risks and uncertainties. I contribute to the literature of sustainable investment in several ways. First, I build a portfolio model based on firms' green performance to hedge against new-based sentiments on climate change. Second, I wish to study if our portfolio construction can hedge against other climate change news, i.e., physical climate change topics. Third, our research also studies whether firms' sustainability performance and disclosure can be used to hedge national-level climate change-induced uncertainty. Overall, for investors who consider sustainability issues in the hedging process, hedging all potential climate change risks should be on their radar.

## 2. Theory and conceptual framework

### *2.1. Corporate social responsibility and asset market.*

The sustainability concept and its impact on different firms can be accessed through two opposite corporate theoretic frameworks in financial researches: shareholder and stakeholder theories. The former believes that the only responsibility of firms is maximising shareholders' profit (Friedman, 1970). Thus, if a company's social or environmental engagements negatively impact the shareholders' future value, it will harm its core purposes. Furthermore, Friedman (1970) also discusses that managers who are in charge of the businesses' money should only do so to fulfil the shareholders' interest accordingly. On the other hand, the stakeholder theory stream declares that a firms' responsibilities are not limited to its shareholder only but all of its stakeholders. Stakeholders include the company's customers, employees, suppliers, governments, environmentalists, social groups, and shareholders (Freeman, 1984). Stakeholder theory believes that when a corporation acts beyond its purpose of maximising profit, it will be rewarded with future value creation for all its stakeholders and itself. The corporate social responsibility (CSR) framework was drawn from this stakeholder theory and considers every social aspect, including community projects, employees' benefits, or environmental protection. These associations are beyond firms' initial activities of making money and leaning towards ethical ideology.

The' triple bottom line' accounting framework introduced by Elkington (1994) suggests how firms can accomplish sustainable growth by taking social, environmental, and economic aspects into account. It is argued that it is essential for firms to play an active role in attaining sustainable development because it can improve their reputations with customers, thus growing their profits while protecting the environment, which is often called a "win-win-win" strategy. Aligning with this notion, Porter and Kramer (2003) examine how social acts related to a business can be accelerated to competitive advantage and economic gains for firms. They believe that economic and social aspects are fundamentally associated, and if corporations are mobilised in such a way that benefits both firms and society, it would be the most effective way to solve world problems. Sustainability engagement increases market confidence and reduces speculation, thereby positively affecting stock return and decreasing return volatility. Regarding financial performance, several studies show the inverse proportional effect of environmental on volatility, for example, Brammer et al. (2006), Renneboog et al. (2008), Barber and Odean (2008), El Ghoul et al. (2011), and Chava (2014). Several researchers, such as Statman and Glushkov (2008), Eccles et al. (2014b), and Statman and Glushkov (2016), supportively argue for the positive relationship between stock performance and environmental engagement. Particularly, Krüger (2015) suggests that investors respond positively to CSR news, while negative news receives adverse reactions.

On the other hand, following shareholder theory, Barnea and Rubin (2010) debate that excessive investing into sustainability can generate conflicts among different shareholders due to the reduction in shareholders' wealth and value of the corporations. Furthermore, information on firms' commitments towards sustainability initiatives may also create asymmetric information problems. Some researchers even find no effect of ESG on expected return, such as Bauer et al. (2005) and Plantinga et al. (2008). Interestingly, Bolton and Kacperczyk (2020a) discover that heavy greenhouse gases emitters achieve higher stock returns than those that emit less. Studies related to the relationship between financial performance and environmental have had diverse outcomes.

### *2.2. ESG investments and how climate change affects asset markets.*

As per the debate on whether trades are made based on companies' CSR disclosure, the empirical results also pose mixed findings. There is considerable evidence supporting the notion that sin stocks tend to outperform other benchmarks. The most arguably prominent and cited article in this area is Hong and Kacperczyk (2009). The paper defines sin-stock as firms operating in tobacco, alcohol, and gambling industries and finds that these stocks outperform comparable by 3-4% annually. The argument was made based on Merton (1973) that stocks held by a small segment of investors will tend to have depressed prices, thus, leads to higher future returns. Supporting these findings, Trinks and Scholtens (2017) indicate that sin stocks selected at the individual stock level also exhibit high returns in several international markets. However, the use of industry-based classification for sin stock may raise a concern that variables may pick up the effect of industry characteristics rather than that of the firm-level exposure to carbon risk. Therefore, literature moves to construct portfolios based on composite measures either within ESG elements or overall ESG measures. Using industry-adjusted ESG score from KLD (now MSCI), Kempf and Osthoff (2007) find a positive relationship between returns and ratings by constructing long-short value-weighted portfolios between 1992 and 2004 from S&P500 and DS400 stocks. The finding is confirmed later on by Statman and Glushkov (2008) based on 1992-2007 data. Humphrey and Tan (2014) employ the KLD ratings and SIC codes to construct four SRI portfolios based on positive and negative screening, although the test powers for these portfolios are not too high. Firms with higher ESG scores have better valuations than those without; however, it is inconclusive whether firms with better ESG enjoy higher returns.

Moving on from overall ESG performance scores, researchers then access each factor of ESG separately. The literature shows that Social and Governance factors have been studied in several papers[11], while evidence on investor returns to environmental screens is limited and produces mixed results. Derwall et al. (2005) examine the returns to a strategy based on corporate eco-efficiency extracted from Innovest Strategic Value Advisors. They find that more eco-efficient firms earn higher stock returns than their less eco-efficient counterparts over the period 1995-2003. Guenster et al. (2011) correlate the Innovest eco-efficiency data with equity valuation and operating performance measures. They find that, during the sample period, eco-efficient firms become relatively more expensive, estimated by Tobin's Q. This finding suggests that the return outperformance results from changes in valuation: either eco-efficient firms were undervalued initially or became overvalued later on in the observed period.

Accessing the relationship between ESG performance and asset returns, either by using ESG overall score or by main ESG factors, have two major drawbacks. Firstly, ESG criteria used to construct ESG scores are different among companies from different industries. As a result, ESG data items that are more relevant to a company's industry may be irrelevant for the other companies. For example, GHG emission is an important factor for the transportation or mining industry but not relevant to financial firms. The second drawback is that, up until now, most ESG disclosed data are voluntary, and there are no uniform standards to ensure comparability of those items across companies. Moreover, there are different ESG data providers, and each has its own approach and ranking, which shows low correlations across them. Therefore, ESG data is collected irregularly and meagrely, and the data collection and firm rankings by ESG data providers add more noise to integrating ESG into portfolio construction. Therefore, researchers need to choose ESG performance scores that compare companies to their industry's benchmarks rather than ones that score firms cross-sectionally.

Apart from environmental performance, arguments on sustainability information are divided into two directions based on how investors interpret disclosed information. First of all, the optimistic perspective believes sustainability information can maximise the company's value in the future by showing the firm's wealth creation, although it might not affect the current value. The companies' commitment to a sustainable business promises an increase in long-term performance, enhances market participants' confidence, and reduces price volatility (Dhaliwal et al., 2012). On the other hand, sustainability disclosure can increase information asymmetry, which leads to dispersed opinions on published information (Harjoto and Jo, 2015). With different interpretations over the same piece of

[11] For example, see Edmans (2011), Edmans (2012) for social screening and Gompers, Ishii and Metrick (2003), Bebchuk, Cohen and Wang (2013), Gu and Hackbarth (2013), and Auer (2016) for Governance screening.

news, the stock will be evaluated differently, leading to higher stock price volatility and stock price bubbles (Jo and Na, 2012, Orlitzky and Shen, 2013).

### *2.3. Asset and climate change: Disagreement and uncertainty sentiments*

The nature of climate change and global warming is that their impacts are hardly measured. Therefore, the consequences of climate change are uncertain. Empirically, uncertainty sentiment has been shown to affect asset prices and have explanatory power on some well-recognised anomalies in asset pricing (Fama and French, 2007, Carlin et al., 2014, Antoniou et al., 2015, Banerjee et al., 2019). For instance, Antoniou et al. (2015) show that the low-volatility anomaly emerges when the stocks with greater valuation uncertainty are overvalued during a high sentiment period, the effect of which is strengthened by investor overconfidence is expected that when volatility is high, the price will be pushed up, leading to lower in return as in the notion of efficient market hypothesis. However, Yu and Yuan (2011) claim that noise traders are more likely to trade in the market during high sentiment periods, leading to short-sale constraints. In line with theoretical framework, Yu (2011) and Hong and Sraer (2016) report that investors' disagreement results in overpricing during the period of short-sale impediments. Also, individual investors are generally hesitant to short stocks when they have limited knowledge or behavioural biases (Barber and Odean, 2008). Thereby, short-sale constraint is generally stronger during high sentiment periods because of increased tendency to avoid short selling of stocks resulting from the increased number of individual investors. Nevertheless, Shleifer and Vishny (1997) argue that although stocks are overvalued, the stock prices may continue to accelerate for a short time before falling back to its fundamental values. It is difficult to predict stock price movement in a short-term due to the dominance of irrational and inexperienced investors during the period of high sentiment.

In another literature streamline, the debate on whether ESG disclosures can help maximise shareholder value is likely to be the reason to limit large-scale capitals to invest in a low carbon economy. In order to support the international transition to a low carbon economy, it is needed to demonstrate investment portfolios that are constructed in line with investor's return target with a more climate-resilient economy.

Therefore, I seek to construct a portfolio that can hedge against the risk posed by disagreement and uncertainty in climate change news.

**Hypothesis 1a**: Firms' ESG performance and reporting scores can hedge against disagreement and uncertainty sentiment in climate news.

### *2.4. Asset and climate change: Other uncertainty measures.*

We also examine whether our portfolio construction based on ESG performance and reporting scores can hedge against national-level uncertainty. Literature suggests that equity market volatility increases following extreme high-temperature events, especially with unforeseen uncertainties about physical climate risk (Griffin et al., 2019). Climate change can impact businesses in several ways, such as rising sea levels, extreme weather, human health risks, or pressure on water and foods (Henderson et al., 2018, Jia and Li, 2020). Thus, a country's vulnerabilities to natural disasters raised by climate change pose significant risks to corporate profits. Since our portfolio is built to hedge the impact of climate risks solely, I then examine whether these portfolios can hedge against risk induced by the country's vulnerability to climate change.

**Hypothesis 1b**: Firms' ESG performance and reporting scores can hedge against national-level climate change-induced uncertainty.

### *2.5. Asset and climate change: Physical climate change coverage in the news*

Trading on the financial market is heavily impacted by company-specific, political information and macroeconomic. News sentiments are only a few aspects of what news conveys to investors. Therefore, the topics mentioned in the news are also important since they reflect the areas being discussed. According to Hisano et al. (2013), an abnormal large trading volume in the stock market can be partially explained by flows and topics for 206 major stocks in the S&P US stock index. This research focuses on climate change news; thus, the concentration regarding policies or technology topics could potentially influence the firms' sustainability performance. Therefore, the hypothesis suggests that a higher ESG score can assure investors in the events of changing political flows, changing weather, or introducing new regulations.

In accordance with the risk factor, decision-makers - here, the investors - tend to consider firms with negative ESG scores as riskier when they are uncertain about the situations. It is aligned with the findings in behavioural literature that when investors face a higher possibility of losses, they tend to embrace the ambiguity (Wakker et al., 2007b), meaning that when there is a rise in negativity, the effect of uncertainty is more extensive. Therefore, as the increase in using ESG for investment, a lower ESG score represents a negative position of a firm in the eyes of investors. Several studies already claim that lower ESG scores or CSR engagement leads to higher firm risk. Thus, putting an asset in a situation of risen concern about physical or policy climate change could imply an increase in the firm risk of those with lower ESG scores and worsen their profitable level in the investors' minds. According to stakeholder theory, these risks can be mitigated with firms' sustainability investment (Eccles et al., 2014b; Statman and Glushkov, 2016). We, therefore, perform another research question regarding different types of climate change news.

**Hypothesis 2**: Firms' ESG performance and reporting scores can hedge against physical climate change topics in climate news.

## 3. Data

### *3.1. Measuring hedge targets*

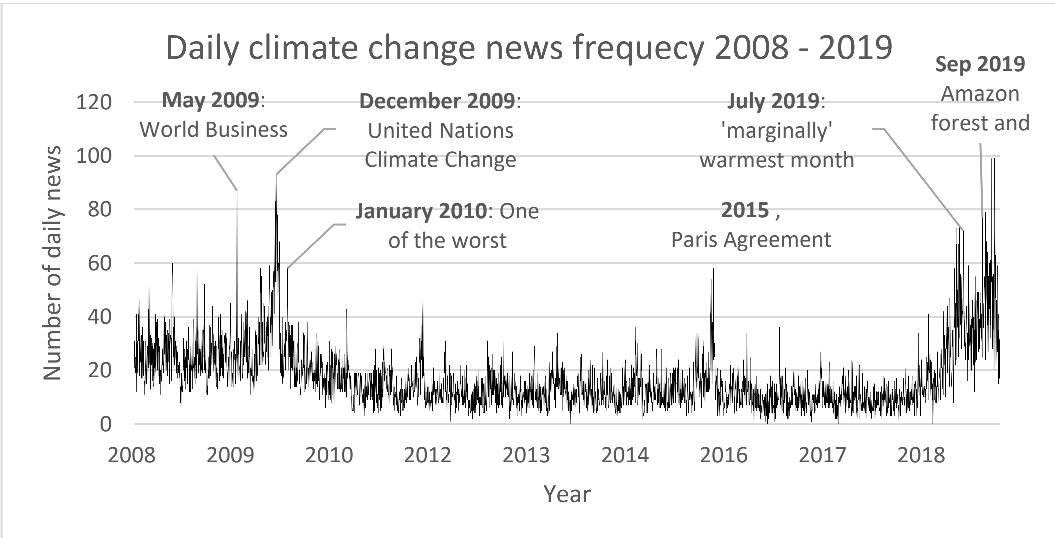
#### *3.1.1 Climate change news sentiments*

*Step 1: Text Extract:*

News for this research is extracted from the ProQuest database. I used advanced search to search for particular 'Climate change' or 'Global Warming' newspapers from 01/01/2008 to 31/12/2019. There is 65,957 news collected at first. I then remove the duplicate articles to prevent repeated news. The duplicate articles may affect the accuracy of the sentiment presented in the articles when targeted words appear more than once. As a result, I collect a sample of 52,326 climate-related news. In order to obtain only the informative content from the news, I pre-process our news files.

Furthermore, I strip out several words that do not add any value to the information conveyed by the news. These words are defined in several categories, namely: currencies, dates, and numbers, generic, and names, which are defined in Loughran and Mcdonald (2011). Figure 5 shows a time series of climate change news from our data source. It shows that the number of climate-related news spike at the time of significant climate change events, such as the United Nations Climate Change conference in 2009 or the latest Amazon Forest and ongoing Australian fire began in September 2019 and lasts months after that.

**Figure 5: News frequency and events graph 2008 - 2019**



As seen from the above graph of news frequency, I can see how news reflects the climate change acts and political events. Therefore, I examine both the sentiments within the news and topics discussed because they may impact how investors interpret it and apply it to their portfolios.

*Step 2: Cleaning and Pre-processing:*

In order to get accurate, informative content from the news, it is essential to do pre-processing for the files I have. I deploy Python and Java to strip out punctuation, stop-word lists, and publication information since it does not add any value to the information conveyed by the news.

The stop-word lists are retrieved from Loughran and McDonalds (2011) to get the news' sentiments; there are four lists, including currencies, dates, and numbers, generic, and names. For semantic tagging below, I do not take out the stop-words because it is arguable that stripping out stop-words may affect the information in the topics and what they refer to. For example, the sentence is "The weather is not good", if I remove the single word "not" as an individual stop word without considering the whole context, the result will be '*good weather*, leading to a different meaning.

*Step 3: Annotation:*

For disagreement sentiment, negative and positive words are classified based on (i) the financial lexicon dictionary from Loughran and Mcdonald (2011) and (ii) semantic tagging from the WMatrix tool. LM dictionary is a well-established and highly influential word list that better indicates tone in the economic context[12]. In WMatrix semantic tagging tool, climate change news is analysed using the corpus analysis tool developed by Lancaster University Centre for Corpus Research on Language (Rayson, 2008). This tool allows us to categorise the keyness words based on semantic categories. WM dictionary is based on British National Corpus; thus, negative and positive classifications are broader and more general than the LM dictionary.

Uncertainty sentiment is also classified based on LM and WM dictionary. Similar to negative and positive sentiments, WM offers a broader range for uncertainty sentiment than the LM dictionary. For instance, the word "uncertainty" has its lexical synonym: 'contentious' or 'unsure' which are not included in the LM dictionary.

Following word classification, each positive and negative sentiment are calculated by counting the probability a sentiment occurs within a day worth of news:

[12] See https://www3.nd.edu/~mcdonald/Word_Lists.html.

$$X_{p,t} = \frac{N_{p,t}}{N_{all,t}}$$

and

$$X_{n,t} = \frac{N_{n,t}}{N_{all,t}}$$

In which $X_{p,t}$ and $X_{n,t}$ are positive and negative proportion; $N_{p,t}$ and $N_{n,t}$ are number of positive and negative from the dictionary that appears in the news on day $t$ and $N_{all,t}$ is total informative words appear in that day.

From negative and positive sentiments, I follow the paper of Siganos et al. (2017) in using the divergence of sentiment rather than using solely average of either positive or negative sentiment. However, in their paper, the disagreement is extracted from a subjective source of sentiment - Facebook status. The disadvantage of that research then restricted to the limitation of investors' credit from Facebook users. Not every user is an investor, and not every investor uses Facebook. In order to overcome this limitation, our research uses published news as an alternative source that shows how investors interpret the news, and presumably, all investors read the news to collect the necessary information.

Following Siganos et al. (2017) 's paper, I employ sentiment analysis to calculate the divergence of positive and negative as follow:

$$DoS_t = \left| \frac{x_{p,t} - x_{p,all}}{\sigma_{p,all}} + \frac{x_{n,t} - x_{n,all}}{\sigma_{n,all}} \right|$$

In which, $\frac{x_{p,t} - x_{p,all}}{\sigma_{p,all}}$ and $\frac{x_{n,t} - x_{n,all}}{\sigma_{n,all}}$ are positive and negative sentiments where $x_{p,all}$ and $x_{n,all}$ are the average percentage of positive and negative sentiment detected during the time frame of the data set and $\sigma_{p,all}$ and $\sigma_{n,all}$ are standard deviation for those variables.

Similarly, I also calculate the uncertainty sentiment to be the absolute value of change in uncertainty proportion:

$$UNC_t = \left| \frac{x_{u,t} - x_{u,all}}{\sigma_{u,all}} \right|$$

In which, $x_{u,t}$ is the uncertainty proportion calculated as the number of uncertainty words over the total of words in day *t*, $X_{u,t} = \frac{N_{u,t}}{N_{all,t}}$ ; $x_{u,all}$ is the average percentage of uncertainty that appeared during the dataset and $\sigma_{u,all}$ is the standard deviation of these variables. The absolute value indicates the distance of uncertainty counts on day $t$ to the mean uncertainty of the whole sample.

We have got two sets of sentiment from this step: the divergence of sentiment and uncertainty sentiments from Loughran and McDonald's dictionary, and the other is those sentiments from WMatrix. I then denote them to be $DoS\_LM_t$ and $UNC\_LM_t$ (from Loughran and McDonald's method) and $DoS\_WM_t$ and $UNC\_WM_t$ (from WMatrix semantic tagging).

Initially, news sentiments are measured in daily frequency. However, because our ESG scores are only available on a monthly basis, I calculate all sentiment on the monthly average.

**Figure 6: Binscatter plot of DoS_LM and DoS_W**

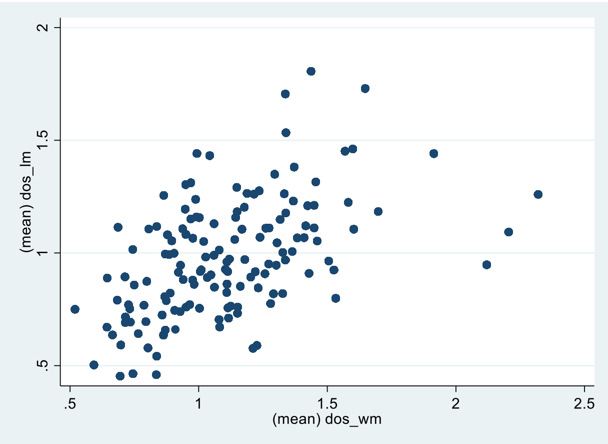



**Figure 7: Binscatter plot of UNC_LM and UNC_WM**

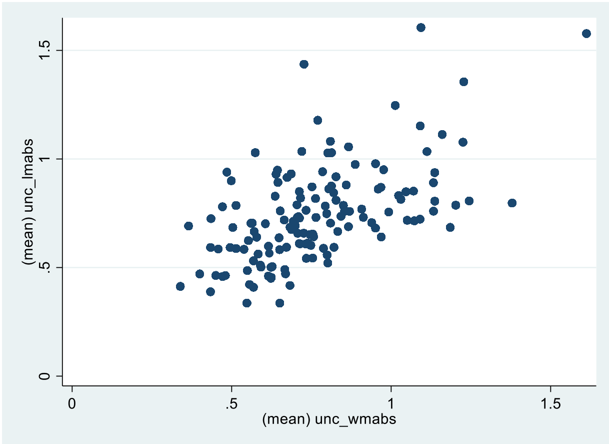



Figure 6 shows a scatterplot highlighting the correlation across our two disagreement climate hedge targets, DoS_LM and DoS_WM, and figure 7 shows a scatterplot highlighting the correlation across our two uncertainty climate hedge targets, UNC_LM and UNC_WM. Each observation corresponds to 1 month between January 2008 to December 2019. The correlation coefficient of disagreement sentiment is 0.50. The correlation coefficient is 0.56.

In order to cross-validate our disagreement/uncertainty index as an interpretation for the sentiment of our investors, I follow Sun et al. (2016) and run the regressions below:

$$DoS_t = \beta_t + \beta_1 Proxy_t + \varepsilon_t \quad (a)$$

In which $DoS_t$ is the divergence of sentiment from both dictionaries used throughout our research: Loughran and McDonald and WMatrix measured at month $t$. $Proxy_t$ presents alternative proxies for the sentiment. Since disagreement sentiment is rarely studied, let alone a defined disagreement index, thus I use two proxies for general sentiment, namely: Baker and Wurgler (2006) 's sentiment (BW) and consumer sentiment index from the University of Michigan (UM). I consider both BW and its counterparts $BW^{\perp}$ which is orthogonal to macroeconomic set stated in Baker and Wurgler (2006).

For uncertainty sentiment, I consider the Economic Policy Uncertainty (EPU) index from (Baker et al., 2016) and the World Uncertainty Index (WUI) generated by the International Monetary Fund (IMF), both specified for the UK, as alternative proxies for the following regression:

$$UNC_t = \beta_t + \beta_1 Proxy_t + \varepsilon_t \tag{b}$$

We transformed our daily sentiment to monthly frequency because these independent variables are in a monthly format. The sample period ranges from January 2008 to December 2018 because the BW dataset is currently available up to 2018.

**Table 18: Climate news sentiment cross-validation:**
Panel A reports results from the following regression

$$DoS_t = \beta_t + \beta_1 Proxy_t + \varepsilon_t$$

Where $DoS_t$ is the divergence of sentiment as the results from Loughran and McDonald (DoS_LM) and WMatrix (DoS_WM). Proxy denotes an alternative proxy for investor sentiment. I consider three proxies: the investor sentiment index from (Baker and Wurgler, 2006) (BW), the orthogonal counterpart BW⊥, and the University of Michigan consumer sentiment index (UM). The data set is in monthly frequency, t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and *, respectively. The sample period is from January 2008 to December 2018.

*Panel A: DoS versus BW, orthogonal BW, and UM*

| | DoS_LM | | | DoS_WM | | |
|---|---|---|---|---|---|---|
| Sentiment proxy | *β₀* | *β₁* | *Adj.* R2 | *β₀* | *β₁* | *Adj.* R2 |
| *BW* | 1.04222*** | 0.20755*** | 3.20 | 1.216019*** | 0.379907*** | 7.70 |
| | (29.78) | (2.07) | | (30.22) | (3.29) | |
| $BW^{\perp}$ | 1.0186*** | 0.22327*** | 5.80 | 1.162639*** | 0.336738*** | 9.60 |
| | (40.88) | (2.84) | | (40.44) | (3.72) | |
| *UM* | 0.1209 | 1.071462*** | 27.68 | 0.324912*** | 0.977129*** | 16.60 |
| | (0.97) | (7.05) | | (2.06) | (5.08) | |

Panel B reports results from the following regression

$$UNC_t = \beta_t + \beta_1 Proxy_t + \varepsilon_t$$

Where $UNC_t$ is the divergence of sentiment as the results from Loughran and McDonald (DoS_LM) and WMatrix (DoS_WM). Proxy denotes an alternative proxy for investor sentiment. I consider two proxies: Baker et al.(2016) Economic Policy Uncertainty (EPU) and the IMF (2020) World Uncertainty Index (WUI).

*Panel B: UNC vs. EPU, and WUI*

| | UNC_LM | | | UNC_WM | | |
|---|---|---|---|---|---|---|
| Sentiment proxy | *β₀* | *β₁* | *Adj.* R2 | *β₀* | *β₁* | *Adj.* R2 |
| *EPU* | 0.618561*** | 0.085953*** | 7.2 | 0.743037*** | 0.022371 | 0.5 |
| | (13.79) | (3.19) | | (16.32) | (0.82) | |
| *WUI* | 0.523156*** | 0.001064*** | 7.78 | 0.567841*** | 0.000992*** | 7.05 |
| | (7.35) | (3.27) | | (8.11) | (3.12) | |

We can see the results reported in table 18. Our disagreement/uncertainty index has a positive and significant relationship with all regressors except for *UNC_WM* with *WUI,* in which the relationship is still positive although not significant. In detail, disagreement sentiments from both LM and WM dictionaries are found to have highly significant and positive relationships with both BW (raw and orthogonalised) and UM Interestingly, visually graph inspection in Figure 8 shows that *DoS_LM* seems to move much closer to *BW* and *UM*. At the same time, there is a gap between *DoS_WM* moves versus these sentiment benchmarks. This gap can be explained by the differences in how each disagreement index was composed. Loughran and McDonald's dictionary is more established with several usages among researchers, while WMatrix expresses a more generic collection of words used in the news and at the early stage of its development. The disagreement index was calculated as the distance between positive and negative sentiment within a day. An increase in sentiment can either rise in both negative and positive sentiment (resulting in less divergence of sentiments) or raise in negative or positive sentiment while the other remains the same (resulting in further divergence of sentiments).

**Figure 8: Movements between BW, UM and DoS_LM and DoS_WM**

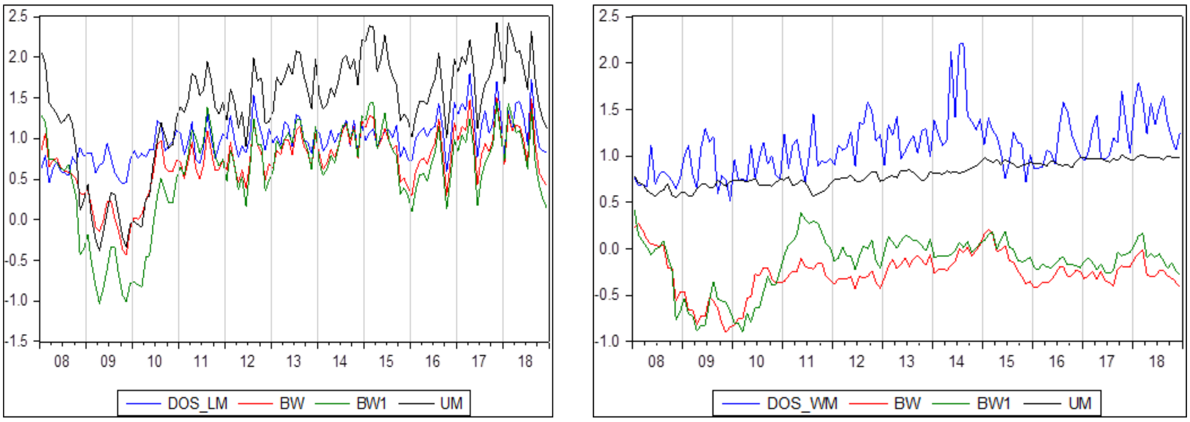
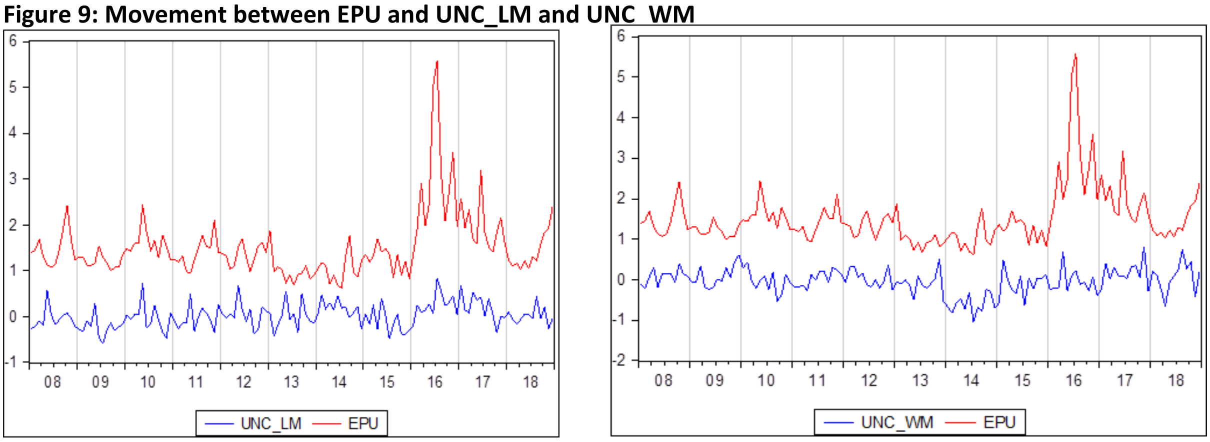



**Figure 9: Movement between EPU and UNC_LM and UNC_WM**




Overall, I conclude that the above results support the view that our disagreement (*DoS_LM, DoS_WM*) and uncertainty (*UNC_LM, UNC_WM*) index from both dictionaries can capture investor's sentiments.

### 3.1.2 Physical climate change topics

For content analysis, I extract three physical climate-related categories: World and environment (semantic tag: W), Food (semantic tag: F), and Housing (semantic tag: H). I obtain each category's frequency each day and then calculate the monthly average index to combine it with the panel data from market data. Regarding the argument, I measure the *PHY* index (physical climate content in climate change news) equals the sum relative frequency of environment, food, and housing topics.

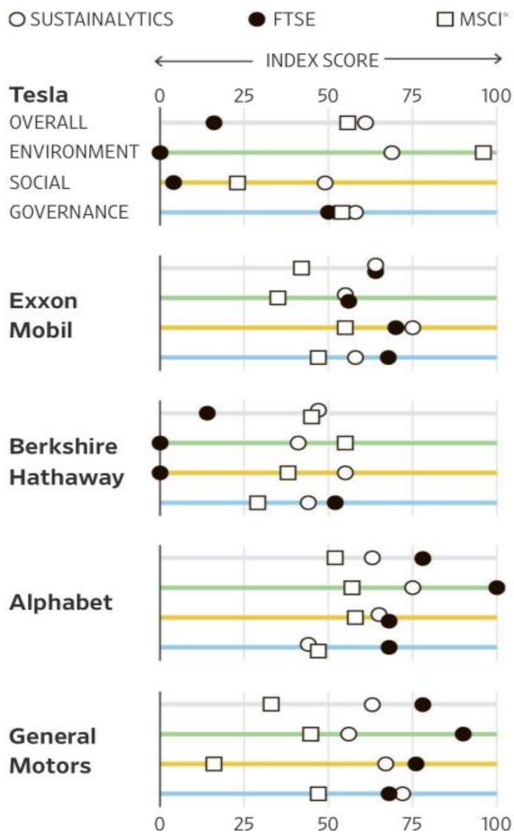
### 3.1.3 Climate change-induced uncertainty

For external uncertainties, I follow Jia and Li (2020) and collect the vulnerability index as our climate change-induced uncertainty (*CCU*) from The Notre Dame Global Adaptation (ND-GAIN). The ND-GAIN is measured based on two key adaptation dimensions: vulnerability and readiness; however, I only collect the vulnerability index to measure climate change-induced uncertainty for this research. The vulnerability dimension measures each country's exposure, capacity, and sensitivity to acclimatise to the negative impact of climate change. The index considers six sectors to measure the vulnerability levels: health, water, food, human habitat, ecosystem service, and infrastructure. I denote this variable as *CCU* in this paper.

## 3.2. Measuring climate risk exposures

Although more and more investors rely on ESG scores to make their investment decision, the current frameworks and mechanisms are not adequate. Choosing ESG data is critical since I have many different ESG score providers with different methods and approaches.

There is a big argument now on how different ESG ratters have different ratings for the same companies. One of the root causes for it is that they have different methodologies for their scale. For example, Mackintosh (2018) compares the three widely used ESG scores: Sustainalytics, FTSE, MSCI, and shows the different results for some outstanding companies in the figure on the right.




Mackintosh (2018)

It is critical to choose a source of ESG scores for the purpose of this research. Some papers have been criticised the ESG rating measurement for over a decade. One of the first ESG rating scores was introduced by KLD in 2008 when firms and governments realise, they need to take corporations' sustainable development into account. In the last ten years, ESG rating providers have been through several consolidations, both with processes of merging and acquisition among already existing ESG providers and the appearance of new raters.

**Table 19: ESG rating scales comparison**

| No. | ESG Rating agencies | ESG rating scales | Number of companies covered | Other notes |
|---|---|---|---|---|
| 1 | ASSET4 | REFINITIV | 22,000 | Cover 87 countries |
| 2 | Oekom | ISS-Oekom | 20,000 | Cover 150 markets, used by 2,000 institutional clients |
| 3 | SIRI Company | Sustainalytics | 11,000 | Cover 42 sectors worldwide |
| 4 | Bloomberg | Bloomberg ESG Disclosure Scores | 10,000 | Nearly 18,000 customers by 2019 |
| 5 | KLD Research & Analytics | MSCI ESG Research | 7,000 | 6,000 global companies and more than 400,000 securities |
| 6 | SAM | RobecoSAM | 4,500 | Cover 60 countries |
| 7 | EIRIS | FTSE Russell ESG Rating | 4,100 | Used by 46/50 top asset managers and 1,200 investors globally |
| 8 | ECP | ECP | 4,000 | Covers 47 markets |

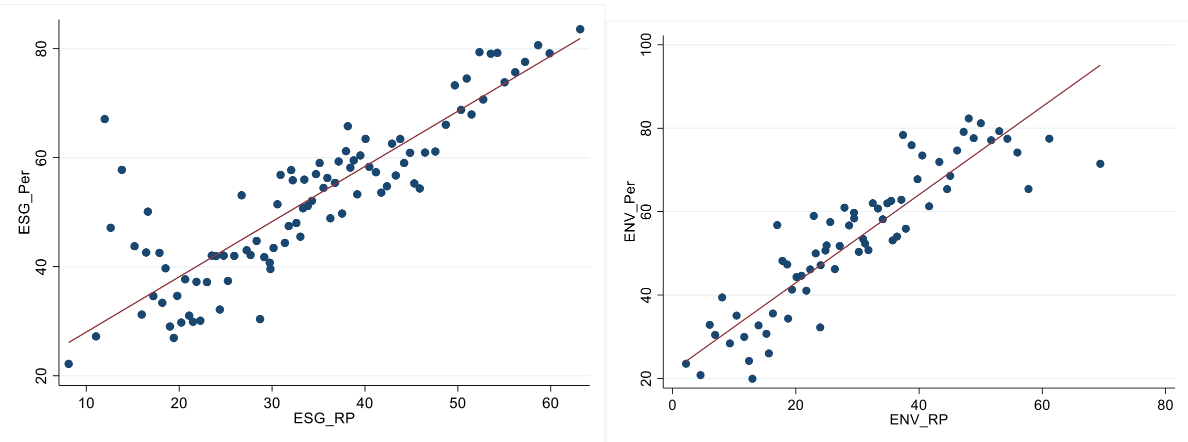
This table compares several ESG rating agencies and their ESG rating scales based on the number of companies covered and other specialities. This data is collected from Escrig-Olmedo et al. (2019)

As I observed in the comparison table 19 above, The REFINITIV Asset4 rating has the broadest range of companies in their account and ISS-Oekom and Sustainalytics. It is shown that from the combination of a comprehensive set of criteria and number of covered firms, as the ESG investing is used as an active approach for long-term value creation, it is reasonable to choose the ones with an intergenerational perspective. It is also shown in the work of Escrig-Olmedo et al. (2019) that those three rating schemes follow the stakeholder approach, and they include the needs and expectations of a wide range of stakeholders, such as suppliers, customers relationship management. Thus, it is suitable for the hypothesis of the research.

We then choose ASSET4 ESG scores for our environmental performance score. I collect both the total ESG score and total environment score. REFINITIV Asset4 determines each of the Environment - “E”, Social - “S” and Governance - “G” scores, ASSET4 uses several subcategories and evaluates each firm’s score compared to its peer in the same TRBC industry groups for Environmental and Social categories and against countries for G score. Since this paper aims to measure different firms’ exposures to climate risk, I obtain the overall ESG performance score (ESG_Per) and Environment performance score (ENV_Per).

Apart from environmental performance, I also choose the ESG disclosure score from Bloomberg for our environment reporting score. It is believed that sustainability information can maximise a company’s value in the future by showing the firm’s wealth creation, although it might not affect the current value. In addition, the companies’ commitment to a sustainable business promises an increase in long-term performance, enhances market participants’ confidence, and reduces price volatility (Dhaliwal et al., 2012). Similar to the ESG performance score, I also collect the total ESG reporting score (*ESG_RP*) and the Environmental reporting score (*ENV_RP*). For both ESG performance and reporting measures, these scores are ranged from 0 to 100, and I use them as absolute values.

**Figure 10: Correlation between ESG performance score and ESG reporting scores.**




This figure shows a binned scatterplot that highlights the correlation across the ASSET4 ESG performance score and Bloomberg disclosure scores for all 408 firms in our sample. The correlation coefficient between two ESG scores is 0.65, and those between two environment scores is 0.63.

In summary, I have a monthly panel data set for 408 companies, running from January 2008 to December 2019, and a total of 58,752 observations. A detailed list of our variables is provided in Appendix.

## 4. Methodology

We adapt the following model from Engle et al. (2020) for hedge portfolios:

$$r_{t,x} = \alpha + \beta_{CC}^{x}\{\gamma_{CC} + (CC_t - E[CC_t])\} + \sum_{v=1}^{v} \beta_v^x(\gamma_v + v_t)$$

In which, $r_{t,x}$ is the return of portfolio x at time t. $CC_t$ is the innovation in climate news: this can be uncertainty sentiment or different climate change topics (or other national-level uncertainties). $\beta_{CC}^{x}$ is the risk exposure of *n* assets in portfolio *x* to climate change news factors. $\gamma_{CC}$ is corresponding risk premia to climate change news factor. $E[CC_t]$ is expected innovation in climate news. $\beta_v^x$ is the risk exposure of *n* assets in portfolio *x* to other factors $v$. $\gamma_v$ is corresponding risk premia to other factors $v$.

In this paper, I make use of the mimicking portfolio approach introduced in Engle et al. (2020). In the mimicking portfolio approach, the climate risk factor $CC_t$ will be directly projected onto a set of excess returns of a set of portfolios, $\widetilde{r_t}$:

$$CC_t = \mathcal{E} + w'\widetilde{r_t} + e_t \tag{1}$$

The excess return of the portfolio is $h_t^{CC}$ = $w'\widetilde{r_t}$ which presents the total excess return is equal to the weight of each asset multiply by that asset's excess return. The vector $e_t$ indicate the error of measurement in the climate risk factor $CC_t$.

As I only want to create a portfolio that hedges against climate risk with the assets themselves, I should only include firm-level characteristics. These characteristics will be the primary criteria for investors to change their portfolio to avoid climate news risk without adjusting other risk exposure. This method ensures that the portfolio has constant risk exposure for a fixed set of assets.

The excess return $\tilde{r}_t$ is now calculated as the value of the firm-level characteristic $Z_t$ multiply the excess return of individual stocks $r_t$:

$$\tilde{r}_t = Z_{t-1} r_t$$

Here I choose lag 1 of firm-level characteristics because these characteristics are typically measured annually; thus, they cannot reflect straight away into returns at time *t*. Combing the equation (3) and (4), I have the following equation:

$$CC_t = \mathcal{E} + w' Z_{t-1} r_t + e_t \tag{2}$$

In order to calculate the weight of assets for a climate change hedge portfolio, I need the following steps:

i $CC_t$: Hedge target. Here I account for the innovation in news., topics mentioned in the news, or climate change uncertainty induced in the news.

ii $Z_{t-1}$: firm-level characteristics. These are ESG performance score, ESG reporting score, size, market share, and market value.

iii Each firm's weight in the hedge portfolio will be determined by the sum of $w'Z_{t-1}r_t$ for all its characteristics.

The hedge portfolio then will be constructed for the three hedge targets described in section 3.1: (i) disagreement and uncertainty sentiment in climate news, (ii) physical climate coverage in the news, and (iii) climate change-induced uncertainty) using the mimicking portfolio approach mentioned above. As shown in section 3.2, I use (a) total ESG and environment performance score and (b) total ESG and environment reporting score as climate risk exposures used to hedge against climate change uncertainties. For example, if ESG performance score is used to hedge against disagreement sentiment in climate change news, the regression (2) will then become:

$$DoS\_LM_t = \mathcal{E} + \omega_{ESG\_Per} Z_{t-1}^{ESG\_Per} r_t + \omega_{BTM} Z_{t-1}^{BTM} r_t + \omega_{SIZE} Z_{t-1}^{SIZE} r_t + \omega_{MV} Z_{t-1}^{MV} r_t + e_t \qquad (3)$$

In which, $\omega_{ESG\_Per}$, $\omega_{BTM}$, $\omega_{SIZE}$, and $\omega_{MV}$ are the weights of corresponding stocks in the hedge portfolio with *DoS_LM* as a hedge target.

In order to examine how well our hedge portfolios perform, I compared them to portfolios that formed using returns from other green exchange-traded funds (ETF). I construct hedge portfolios based on ICLN and TAN ETFs as comparable portfolios. The ICLN fund is iShare Global Clean Energy with MAC Global solar energy as its underlying index, and TAN is Invesco Solar ETF that focuses on S&P global clean energy sector.

# 5. Results

## *5.1. In-sample fit results*

We first run various versions of the model (3) with different hedge targets and climate change exposures. Table 20 presents results for regression when the hedge target is the LM disagreement sentiment. Columns 1 and 2 of Table 20 indicate a significant and positive relationship between portfolios using performance scores and LM disagreement sentiment. It suggests that a portfolio constructed with higher performance scores will obtain higher excess returns during the time of higher disagreement sentiment level in climate news. Columns 3 and 4 of Table 20 demonstrate that ESG and environment reporting scores are also significantly and positively associated with LM disagreement sentiment *DoS_LM*. When comparing the R-Square between models of performance and reporting score, I observe that the R-squared measures in the regression of *DoS_LM* on reporting scores are similar to those on performance score, indicating that both risk exposure measures can hedge around 40% variation in *DoS_LM.*

**Table 20: In-sample regressions: Hedge innovation in LM uncertainty sentiments.**

| VARIABLES | (1)<br>DoS_LM | (2)<br>DoS_LM | (3)<br>DoS_LM | (4)<br>DoS_LM | (5)<br>DoS_LM | (6)<br>DoS_LM |
|---|---|---|---|---|---|---|
| ESG_Per | 0.103*** | | | | | |
| | (3.849) | | | | | |
| ENV_Per | | 0.104*** | | | | |
| | | (3.358) | | | | |
| ESG_RP | | | 0.117*** | | | |
| | | | (3.110) | | | |
| ENV_RP | | | | 0.215*** | | |
| | | | | (3.974) | | |
| ICLN | | | | | 0.0016*** | |
| | | | | | (16.91) | |
| TAN | | | | | | 5.97e-05 |
| | | | | | | (0.959) |
| BTM | 0.00479 | 0.00640 | -0.00928 | 0.0154 | 0.00709 | 0.00586 |
| | (0.526) | (0.705) | (-0.699) | (0.255) | (1.205) | (0.998) |
| SIZE | 0.0143 | 0.00772 | 0.00698 | 0.0159 | 0.0110 | 0.0126* |
| | (1.455) | (0.748) | (0.711) | (1.003) | (1.585) | (1.835) |
| MV | 0.00160 | 0.00191 | 0.00592 | 0.00405 | 0.00388 | 0.00383 |
| | (0.160) | (0.191) | (0.430) | (0.279) | (0.397) | (0.393) |
| Constant | 0.680*** | 0.680*** | 0.679*** | 0.681*** | 0.769*** | 0.694*** |
| | (101.3) | (101.0) | (117.8) | (105.3) | (148.2) | (160.3) |
| Observations | 20,173 | 20,159 | 17,955 | 15,767 | 53,841 | 54,627 |
| R-squared | 0.408 | 0.407 | 0.403 | 0.398 | 0.384 | 0.401 |

This table shows various in-sample regressions of model 3. The hedge target used in these portfolios is climate news disagreement sentiment. The sentiment is classified based on Loughran and McDonald's lexicon. The data set is in monthly frequency, t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and *, respectively. The sample period is from January 2007 to December 2019.

In addition, columns 5 and 6 of table 20 uses returns of *ICLN* and *TAN* in the regression. I observe that the in-sample fit for *ICLN* is significant but lower than any regression using our risk exposure measures from columns 1 to 4. On the other hand, the portfolio that includes *TAN* returns is not significant.

Table 21 also represents the regression of disagreement sentiment on our ESG and environment scores, but the disagreement sentiment is classified using WMatrix semantic tagging (*DoS_WM*). Similar to the regression of *DoS_LM*, columns 1 to 4 show that all of our climate risk exposure measures are positively and significantly related to *DoS_WM*. Additionally, columns 5 and 6 show that the portfolios constructed using *ICLN* and *TAN* index return are significantly less positive than our characteristic-weighted portfolio. The R-squared measures of these two regressions are also smaller than those in columns 1 to 4. Interestingly, regression on reporting scores can hedge better than those on performance scores (51.6% of the variation in *DoS_WM*) regarding R-squared measures. Overall, the performances of hedge portfolios using ESG, and environmental scores are positive and similar in both disagreement sentiments measures. Interestingly, in both disagreement sentiment measures, the hedge portfolios constructed using reporting scores have a better fit than the fit of hedge portfolio using performance scores.

**Table 21: In-sample regressions: Hedge innovation in WM disagreement sentiments.**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | DoS_WM | DoS_WM | DoS_WM | DoS_WM | DoS_WM | DoS_WM |
| ESG_Per | 0.181*** | | | | | |
| | (5.857) | | | | | |
| ENV_Per | | 0.207*** | | | | |
| | | (5.789) | | | | |
| ESG_RP | | | 0.216*** | | | |
| | | | (4.487) | | | |
| ENV_RP | | | | 0.335*** | | |
| | | | | (4.906) | | |
| ICLN | | | | | 0.0039*** | |
| | | | | | (36.54) | |
| TAN | | | | | | 0.0014*** |
| | | | | | | (19.83) |
| BTM | 0.00476 | 0.00688 | 0.000266 | 0.0187 | 0.00955 | 0.00831 |
| | (0.454) | (0.658) | (0.0157) | (0.245) | (1.403) | (1.218) |
| SIZE | 0.0202* | 0.00615 | 0.0239* | 0.0313 | 0.000194 | 0.00194 |
| | (1.784) | (0.518) | (1.902) | (1.557) | (0.0242) | (0.244) |
| MV | -0.00140 | -0.00160 | -0.00147 | 0.00666 | -0.00239 | -0.00237 |
| | (-0.122) | (-0.139) | (-0.0834) | (0.362) | (-0.211) | (-0.210) |
| Constant | 0.782*** | 0.782*** | 0.781*** | 0.783*** | 0.859*** | 0.795*** |
| | (101.2) | (100.9) | (105.8) | (95.71) | (142.9) | (158.1) |
| Observations | 20,173 | 20,159 | 17,955 | 15,767 | 53,841 | 54,627 |
| R-squared | 0.452 | 0.452 | 0.516 | 0.516 | 0.447 | 0.449 |

This table shows various in-sample regressions of model 3. The hedge target used in these portfolios is climate news disagreement sentiment. The sentiment is classified based on WMatrix semantic tagging. The data set is in monthly frequency, t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and *, respectively. The sample period is from January 2007 to December 2019.

**Table 22: In-sample regressions: Hedge innovation in LM uncertainty sentiments.**

| VARIABLES | (1)<br>UNC_LM | (2)<br>UNC_LM | (3)<br>UNC_LM | (4)<br>UNC_LM | (5)<br>UNC_LM | (6)<br>UNC_LM |
|---|---|---|---|---|---|---|
| ESG_Per | 0.0907*** | | | | | |
| | (3.936) | | | | | |
| ENV_Per | | 0.103*** | | | | |
| | | (3.872) | | | | |
| ESG_RP | | | 0.0935*** | | | |
| | | | (3.138) | | | |
| ENV_RP | | | | 0.0623* | | |
| | | | | (1.985) | | |
| ICLN | | | | | 0.001*** | |
| | | | | | (11.89) | |
| TAN | | | | | | 5.86e-05 |
| | | | | | | (1.083) |
| BTM | 0.00321 | 0.00428 | -0.00532 | 0.0654 | 0.00221 | 0.00155 |
| | (0.409) | (0.548) | (-0.507) | (1.392) | (0.431) | (0.303) |
| SIZE | 0.00382 | -0.00320 | -0.00357 | -0.00866 | 0.00421 | 0.00499 |
| | (0.451) | (-0.360) | (-0.460) | (-0.702) | (0.697) | (0.838) |
| MV | -0.00231 | -0.00239 | 0.0159 | 0.0160 | 0.00149 | 0.00105 |
| | (-0.268) | (-0.277) | (1.462) | (1.417) | (0.175) | (0.124) |
| Constant | 0.513*** | 0.513*** | 0.508*** | 0.508*** | 0.506*** | 0.473*** |
| | (88.69) | (88.43) | (111.4) | (101.2) | (111.7) | (125.6) |
| Observations | 20,173 | 20,159 | 17,955 | 15,767 | 53,841 | 54,627 |
| R-squared | 0.413 | 0.413 | 0.390 | 0.393 | 0.404 | 0.420 |

This table shows various in-sample regressions of model 3. The hedge target used in these portfolios is climate news uncertainty sentiment. The sentiment is classified based on Loughran and McDonald's lexicon. The data set is in monthly frequency, t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and *, respectively. The sample period is from January 2007 to December 2019.

We further investigate hedge portfolios with uncertainty sentiments in climate news as the hedge innovations. Tables 22 and 23 show the results for the regression of *UNC_LM* and *UNC_WM,* respectively. I observe that whether I try to hedge LM uncertainty sentiment or WM uncertainty sentiment, our hedge portfolios sorted by ESG and environment scores (columns 1-4 in tables 22 and 23) all have significant and positive relationships with the hedge innovation. It indicates that when there is more uncertainty sentiment in climate change news, a portfolio with better ESG and environment scores will have relatively better excess returns. In other words, our portfolio approach can hedge against uncertainty sentiment in the news. In both tables 22 and 23, as shown in columns 5 and 6, the in-sample fit of portfolios based on *ICLN* and *TAN* are significantly less positive than our hedge portfolios.

Noticeably, the fits of hedge portfolios created with performance scores and reporting scores are similar when hedge innovations in LM uncertainty sentiment. However, in the model that hedges against WM uncertainty sentiment, hedge portfolios using reporting scores seem to have a relatively better fit than those based on performance scores.

**Table 23: In-sample regressions: Hedge innovation in WM uncertainty sentiments.**

| VARIABLES | (1)<br>UNC_WM | (2)<br>UNC_WM | (3)<br>UNC_WM | (4)<br>UNC_WM | (5)<br>UNC_WM | (6)<br>UNC_WM |
|---|---|---|---|---|---|---|
| ESG_Per | 0.119*** | | | | | |
| | (5.153) | | | | | |
| ENV_Per | | 0.138*** | | | | |
| | | (5.166) | | | | |
| ESG_RP | | | 0.168*** | | | |
| | | | (5.456) | | | |
| ENV_RP | | | | 0.256*** | | |
| | | | | (5.879) | | |
| ICLN | | | | | 0.0030*** | |
| | | | | | (37.74) | |
| TAN | | | | | | 0.0017*** |
| | | | | | | (32.07) |
| BTM | 0.0123 | 0.0137* | -0.0103 | 0.0233 | 0.0115** | 0.0110** |
| | (1.565) | (1.742) | (-0.946) | (0.479) | (2.274) | (2.174) |
| SIZE | 0.00872 | -0.000752 | 0.0214*** | 0.0311** | 0.00558 | 0.00657 |
| | (1.025) | (-0.0843) | (2.663) | (2.425) | (0.936) | (1.117) |
| MV | 0.00316 | 0.00297 | 0.00958 | 0.00781 | 0.00640 | 0.00720 |
| | (0.365) | (0.343) | (0.849) | (0.667) | (0.762) | (0.861) |
| Constant | 0.576*** | 0.576*** | 0.576*** | 0.578*** | 0.608*** | 0.566*** |
| | (99.28) | (99.02) | (122.1) | (110.9) | (136.1) | (152.2) |
| Observations | 20,173 | 20,159 | 17,955 | 15,767 | 53,841 | 54,627 |
| R-squared | 0.394 | 0.394 | 0.467 | 0.467 | 0.412 | 0.419 |

This table shows various in-sample regressions of model 3. The hedge target used in these portfolios is climate news uncertainty sentiment. The sentiment is classified based on WMatrix semantic tagging. The data set is in monthly frequency, t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and *, respectively. The sample period is from January 2007 to December 2019.

We continue to run the in-sample regressions for different varieties of the model (3) to hedge against the physical climate covered in the news. As shown in columns 1 and 2 of table 24, both ESG score and environment performance score are positively related to the news coverage of physical climate. However, the R-squared measures in these regressions are lower than those in the model that hedging innovations to disagreement or uncertainty sentiments in table 20-23. Firms' sustainability scores can hedge an average of 32.2% effect of physical climate topics conveyed in the news. Similar results are found in columns 3 and 4 of table 24 when firms' sustainability reporting scores are used. As presented in column 3, firms with higher ESG reporting scores experience higher excess returns during the time of more physical climate coverage in the news. I find an insignificant association between *ENV_RP* and *PHY* variables; however, the estimated coefficient remains positive. Although portfolios constructed from *ICLN* and *TAN* index returns in columns 5 and 6 show better R-squared measures, the coefficient estimation in these regressions is smaller than that of all regression in columns 1-4. This result suggests that our portfolios that sort firms by sustainability performance and reporting scores might better hedge climate news topics than those heavily investing in purely green energy ETFs.

**Table 24: In-sample regressions: Hedge innovation in physical climate change covered in the news.**

| VARIABLES | (1)<br>PHY | (2)<br>PHY | (3)<br>PHY | (4)<br>PHY | (5)<br>PHY | (6)<br>PHY |
|---|---|---|---|---|---|---|
| ESG_Per | 0.125*** | | | | | |
| | (4.559) | | | | | |
| ENV_Per | | 0.163*** | | | | |
| | | (5.150) | | | | |
| ESG_RP | | | 0.117*** | | | |
| | | | (2.588) | | | |
| ENV_RP | | | | 0.0995 | | |
| | | | | (1.573) | | |
| ICLN | | | | | 0.0037*** | |
| | | | | | (38.80) | |
| TAN | | | | | | 0.0027*** |
| | | | | | | (42.23) |
| BTM | -0.0122 | -0.0113 | -0.0180 | -0.0847 | -0.00242 | -0.00208 |
| | (-1.308) | (-1.219) | (-1.137) | (-1.197) | (-0.401) | (-0.345) |
| SIZE | 0.00958 | -0.00222 | 0.0119 | 0.0263 | -0.00222 | -0.00257 |
| | (0.955) | (-0.211) | (1.013) | (1.412) | (-0.312) | (-0.367) |
| MV | -0.00776 | -0.00850 | -0.00242 | -0.00142 | -0.00699 | -0.00654 |
| | (-0.759) | (-0.831) | (-0.147) | (-0.0833) | (-0.698) | (-0.656) |
| Constant | 2.383*** | 2.383*** | 2.381*** | 2.381*** | 2.353*** | 2.384*** |
| | (347.7) | (346.9) | (345.3) | (314.8) | (441.4) | (537.3) |
| Observations | 20,173 | 20,159 | 17,955 | 15,767 | 53,841 | 54,627 |
| R-squared | 0.322 | 0.322 | 0.319 | 0.319 | 0.348 | 0.344 |

This table shows various in-sample regressions of model 3. The hedge target used in these portfolios is the physical climate topic covered in climate news. The topic is classified based on WMatrix semantic tagging. The data set is in monthly frequency, t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and *, respectively. The sample period is from January 2007 to December 2019.

Table 25 presents the regressions set similar to tables 20-24, but the climate change-induced uncertainty (*CCU*) is used as a hedge target. As before, the results show a positive and significant relationship between firms' sustainability performance and reporting scores and climate-induced uncertainty *CCU*. However, the R-squared measures obtained in column 1-4 of table 25 are relatively small, which suggest that our hedge portfolios can only hedge 0.3%-0.4% of the in-sample variation in climate change-induced uncertainty. Columns 5 and 6 replace the characteristic-sorted returns with the *ICLN* and *TAN* index returns. Similar to tables 20-24, the in-sample fit of *CCU* on *ICLN,* and *TAN* returns are smaller than that of our characteristic-sorted portfolios. However, the regressions on *ICLN* and *TAN* seem to be better in hedging innovations in *CCU* with R-squared measures of 1.3% and 1.0%, respectively. Overall, it implies that our characteristics-weighted portfolios can hedge some but not all of the negative impact of climate change-induced uncertainty.

**Table 25: In-sample regressions: Hedge innovation in climate change-induced uncertainty.**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | CCU | CCU | CCU | CCU | CCU | CCU |
| ESG_Per | 0.0709*** | | | | | |
| | (6.156) | | | | | |
| ENV_Per | | 0.0831*** | | | | |
| | | (6.246) | | | | |
| ESG_RP | | | 0.0843*** | | | |
| | | | (4.662) | | | |
| ENV_RP | | | | 0.107*** | | |
| | | | | (4.217) | | |
| ICLN | | | | | 0.0009*** | |
| | | | | | (25.35) | |
| TAN | | | | | | 0.0006*** |
| | | | | | | (22.62) |
| BTM | -0.00235 | -0.00152 | -0.00221 | 0.0813*** | 0.00194 | 0.00175 |
| | (-0.619) | (-0.404) | (-0.358) | (2.943) | (0.786) | (0.701) |
| SIZE | 0.00495 | -0.000762 | 0.00290 | 0.0101 | -0.0062** | -0.00520* |
| | (1.196) | (-0.175) | (0.626) | (1.360) | (-2.090) | (-1.745) |
| MV | 0.000424 | 0.000376 | 0.00836 | 0.00859 | 0.00258 | 0.000908 |
| | (0.0962) | (0.0854) | (1.128) | (1.122) | (0.597) | (0.208) |
| Constant | 30.28*** | 30.28*** | 30.26*** | 30.26*** | 30.28*** | 30.28*** |
| | (17,004) | (17,015) | (17,325) | (15,604) | (33,529) | (33,406) |
| Observations | 18,100 | 18,086 | 16,599 | 14,351 | 49,125 | 49,911 |
| R-squared | 0.003 | 0.003 | 0.004 | 0.004 | 0.013 | 0.010 |

This table shows various in-sample regressions of model 3. The hedge target used in these portfolios is the vulnerability index collected from The Notre Dame Global Adaptation. The data set is in monthly frequency, t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and *, respectively. The sample period is from January 2007 to December 2019.

**Table 26: Largest average short and long positions (by industry codes)**

*Panel A. Disagreement sentiment*

| **E-score performance** | | **E-score reporting score** | |
|---|---|---|---|
| ***Top negative portfolio weight*** | ***SIC 4*** | ***Top negative portfolio weights*** | ***SIC 4*** |
| Hotels & Motels | 7011 | Services-Legal Services | 8111 |
| Storage Batteries | 3691 | General Industrial Machinery & Equipment, NEC | 3569 |
| Service, NEC | 8999 | Motion Picture Theaters | 7832 |
| Oil & Gas Field Services, NEC | 1389 | Medicinal Chemicals & Botanical Products | 2833 |
| ***Top positive portfolio weight*** | ***SIC 4*** | ***Top positive portfolio weight*** | ***SIC 4*** |
| Motor Vehicle Parts & Accessories | 3714 | Aircraft Engines & Engine Parts | 3724 |
| Aircraft | 3721 | Semiconductors & Related Devices | 3674 |
| Motion Picture Theaters | 7832 | Highway and Street Construction | 1611 |
| Wholesale-Groceries, General Line (merchandise) | 5141 | Colleges, Universities, and Professional Schools | 8221 |

*Panel B. Uncertainty sentiment*

| **E-score performance** | | **E-score reporting score** | |
|---|---|---|---|
| ***Top negative portfolio weight*** | ***SIC 4*** | ***Top negative portfolio weights*** | ***SIC 4*** |
| Hotels & Motels | 7011 | Aircraft Engines & Engine Parts | 3724 |
| Services, NEC | 8999 | Ship Building and Repairing | 3731 |
| Storage Batteries | 3691 | Sausages & Other Prepared Meat Products | 2013 |
| Search, Detection, Navigation, Guidance, Aeronautical Sys | 3812 | Operative Builders | 1531 |
| ***Top positive portfolio weight*** | ***SIC 4*** | ***Top positive portfolio weight*** | ***SIC 4*** |
| Retail-Catalog & Mail-Order Houses | 5961 | Semiconductors & Related Devices | 3674 |
| Miscellaneous Nonmetallic Minerals | 1499 | Search, Detection, Navigation, Guidance, Aeronautical Sys | 3812 |
| General Contractors-Nonresidential Buildings | 1542 | Telephone Communications (No Radiotelephone) | 4813 |
| Semiconductors & Related Devices | 3674 | Credit Reporting Services | 7323 |

*Panel C. Physical climate news topics*

| E-score performance | | E-score reporting score | |
|---|---|---|---|
| ***Top negative portfolio weight*** | ***SIC 4*** | ***Top negative portfolio weights*** | ***SIC 4*** |
| Manifold Business Forms | 2761 | Aircraft Engines & Engine Parts | 3724 |
| Fluid Milk | 2026 | Highway and Street Construction | 1611 |
| Motor Vehicle Parts & Accessories | 3714 | Telephone Communications (No Radiotelephone) | 4813 |
| Medicinal Chemicals & Botanical Products | 2833 | Services-Legal Services | 8111 |
| ***Top positive portfolio weight*** | ***SIC 4*** | ***Top positive portfolio weight*** | ***SIC 4*** |
| Hotels & Motels | 7011 | Semiconductors & Related Devices | 3674 |
| Land Subdividers & Developers (No Cemeteries) | 6552 | Ship Building and Repairing | 3731 |
| Services, NEC | 8999 | Colleges, Universities, and Professional Schools | 8221 |
| Highway and Street Construction | 1611 | Bowling Centers | 7933 |

*Panel D. Climate change induced uncertainty*

| E-score performance | | E-score reporting score | |
|---|---|---|---|
| ***Top negative portfolio weight*** | ***SIC 4*** | ***Top negative portfolio weights*** | ***SIC 4*** |
| Retail-Family Clothing Stores | 5651 | Bowling Centers | 7933 |
| Radiotelephone Communications | 4812 | General Industrial Machinery & Equipment, NEC | 3569 |
| Search, Detection, Navigation, Guidance, Aeronautical Sys | 3812 | Motion Picture Theaters | 7832 |
| Water, Sewer, Pipeline, Comm & Power Line Construction | 1623 | Services-Legal Services | 8111 |
| ***Top positive portfolio weight*** | ***SIC 4*** | ***Top positive portfolio weight*** | ***SIC 4*** |
| Aircraft Engines & Engine Parts | 3724 | Retail-Family Clothing Stores | 5651 |
| Motor Vehicle Parts & Accessories | 3714 | Individual and Family Social Services | 8322 |
| Aircraft | 3721 | Search, Detection, Navigation, Guidance, Aeronautical Sys | 3812 |
| Automobiles and other Motor Vehicles | 5012 | Colleges, Universities, and Professional Schools | 8221 |

The previous results show that our hedge portfolios constructed from sustainability performance and reporting scores can hedge against innovations in disagreement sentiment, uncertainty sentiment in news, physical climate coverage in news as well as climate change-induced uncertainty. In order to determine the weight for each firm in the portfolio, I calculate the sum:

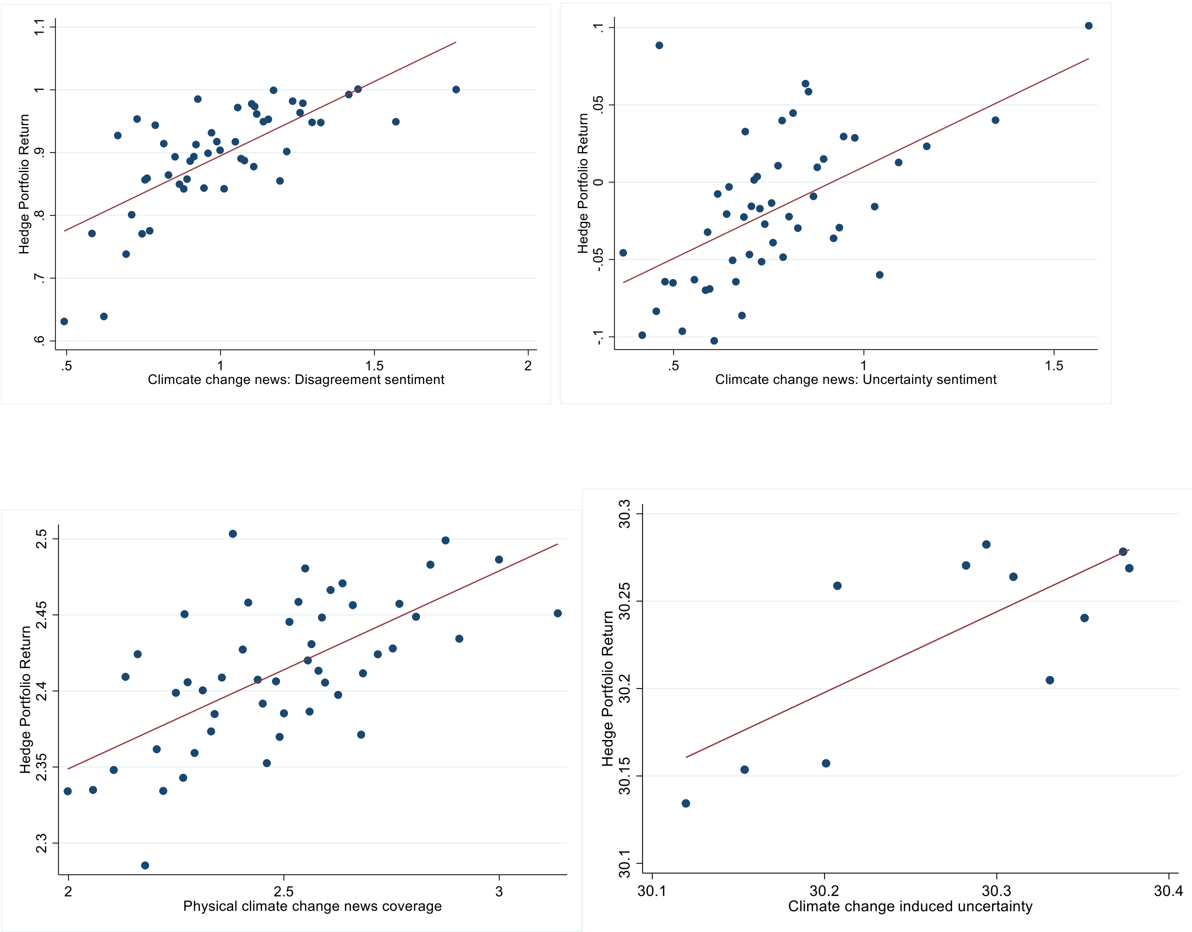
$$Weight_{2020} = \widehat{\omega}_{ESG\_Per} Z_{i,Dec19}^{ESG\_Per} + \widehat{\omega}_{BTM} Z_{i,Dec19}^{BTM} + \widehat{\omega}_{SIZE} Z_{i,Dec19}^{SIZE} + \widehat{\omega}_{MV} Z_{i,Dec19}^{MV} \quad (4)$$

In which $Z_{i,t}$ is variable values of December 2019 and $\widehat{\omega}$ is coefficient estimations I get from various versions of the model (3). Using this sum, investors can determine firms' weight in portfolios based on firms' sustainability performance and reporting scores, book-to-market ratio, size, and market value. The firms' weight calculated based on values in December 2019 can hedge climate risks posed at the beginning of 2020. I present industries' average portfolio positions classified by 4-digit SIC codes. For brevity purposes, I show only the top four industries that have positive and negative portfolio weights. I also skip average portfolio positions resulted from WM disagreement and uncertainty sentiment because the results are similar to portfolios using LM disagreement and uncertainty sentiments. I also show portfolios constructed using environment scores only. As shown in table 26, panel A, when I construct portfolios using environment performance score to hedge innovations in disagreement sentiments, the top three short positions are "Hotels & Motel", "Storage Batteries", and "Service, NEC". Interestingly, these three industries also have the most significant short position when I want to hedge against uncertainty sentiments. From these average portfolio positions, investors can find optimal portfolios depending on which sources of climate change risk they want to hedge against.

### *5.2. Out-of-sample fit results*

In order to conclude the usefulness of our portfolios, I follow Engle et al. (2020) and construct two measures to analyse the out-of-sample performance. First, I construct the measure by running model 3 from the first month in our dataset to the day before day *t* (between $t_{first}$ and *t-1*). After running out-of-sample for the data in the period of $t_{first}$ and *t-1*, I calculate expected portforlios returns from corresponding estimated coefficients and compare it with our hedge targets at day *t*.

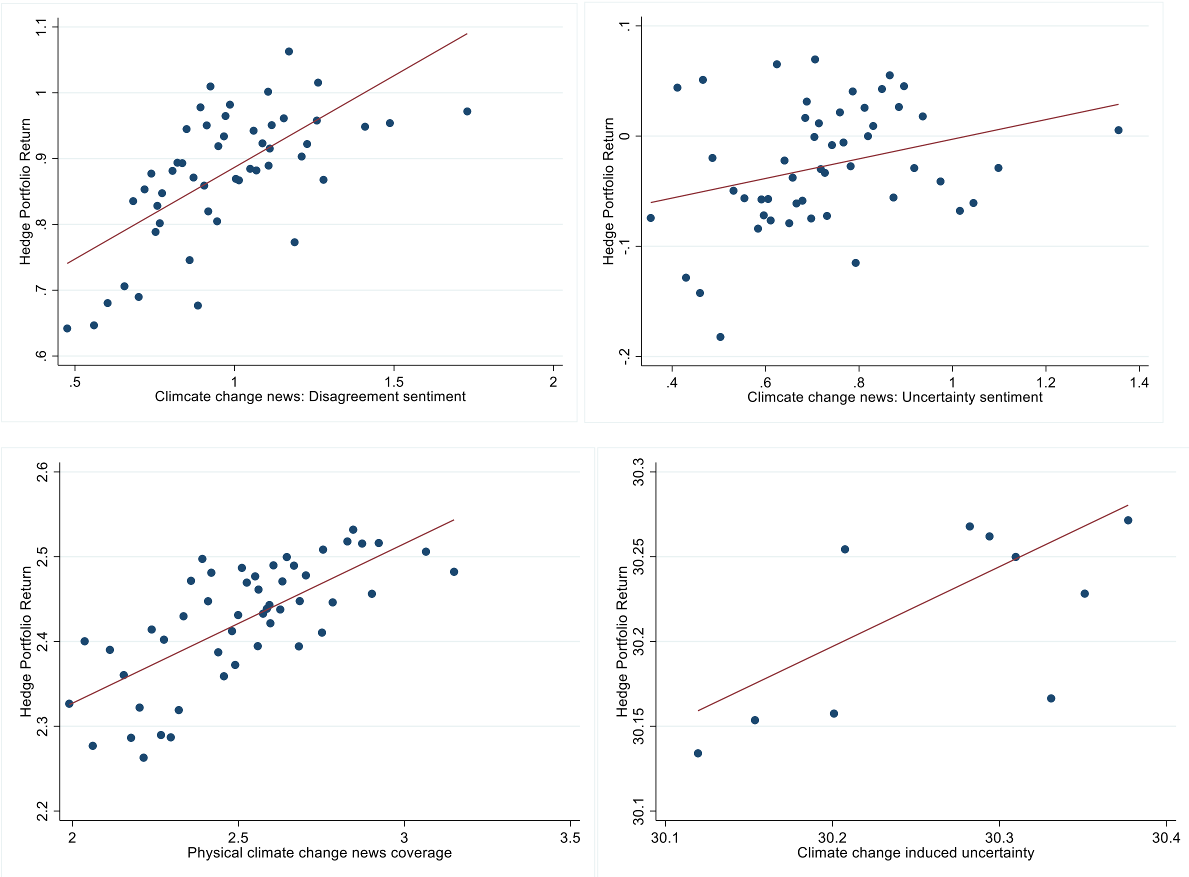
**Figure 11: Environment performance score hedge portfolio: out of sample fit.**




The out-of-sample performance of hedge portfolios using environment performance score are shown in figure 11. The four panels show the portfolios' performance using different hedge targets: disagreement sentiment, uncertainty sentiment, physical climate topic, and climate change-induced uncertainty. In all cases, it shows a significant positive out-of-sample correlation with all sources of climate change risks. It indicates that our hedge portfolios using environment performance scores gain better returns when higher climate change risks occur.

Similarly, when using environment reporting scores as climate risk exposure measures, I also obtain positive out-of-sample relationships with all sources of climate change risks. Both climate risk exposure measures used in our analysis show that firms with better green engagement (bother in performance in reporting activities) obtain higher returns during the period of higher climate change uncertainties and risks.

**Figure 12: Environment reporting score hedge portfolio: out of sample fit.**




We also report the correlations in Table 27 to study in more detail the relationships between portfolios' out-of-sample fit and the climate change risks. For example, panel A of Table 27 shows the positive associations between *ENV_Per, ENV_RP* out-of-sample returns, and disagreement sentiment conveyed in climate change news. Noticeably, in all cases from panel A to D of table 27, the hedge portfolios constructed using reporting scores outperform those using performance scores. Furthermore, our portfolios' out-of-sample returns are significantly more positive than returns from *ICLN* and *TAN* ETFs. Additionally, the positive signed relationships between our hedge portfolios and returns of both solar energy ETF (ICLN) and green energy ETF (TAN) indicate that our hedge portfolios tend to place those solar and green energy firms in long positions.

**Table 27: Out-of-sample fit results**

| *Panel A. Disagreement sentiments* | | | | | |
|---|---|---|---|---|---|
| Variables | DoS_LM | ENV_Per (OOS) | ENV_RP (OOS) | r_ICLN | r_TAN |
| DoS_LM | 1.000 | | | | |
| ENV_Per (OOS) | 0.416 | 1.000 | | | |
| ENV_RP (OOS) | 0.422 | 0.851 | 1.000 | | |
| r_ICLN | 0.076 | 0.154 | 0.154 | 1.000 | |
| r_TAN | 0.071 | 0.119 | 0.105 | 0.938 | 1.000 |

| *Panel B. Uncertainty sentiments* | | | | | |
|---|---|---|---|---|---|
| Variables | UNC_LM | ENV_Per (OOS) | ENV_RP (OOS) | r_ICLN | r_TAN |
| UNC_LM | 1.000 | | | | |
| ENV_Per (OOS) | 0. 119 | 1.000 | | | |
| ENV_RP (OOS) | 0. 212 | 0.773 | 1.000 | | |
| r_ICLN | 0.100 | 0.025 | 0.007 | 1.000 | |
| r_TAN | 0.073 | 0.035 | 0.016 | 0.938 | 1.000 |

| *Panel C. Physical climate coverage in the news* | | | | | |
|---|---|---|---|---|---|
| Variables | PHY | ENV_Per (OOS) | ENV_RP (OOS) | r_ICLN | r_TAN |
| PHY | 1.000 | | | | |
| ENV_Per (OOS) | 0.310 | 1.000 | | | |
| ENV_RP (OOS) | 0.372 | 0.754 | 1.000 | | |
| r_ICLN | 0.174 | 0.225 | 0.175 | 1.000 | |
| r_TAN | 0.131 | 0.190 | 0.134 | 0.938 | 1.000 |

| *Panel D. Climate change induced uncetainty* | | | | | |
|---|---|---|---|---|---|
| Variables | CCU | ENV_Per (OOS) | ENV_RP (OOS) | r_ICLN | r_TAN |
| CCU | 1.000 | | | | |
| ENV_Per (OOS) | 0.605 | 1.000 | | | |
| ENV_RP (OOS) | 0.640 | 0.813 | 1.000 | | |
| r_ICLN | 0.122 | 0.137 | 0.152 | 1.000 | |
| r_TAN | 0.100 | 0.111 | 0.125 | 0.938 | 1.000 |

This table presents cross-correlations of various portfolios' out-of-sample returns and four sources of climate change risks and uncertainty: disagreement sentiment, uncertainty sentiment, physical climate coverage in the news, and climate change-induced uncertainty.

Another robustness measure for hedge portfolios – cross-validation – is shown in table 28. In order to construct the cross-validation measures, I run model 3 for every month *t'* that is different from month *t* and form the hedge portfolio using the estimations obtained from these regressions. I then compare returns of hedge portfolios with different hedge targets and report in Panel A-D of table 28. The portfolio using environment reporting score outperforms those using environment performance scores in all cases. Interestingly, except for the model of climate change-induced uncertainty in panel

D, returns of *ICLN* and *TAN* ETFs seem to outperform our hedge portfolios cross-validation fit. Overall, the out-of-sample and cross-validation analysis confirm the forecasting ability of our hedge portfolios.

**Table 28: Cross-validation fit**

| *Panel A. Disagreement sentiments* | | | | | |
|---|---|---|---|---|---|
| Variables | DoS_LM | ENV_Per (Cross) | ENV_RP (Cross) | r_ICLN | r_TAN |
| DoS_LM | 1.000 | | | | |
| ENV_Per (Cross) | 0.004 | 1.000 | | | |
| ENV_RP (Cross) | 0.042 | 0.240 | 1.000 | | |
| r_ICLN | 0.127 | 0.013 | 0.045 | 1.000 | |
| r_TAN | 0.078 | 0.011 | 0.037 | 0.938 | 1.000 |

| *Panel B. Uncertainty sentiments* | | | | | |
|---|---|---|---|---|---|
| Variables | UNC_LM | ENV_Per (Cross) | ENV_RP (Cross) | r_ICLN | r_TAN |
| UNC_LM | 1.000 | | | | |
| ENV_Per (Cross) | 0.002 | 1.000 | | | |
| ENV_RP (Cross) | 0.007 | 0.595 | 1.000 | | |
| r_ICLN | 0.133 | -0.003 | 0.029 | 1.000 | |
| r_TAN | 0.084 | -0.002 | 0.022 | 0.938 | 1.000 |

| *Panel C. Physical climate coverage in the news* | | | | | |
|---|---|---|---|---|---|
| Variables | PHY | ENV_Per (Cross) | ENV_RP (Cross) | r_ICLN | r_TAN |
| PHY | 1.000 | | | | |
| ENV_Per (Cross) | 0.003 | 1.000 | | | |
| ENV_RP (Cross) | 0.083 | 0.478 | 1.000 | | |
| r_ICLN | 0.236 | 0.007 | 0.060 | 1.000 | |
| r_TAN | 0.214 | 0.006 | 0.049 | 0.938 | 1.000 |

| *Panel D. Climate change-induced uncertainty* | | | | | |
|---|---|---|---|---|---|
| Variables | CCU | ENV_Per (Cross) | ENV_RP (Cross) | r_ICLN | r_TAN |
| CCU | 1.000 | | | | |
| ENV_Per (Cross) | 0.008 | 1.000 | | | |
| ENV_RP (Cross) | 0.159 | 0.630 | 1.000 | | |
| r_ICLN | 0.114 | 0.007 | 0.100 | 1.000 | |
| r_TAN | 0.101 | 0.005 | 0.084 | 0.938 | 1.000 |

This table presents cross-correlations of various portfolios' cross-validation returns and four sources of climate change risks and uncertainty: disagreement sentiment, uncertainty sentiment, physical climate coverage in the news, and climate change-induced uncertainty.

## 6. Summary of the chapter

Being motivated by increasing uncertainties around climate change and its consequences on the economy, the paper examines how different climate change risks can be hedged using firms' sustainability performance scores and reporting scores. I extend the mimick portfolio approach studied in Engle et al. (2020). Specifically, I use four hedge targets that present climate risks:

disagreement sentiments, uncertainty sentiment, physical climate coverage, and climate change-induced uncertainty. The findings support stakeholder theory and disclose that throughout all models of the four hedge targets, the hedge portfolio constructed using environmental reporting scores and performance score perform similarly to each other in in-sample models. However, the former performs better in out-of-sample models than the latter. These findings are in line with prior researches in relationship between firms' environmental investment and stock performance, such as Eccles et al. (2014b) and Statman and Glushkov (2016). Noticeably, when comparing out-of-sample and cross-validation fit, the significant differences in the results between these two measures imply that our hedge portfolios' returns are dependent on the training set's time series. This may result from the lack of consistent ESG and environment scores for all firms. Since the growing evidence that a firm's sustainable engagement connects strongly to performance is focusing investor's attention on ESG, our hedge portfolio can benefit from a more completed and regulated ESG data system.

Our findings have several implications for investors, academics, and policymakers. Firstly, for investors, these findings are valuable, especially for those who look for portfolios that can hedge against climate risks. Our findings imply that firms whose better sustainability engagement (both in performance and reporting) induce higher excess returns than other firms. Although our hedge portfolios cannot be viewed as the best hedges against climate risks and uncertainties, our results confirm that it is possible to mitigate these risks using firm-level characteristics and sustainability scores. Second, for academics, besides environment performance scores that are studied extensively in prior literature, I also emphasise the importance of reporting scores. Our results show that hedge portfolios based on reporting scores seem to outperform those based on performance scores in some cases. Firms with higher ESG reporting scores do not necessarily guarantee a better ESG performance. However, ESG disclosure can lessen the information asymmetry between firms and investors, thus, reducing transactions costs of identifying stocks with desirable characteristics. Therefore, it is in the best interest of companies to disclose as much sustainability information as possible to their shareholders. The benefit of accurate and regulated ESG disclosure should be on the radar of directors and managers.

Regarding limitations, our findings also highlight that hedge portfolios perform the worst against innovations in climate change-induced uncertainty. This suggests a different set of characteristics to be chosen to adequately capture cross-sectional variation in exposure to this type of climate change risk. I leave these topics for future research. Furthermore, when comparing out-of-sample and cross-validation fit, the significant differences in the results between these two measures imply lack of consistent ESG and environment scores for all firms. Future research can benefit from a more completed and regulated ESG data system.

Appendix: List of variables

| VARIABLES | ABBREVIATION | MEASUREMENT | SOURCE |
|---|---|---|---|
| **HEDGE TARGETS – CLIMATE CHANGE RISKS AND UNCERTAINTIES** | | | |
| Disagreement sentiment | DoS_LM/DoS_WM | $$DoS_t = \left\| \frac{x_{p,t} - x_{p,all}}{\sigma_{p,all}} + \frac{x_{n,t} - x_{n,all}}{\sigma_{n,all}} \right\|$$ In which: $x_{p,t}$ and $x_{n,t}$ are positive and negative probabilities based on Loughran and McDonald's (2011) classification. $x_{p,all}$ and $x_{n,all}$ are the average percentage of positive and negative probabilities detected during the time frame of the data set. $\sigma_{p,all}$ and $\sigma_{n,all}$ are standard deviation for positive and negative sentiments | News collected from ProQuest. |

| | | | |
|---|---|---|---|
| | DoS_WM | $$DoS_t = \left\| \frac{x_{p,t} - x_{p,all}}{\sigma_{p,all}} + \frac{x_{n,t} - x_{n,all}}{\sigma_{n,all}} \right\|$$ In which: $x_{p,t}$ and $x_{n,t}$ are positive and negative probabilities based on the WMatrix corpus analysis tool. $x_{p,all}$ and $x_{n,all}$ are an average percentage of positive and negative probabilities detected during the time frame of the data set. $\sigma_{p,all}$ and $\sigma_{n,all}$ are standard deviation for positive and negative sentiments | News collected from ProQuest. |
| Uncertainty sentiment | UNC_LM | $$UNC_t = \left\| \frac{x_{u,t} - x_{u,all}}{\sigma_{u,all}} \right\|$$ $x_{u,t}$ is uncertainty probability based on Loughran and McDonald's (2011) classification. $x_{u,all}$ is average percentage uncertainty probability detected during the time frame of the dataset. $\sigma_{p,all}$ and $\sigma_{n,all}$ are standard deviation for uncertainty probability. | News collected from ProQuest. |

| | | | |
|---|---|---|---|
| | UNC_WM | $$UNC_t = \left\| \frac{x_{u,t} - x_{u,all}}{\sigma_{u,all}} \right\|$$ $x_{u,t}$ is uncertainty probability based on the WMatrix corpus analysis tool. $x_{u,all}$ is average percentage uncertainty probability detected during the time frame of the data set. $\sigma_{p,all}$ and $\sigma_{n,all}$ are standard deviation for uncertainty probability. | News collected from ProQuest. |
| Climate change uncertainty | CCU | National vulnerability index that measures a country's exposure, sensitivity, and adaptability to the negative impact of climate change | The Notre Dame Global Adaptation Index |
| Physical climate topics | PHY | The climate change news topics are classified using a corpus analysis and comparison tool developed by Lancaster University (Rayson, 2008). For this research, I categorise the PHY index (physical climate change and its impact on climate news) equals to sum relative frequency of ENV, HOU, and FOOD | Calculated by authors, WMatrix |
| **CLIMATE CHANGE EXPOSURES** | | | |
| ESG score | ESG | REFINITIV's ESG Score is an overall company score based on the self-reported information in the environmental, social, and corporate governance pillars. | DataStream |

| | | | |
|---|---|---|---|
| Environmental Score | EnvScore | REFINITIV s environmental score pillar based on the self-reported information | DataStream |
| ESG score | ESG | Bloomberg's disclosure scores that rate companies annually based on their disclosure of quantitative and policy-related ESG data. | Bloomberg |
| Environmental Score | EnvScore | Bloomberg's disclosure scores for the environment pillar. | Bloomberg |
| **FIRM-LEVEL CHARACTERISITCS** | | | |
| Book to Market | BTM | Calculated as cross-sectionally standardised values of book-to-market | DataStream, authors' calculation |
| Company size | SIZE | The natural logarithm of total assets in local currency. Then cross-sectionally standardised, so that half the firms, sorted by market value, have positive weight, and half have negative weight | DataStream, authors' calculation |
| Market value | MV | Cross-sectional standardised total market value. | DataStream, authors' calculation |

# Chapter 3

## CORPORATE GREEN BONDS AND ENVIRONMENTAL PERFORMANCE: THE MODERATING ROLE OF EXTERNAL UNCERTAINTY.

## 1. Overview of the chapter

Environmental, social, and governance (ESG) considerations are increasingly incorporated into corporate policies. Green bonds are newly developed financial instruments with the specific goals of improving environmental impacts and social welfare. Widely speaking, green bonds are fixed-income financial instruments issued by corporate or financial institutions to fund their environmentally friendly plans, for example, pollution prevention, renewable energy, or energy resources management.

European Investment Bank first introduced green bonds as a " climate awareness bond" issued. After that, the introduction of the Paris Agreement in 2015-2016, the first legally binding global climate deal signed by 195 countries, has pushed for rapid investment in renewable energy and other initiatives to reduce global warming. The agreement outlines an action plan to prevent the dangerous effects of climate change and limit global warming to below the threshold of 2 °C. Since then, the green bond market has developed in both size and geographic bases. Although China, US are the market leaders, the green bond market witnesses several first issuances from France, Fiji, Nigeria in 2017; Indonesia, Belgium, Lithuania, Ireland in 2018; and the Netherland, Chile in 2019 (Jones, 2020). According to the Climate Bonds Initiative estimates, the green bond market has passed the milestones of 1 trillion USD in size in early December 2020, promising a substantial impact on climate targets (Jones, 2020).

Despite the rapid growth in the past decade, one of the main obstacles the green bond market faces is the investors' concern about "greenwashing"(Linsell, 2017). This concern results from a lack of uniform standards that verify that funds are used accurately to what firms marketed. When considering green bonds in their fixed asset allocation, the biggest question for investors is: "Are green bonds truly environmentally friendly assets?". The first paper investigates the connection between green bond issuance and firms' investment in sustainability is Flammer (2021). The study finds that green bond issuers improve their environmental performance post-issuance (i.e., higher environmental ratings and lower $CO_2$ emissions) and experience increased ownership by long-term and green investors.

However, whether and how firms' sustainable investment continues after green bonds issuance remains under-investigated. Extending this line of research on firms' environmental commitment, I intend to investigate whether corporate green bonds send a credible signal to the market and whether firms continue to invest under the pressure of external uncertainties. In this paper, I wish to fill these gaps in the literature, that is, to directly compare long-term environmental performance between green bond issuance and non-green bond issuance. With difference-in-difference model modification, this is the first paper that studies the effect of uncertainties in climate change news as well as at the national level on firms' sustainability investment following green bond issuance. I also differ from prior literature by examining the effect of climate media coverage on sustainability following green bond issuance.

This paper contributes to the literature on green bonds in several ways. First, I hope to address the greenwashing concern of investors on the issuance of green bonds. If firms' environmental performance improved post green bond issuance, it will assure investors that their money is invested into green causes as advertised. Second, I wish to study if green bond issuance can help mitigate climate change uncertainties on firms' environmental performance. Regarding the increase of climate change coverage in official news channels, it is evident that researchers and policymakers should not neglect climate-related uncertainties. Third, our research has several implications for investors. It provides evidence suggesting that in addition to institutionalized national characteristics, dynamic national features (e.g., uncertainty at the national level or sentiments from climate-related news) also relate to firms' sustainability performance. Thus, uncertainties in several sources should be on their radar for investors who consider sustainability issues in the investment process.

## 2. Theory and conceptual framework

### *2.1. Green bond market*

The effects of green bond issuances have been explored empirically through two main perspectives: (i) issuer perspective; (ii) investor and market perspective. From the issuers' perspective, green bonds help extend the investor base and increase the company's sustainability images in investors' eyes. The study of Reichelt (2010) argues that green bond issuers can enjoy a broader investor base and that investors determine environmentally friendly instruments for their fixed-income allocation. Furthermore, Bancel and Glavas (2018) identify the main determinants of green bond issuance: state-driven stakeholder motives and agency motives. These findings are in line with the notion that controlling environmental exposure is now a strategy for risk management and profit maximization. Tolliver et al. (2020) demonstrate that the key drivers of green bond market development are national commitment (Paris Agreement) and other institutional and macroeconomic factors that positively drive the issuance of green bonds. For example, CBI certification causes the tightest spread of 18.4 bps for AAA green bonds comparing to government bonds (Katori, 2018). It is consistent with Li et al. (2020), which analyses the Chinese market of green bonds and concludes that certifications, high credit ratings, and CSR all impact lowering the interest costs of issuers.

From the investors' perspective, the issuances of green bonds may reduce the information asymmetry regarding environmentally friendly financial assets. Among the first papers focusing on green bonds, Moroney et al. (2012) find that companies' voluntary environmental data disclosures are significantly boosted by their independent assurance. The greenness enhancer investigated in this study – Climate Bond Initiatives (CBI) and other external reviews – are documented to enhance information quality and influence green bonds' prices. This point of view is supported by (Baulkaran, 2019), Tang and Zhang (2020), and Flammer (2021). For example, Flammer (2021) show pieces of evidence that the issuances of green bonds in the period of 2013-2017 have generated positive return around the announcement date, increase in firms' value and operating outcomes, growth in ownership by long-term and green investors, improvement in environmental performance as well as green innovations.

Despite the promising benefits for both green issuers and investors, a significant barrier limiting the expansion of this market is the lack of commonly acknowledged standards for green bonds. Ethical investors associate investments in green bonds with positive impacts on the environment. Issuing green bonds may cast a signal of companies' commitment towards greener activities, yet companies' promises are not always in line with their actions.

This paper explores green bond issuance via aspects: 1) Are green bonds credible signals? (i.e., firms' green bond indicates company's sustainability commitment); 2) The impact of external uncertainties on firms' environment footprint following green bonds issuance and 3) the impact of climate news coverage on firms' environment footprint post-issuance.

### *2.2. Green bond issuance and firms' environmental performance*

Information asymmetric is one of the leading causes of an increase in transaction cost. There are gaps between information held by investors and companies; thus, the sender (companies) needs to choose whether and how to communicate relevant information to the receiver (investors). This act of sending a "signal" to the market is fundamentally concerned with decreasing information asymmetry between two parties (Spence, 2002). According to signaling theory, to be credible, a signal must be costly for "bad companies" to imitate (Spence, 1973, Riley, 1979). So often, companies' environmental acts are unavailable to the public's eyes (Lyon and Montgomery, 2015). With the current trend in sustainable investment, investors need to have a credible indication to distinguish companies that are highly committed to greener operations from those that are not. By issuing green bonds, firms can send a signal to the market showing their environmental commitment.

Apart from signaling theory, green bonds may serve as a greenwashing tool. Greenwashing is a practice of conveying a false impression or providing misleading information about how a company's products are more environmentally sound (Lyon and Montgomery, 2015, Marquis et al., 2016). If a company issue green bonds regarding greenwashing activities, information asymmetry is not only unimproved but also widens the gap between the company's practices and investors' acknowledgment. Therefore, I wish to investigate whether the issuance of corporate green bonds leads to a green investment of the issuers.

**Hypothesis 1: Green bonds are the credible signal for firms' long-term sustainability investment.**

If green bonds are firms' credible signal, I expect environmental performance after issuing the green bond will reflect sustainability investment. A firm's long-term investments, however, are often affected by several factors. According to real options theory, long-term investments are often negatively impacted in uncertain situations (Bernanke, 1983). As a firm's investment in the green project can act as a long-term investment (Flammer and Bansal, 2017), it is likely to be affected in a period of higher uncertainty. Therefore, following Trumpp et al. (2015) and Jia and Li (2020), it is expected that a higher level of uncertainties increases the value of the option to postpone long-term investment. I study the impact of uncertainties on firms' environmental performance post-issuance through two channels: climate change news and national-level uncertainties.

Since green bonds are a relatively new asset class, only a few papers study the market sentiment related to green bonds. Broadstock and Cheng (2019) demonstrate that the link between green and black bonds is sensitive to news-based sentiment regarding green bonds. In terms of investor sentiment, Piñeiro et al. (2019) show that sentiment retrieved from tweets positively correlated to green bond returns, reflecting the public's positive attitude towards green bonds. However, to the best of our knowledge, no empirical studies have investigated the impact of news-based sentiment on the relationship between green bond issuance and environmental investment. The rise of green bond markets, investors' growing concern for greenwashing, and the increasing climate change coverage on news media led us to consider and test the influence of investor sentiment on the green bond market. Therefore, the following hypothesis is proposed:

**Hypothesis 2a**: **Climate-related sentiments in the news have moderating effect on the relationship between green bond issuance and environmental performance.**

Further expanded from real options theory, other factors that may affect firms' environmental investment following green bond issuance are the national-level uncertainties regarding three aspects: climate change, political instability, and economic policy. First, apart from uncertainty sentiment retrieved from climate change news presented in hypothesis 2a, there are other aspects of climate change uncertainty on the national level. Uncertainty induced from climate change does not only affects the economy in macroeconomy's perspective by resulting in weather extremes (Hsiang and Jina, 2014, Burke et al., 2015, Gregory, 2021) but also impacts firms' operation in several ways (Heal and Park, 2013, Deryugina and Hsiang, 2014, Henderson et al., 2015). Using a sample of 6,804 firms from 72 countries spanning 15 years, Jia and Li (2020) demonstrate that climate change-induced uncertainty negatively affects firms' investment in sustainability. Second, the literature suggests a negative connection between state-level elections and firms' investment (Julio and Yook, 2012, Jens, 2017). Significantly, the study of Jia and Li (2020) demonstrates that political instability negatively affects firms' investment in sustainability. Extending this research line, I examine how political instability can moderate the relationship between green bond issuance and sustainability performance. Third, uncertainties from economic policy also harm corporate investment (Phan et al., 2018, Wang et al., 2014, Baker et al., 2016). Examining more than 50,000 firm-quarter observations in 2003-2012, the study of Wang et al. (2014) finds that the economic policy's uncertainty negatively connects to firms' capital expenditures scaled by total assets in China. This finding is supported by Gulen and Ion (2015), Bonaime et al. (2018), and Jia and Li (2020). Extending the prior researches, I investigate whether uncertainty regarding climate change, political instability, and economic policy can impact the investment in sustainability following green bond issuance.

**Hypothesis 2b: Different sources of national-level uncertainty have moderating effects on the relationship between green bond issuance and environmental performance.**

As an expansion of the real options theory, I anticipate pressure from stakeholders constraints company's options to postpone environmental investment (De Villiers et al., 2011). Such pressure can mainly appear in mass media. According to Chan (1998), mass media is a significant source of social norms, setting society expectations and shaping public behaviours. Several papers in marketing research literature explore that the more significant media coverage that admits climate change, the better sustainable consumption is reinforced (Chen et al., 2019, Holt and Barkemeyer, 2012). Such social norm that driven by media coverage does not only affect the demand side but also set up expectation towards companies' environmental practices. Recently, there has been a stream of research that focus on the media' role in disciplining corporate's sustainability engagement (Tang and Tang, 2016, Kassinis and Vafeas, 2006). For example, Tang and Tang (2016) find that news information about two primary stakeholders: the government and the public, can prompt companies to tackle their pollution issues. Media plays a vital role in informing the public about problems and portraying the public and government's behaviours towards climate change. Therefore, when there is more media coverage regarding physical climate change, public or government actions, firms are more likely to alter their behaviours, thus, improving their environmental footprint.

**Hypothesis 3: Climate change topics in the news encourage green bond issuers to invest in sustainability after issuing green bonds.**

## 3. Data

### *3.1. Green bond data*

We collect bond data from Refinitiv Eikon with the green tag that indicates whether the bond's uses of proceeds are in green projects. Other variables collected for bonds are maturity, coupon, issued amount, yield to maturity, Moody rating, and Fitch rating. The 1,773 green bonds correspond to 127 unique issuer-days, five unique issuer-years from 2015 to 2019, and 36 individual issuers. The average maturity is 1,706 days.

#### *3.1.1 Corporate green bonds across countries*

We collected green bonds from six countries among the top corporate green bond issuers: China, Germany, France, United Kingdom, United States, and Japan. As shown in Table 29 below, the majority of green bonds in our sample come from China. This data structure is comprehensible since China is the world's most enormous green bond resource by 2019. In 2019, $55.58 billion of green bonds are issued in China, which makes up for one-fifth of the total green bond issued globally that year ($257.7 billion) (Yamaguchi and Ahmad, 2021). For this research's purpose, I collect only corporate green bonds.

**Table 29: Green bonds classification by countries.**

***Maturity***

| Countries | Observations | Mean | Median | SD | Min | Max |
|---|---|---|---|---|---|---|
| CHN | 1,704 | 1692.49 | 1826.00 | 831.46 | 731 | 11158 |
| DEU | 1 | 3651.00 | 3651.00 | . | 3651 | 3651 |
| FRA | 4 | 3204.00 | 3652.50 | 899.33 | 1855 | 3656 |
| GBR | 4 | 4817.25 | 3124.50 | 4168.11 | 2034 | 10986 |
| JPN | 28 | 2067.14 | 1829.00 | 784.00 | 1100 | 3654 |
| USA | 17 | 4624.41 | 3652.00 | 3723.78 | 1463 | 10972 |
| Total | 1,758 | 1738.48 | 1826.00 | 974.55 | 731 | 11158 |

***Coupon***

| Countries | Observations | Mean | Median | SD | Min | Max |
|---|---|---|---|---|---|---|
| CHN | 1,677 | 3.987 | 3.800 | 2.750 | 0.000 | 24.750 |
| DEU | 1 | 6.490 | 6.490 | . | 6.490 | 6.490 |
| FRA | 3 | 3.234 | 3.370 | 0.724 | 2.452 | 3.880 |
| GBR | 4 | 4.453 | 4.445 | 0.590 | 3.740 | 5.180 |
| JPN | 27 | 4.609 | 4.000 | 4.119 | 0.375 | 19.000 |
| USA | 16 | 3.355 | 3.775 | 3.319 | 0.000 | 13.000 |
| Total | 1,728 | 3.992 | 3.800 | 2.776 | 0.000 | 24.750 |

***Issued Amount***

| Countries | Observations | Mean | Median | SD | Min | Max |
|---|---|---|---|---|---|---|
| CHN | 1,596 | 10,800,000 | 1,000,000 | 33,400,000 | 50 | 280,000,000 |
| DEU | 1 | 800,000 | 800,000 | . | 800,000 | 800,000 |
| FRA | 4 | 24,900,000 | 1,250,000 | 48,100,000 | 210,880 | 97,000,000 |
| GBR | 4 | 57,700,000 | 1,250,000 | 114,000,000 | 229,000 | 228,000,000 |
| JPN | 24 | 2,894,250 | 950,000 | 6,353,660 | 1,000 | 29,200,000 |
| USA | 14 | 27,900,000 | 1,125,000 | 71,200,000 | 500 | 268,000,000 |
| Total | 1,643 | 11,000,000 | 1,000,000 | 34,100,000 | 50 | 280,000,000 |

### 3.1.2 *Corporate green bonds across industries*

Table 30 shows a breakdown of corporate green bonds by industries. I partition green bonds based on industries according to ICB industry codes. As can be seen, corporate green bonds are more common in industries where the environment is likely core to the firms' operations (e.g., utilities, energy, transportation).

**Table 30: Green bonds classification by industries**

***Maturity***

| Industries | Observations | Mean | Median | SD | Min | Max |
|---|---|---|---|---|---|---|
| Technology | 1 | 1463.00 | 1463.00 | . | 1463 | 1463 |
| Telecommunication | 4 | 1829.25 | 1829.00 | 1.26 | 1828 | 1831 |
| Healthcare | 4 | 7310.50 | 7309.50 | 4224.47 | 3651 | 10972 |
| Financials | 10 | 3091.50 | 1930.50 | 2965.60 | 1096 | 10962 |
| Real Estate | 2 | 1833.00 | 1833.00 | 9.90 | 1826 | 1840 |
| Consumer Discretionary | 6 | 2273.17 | 1827.00 | 1092.10 | 1338 | 3656 |
| Industrials | 1,696 | 1685.01 | 1826.00 | 767.16 | 731 | 10986 |
| Basic Materials | 17 | 2237.24 | 1828.00 | 1000.72 | 1096 | 3657 |
| Energy | 13 | 4046.54 | 1828.00 | 4094.79 | 1098 | 11158 |
| Utilities | 4 | 2653.25 | 2739.50 | 1172.96 | 1465 | 3669 |
| Total | 1,758 | 1738.48 | 1826.00 | 974.55 | 731 | 11158 |

***Coupon***

| Industries | Observations | Mean | Median | SD | Min | Max |
|---|---|---|---|---|---|---|
| Technology | 1 | 13.000 | 13.000 | . | 13.000 | 13.000 |
| Telecommunication | 3 | 3.867 | 3.730 | 0.337 | 3.620 | 4.250 |
| Healthcare | 4 | 4.420 | 5.070 | 2.386 | 1.049 | 6.490 |
| Financials | 7 | 4.262 | 4.200 | 1.060 | 2.960 | 5.990 |
| Real Estate | 2 | 4.230 | 4.230 | 1.061 | 3.480 | 4.980 |
| Consumer Discretionary | 5 | 6.658 | 4.080 | 5.467 | 3.090 | 16.250 |
| Industrials | 1,672 | 3.982 | 3.800 | 2.776 | 0.000 | 24.750 |
| Basic Materials | 17 | 3.437 | 3.740 | 1.539 | 0.125 | 6.030 |
| Energy | 13 | 4.262 | 3.880 | 2.951 | 0.000 | 13.000 |
| Utilities | 4 | 3.087 | 3.825 | 1.984 | 0.187 | 4.510 |
| Total | 1,728 | 3.992 | 3.800 | 2.776 | 0.000 | 24.750 |

***Coupon***

| Industries | Observations | Mean | Median | SD | Min | Max |
|---|---|---|---|---|---|---|
| Technology | 1 | 20,000 | 20,000 | . | 20,000 | 20,000 |
| Telecommunication | 3 | 2,500,000 | 1,500,000 | 2,179,449 | 1,000,000 | 5,000,000 |
| Healthcare | 4 | 17,500,000 | 5,400,000 | 28,000,000 | 150,000 | 59,000,000 |
| Financials | 8 | 27,100,000 | 1,250,000 | 52,000,000 | 100,000 | 141,000,000 |
| Real Estate | 2 | 134,000,000 | 134,000,000 | 189,000,000 | 220,000 | 268,000,000 |
| Consumer Discretionary | 6 | 5,910,313 | 1,250,000 | 11,500,000 | 1,000 | 29,200,000 |
| Industrials | 1,590 | 10,700,000 | 1,000,000 | 33,200,000 | 50 | 280,000,000 |
| Basic Materials | 14 | 29,200,000 | 1,600,000 | 70,600,000 | 100,000 | 228,000,000 |
| Energy | 12 | 3,518,783 | 1,450,000 | 4,724,079 | 390 | 15,000,000 |
| Utilities | 3 | 17,700,000 | 13,000,000 | 15,500,000 | 5,000,000 | 35,000,000 |
| Total | 1,643 | 11,000,000 | 1,000,000 | 34,100,000 | 50 | 280,000,000 |

## 3.2. *Firm-level data*

### 3.2.1 *Data source*

There are two sets of data apart from green bond data. For the firms' outcomes, I collect firms' ESG performance (and separated scores for Environment, Social, and Governance) and $CO_2$ consumptions from DataStream. Following Flammer (2021), other firm-level data that served as control variables are also collected from DataStream: ROA (Return on Asset), LEV (Total debt over total equity), SIZE (logarithm of the total asset), and Tobin's Q.

As I run the difference-in-difference model, although our green bond sample is in the time range 2015-2019, all data are collected in the time range from 2007-2019 to study comprehensively both before and after bond issuance effect. In the end, I have a sample of 58,500 monthly observations for 375 bond issuers from 2007 to 2019.

### 3.2.2 *Summary statistic at the issuer level*

Table 31 compares green bond issuers with other public firms. In order to make the comparison informative, the comparison group only consists of public firms that are bond issuers (but not green bond issuers).

**Table 31: Green bonds and non-green bonds firm-level data comparison.**

| | ***Green bonds*** | | | | ***Non-green bonds*** | | | |
|---|---|---|---|---|---|---|---|---|
| Variables | N | Mean | Median | SD | N | Mean | Median | SD |
| Maturity | 1,758 | 1738.48 | 1826.00 | 974.55 | 67,888 | 3076.73 | 1829.00 | 2805.19 |
| Coupon | 1,728 | 3.99 | 3.80 | 2.78 | 69,046 | 4.04 | 3.99 | 2.35 |
| Issued Amount | 1,643 | 11,000,000 | 1,000,000 | 34,100,000 | 63,821 | 10,500,000 | 1,000,000 | 32,800,000 |
| YtoMat | 1,755 | 2.43 | 2.86 | 1.75 | 63,229 | 54.36 | 3.14 | 6725.69 |
| MoodysR | 744 | A2 | A1 | Aa1 | 19,578 | B1 | A3 | B1 |
| FitchsR | 331 | A- | A | AA | 11,687 | AA+ | A+ | AA+ |
| SIZE | 1,815 | 19.11 | 19.24 | 0.58 | 72,712 | 19.05 | 19.24 | 0.87 |
| ROA | 1,815 | 2.06 | 3.28 | 3.54 | 72,631 | 2.18 | 2.29 | 4.33 |
| LEV | 1,815 | 417.21 | 431.84 | 181.14 | 72,686 | 372.12 | 397.96 | 286.03 |
| Tobin's Q | 1,815 | 0.83 | 0.77 | 0.28 | 72,427 | 0.88 | 0.77 | 0.45 |
| EnvScore | 1,816 | 60.22 | 75.17 | 21.87 | 71,160 | 54.43 | 75.17 | 25.35 |
| SocScore | 1,816 | 72.98 | 79.17 | 10.20 | 71,160 | 67.78 | 79.17 | 16.19 |
| GovScore | 1,816 | 66.56 | 64.48 | 12.47 | 71,160 | 62.02 | 64.48 | 15.83 |
| ESG | 1,820 | 67.36 | 74.40 | 12.45 | 71,347 | 61.81 | 74.40 | 17.76 |
| CO2 | 1,775 | 17,300,000 | 21,500,000 | 6,447,424 | 55,927 | 17,500,000 | 21,500,000 | 10,200,000 |

Table 31 shows that green bonds generally have a shorter maturity, lower yield to maturity than bonds non-green bonds. However, the average coupons of the two bond types are similar. Furthermore, due to Moody's rating, green bonds are generally rated at a higher rate - A2 - while this rating for the non-green bonds is B1. Firms that issue green bonds record higher ESG scores (both overall and each section) regarding environmental performance. Interestingly, the ESG controversy scores are lower for green bond issuers. This score discounts the ESG performance score based on negative media stories for firms. As shown from table 30, most green bond issuers are environmentally sensitive industries (e.g., utilities, energy, transportation); thus, they are exposed more to climate topics, social action, or climate policies mentioned on the news than firms from other industries.

### *3.3. External factors data*

One of the typical rationales for issuing green bonds is to mitigate the risk of external uncertainties (i.e., green bond issuers suffer less impact of climate change news on their stock performance and liquidity). I introduce three sets of external data that may negatively affect the relationship between green bond issuance and firms' outcomes.

The first external data set is disagreement and uncertainty sentiments on climate change news. I collect climate change news using the advanced search function in ProQuest to search for keywords: 'Climate change' or 'Global Warming' from 01/01/2008 to 31/12/2019. Following Tetlock (2007), I narrow our search and download news from well-known four The Wall Street Journal and other U.K broadsheets (The Financial Times, the Daily Telegraph, The Guardians, The Times, and The Independent) in order to have a well-mixed news source of intelligent and respectable publications. Disagreement and uncertainty sentiment are classified based on (i) financial lexicon dictionary from (Loughran and Mcdonald, 2011) and (ii) semantic tagging from the WMatrix tool (Rayson, 2008). I have two sets of disagreement and uncertainty sentiments: *DoS_LM, UNC_LM,* and *DoS_WM, UNC_WM*. For brevity, I only report results for sentiments classified by Loughran and McDonald's lexicon: *DoS_LM, UNC_LM*

For external uncertainties, Economic Policy Uncertainty (*EPU*), which is used for policy uncertainty, was developed by Baker et al. (2016); Climate change-induced uncertainty (*CCU*) is collected from The Notre Dame Global Adaptation Index, and political system stability are retrieved from World Bank's Worldwide Governance Indicators Project. Following Jia and Li (2020), I multiplied minus one with the political system stability index to calculate *PSU* to make that the higher the *PSU* index, the more politically unstable, and vice versa. External uncertainties are collected in monthly data and are different across countries.

Motivated by the suggestion for future research from Engle et al. (2020), I also classified climate change news into separate topics to observe the impact of different climate topics on a firm's outcomes after issuing green bonds. The climate change news topics are classified using the corpus analysis and comparison tool – WMatrix – developed by Lancaster University (Rayson, 2008). In general, the program chooses the appropriate semantic category by taking in POS-tagging information, then considers the general likelihood in accordance with the frequency in English corpus widely, and the area of the discourses as identified by a longer text (for example, a temperature condition would prompt a reading of 'hot' as a weather level instead of the spiciness). For the purpose of this research, I categorize topics in news into physical climate (*PHY)*, social climate (*SOC)* and climate policy (*POL)*. Same as news sentiment data, climate topics are monthly data and the same across companies. A comprehensive list of variables is reported in Appendix.

## 4. Methodology

### *4.1. Firm outcomes*

**Environmental performance measures**

Two measures of environmental performance are used: ESG and environmental rating from ASSET4. Note that the issuance of green bonds does not enter the assessment grid used by ASSET4 to determine the rating (Eikon, 2017). As such, there is no mechanical link between the issuance of green bonds and higher environmental ratings. Therefore, I can eliminate the situation where ASSET4 analysts perceive the issuance of green bonds as good environmental practice and upgrade the company's environmental rating accordingly. In addition, I use two other environmental performance measures to mitigate the issue: $CO_2$ emission (in tonnes) and $CO_2$ emission over company market value.

### *4.2. Control variables*

Regarding control variables at the firm level, I follow Jia and Li (2020), Miska et al. (2018), and Cai et al. (2016) to control for firm size (calculated as the natural logarithm of total assets). This measurement is due to the argument that larger firms have more resources to invest in sustainability activities. Following Cai et al. (2016) and Ioannou and Serafeim (2012), I also control for firms' profitability, leverage (calculated as total liability scaled by total equity). Consistent with Aybars et al. (2018) findings that Tobin's Q seemed to influence ESG score rather than the opposite way, I control for firm's value in our model (e.g., Tobin's Q value - measured as firms' enterprise value divided by total assets). In the model with ESG and environment score, I add the ESG score of the year before as an extra control variable to ensure that changes in ESG scores are not affected by the momentum effect in the prior year.

### *4.3. Matching*

Before examining how corporate green bonds affect firm-level outcomes, I match green bond issuers to non-green bond issuers with similar characteristics. To build the matched control group, I use several matching criteria. First, I only consider bond issuers among the pool of public firms (but not green bond issuers). I match firms based on their characteristics: size (log asset), Tobin's Q, ROA, leverage, ESG score, industry, year. I consider each characteristic in the year preceding the green bond issuance (i.e., at $t-1$).

**Table 32: Treatment and control groups before matching (Company monthly panel data)**

| | | *N* | *Mean* | *Different in Mean* | *St Err* | *t value* |
|---|---|---|---|---|---|---|
| SIZE (t-1) | Green bond | 4,831 | 18.227 | -1.113 | 0.036 | -31.5 |
| | Matched Control | 51,924 | 17.114 | | | |
| ROA (t-1) | Green bond | 4,735 | 5.801 | 0.962 | 0.115 | 8.35 |
| | Matched Control | 51,573 | 6.764 | | | |
| LEV (t-1) | Green bond | 4,824 | 40.98 | 26.775 | 14.534 | 1.85 |
| | Matched Control | 50,580 | 67.755 | | | |
| Tobin's Q (t-1) | Green bond | 4,603 | 1.181 | 0.306 | 0.02 | 15.35 |
| | Matched Control | 50,828 | 1.486 | | | |
| ESG (t-1) | Green bond | 5,304 | 37.197 | 12.572 | 0.414 | 30.4 |
| | Matched Control | 53,196 | 49.77 | | | |

Table 32 shows that treatment and control groups were different in terms of all considered characteristics before matching. I use Chi-square tests for proportions and t-tests for continuous variables.

This matching procedure is designed following Flammer (2021) to ensure that control firms are highly similar to the treated firm's ex-ante. First, I consider firms that have their ESG, and environmental information disclosed. I exclude firms that are not bond issuers then divide them into two groups of non-green bond issuers and green bond issuers. Second, I sort control firms that operate in the same countries and same industries as our treated firm. Third, to further mitigate the impact of endogeneity, from our remaining firms, I select the nearest neighbour by using propensity score matching approach to match each member of the green bond issuer (treatment group) with the non-green bond issuer (control group) sharing the similar characteristics: size, Tobin's Q, ROA, leverage, and the ESG rating. For each characteristic, I consider the variable in the year of green bond issuance (i.e., at t – 1), as well as the "pre-trend" (i.e., the change from t–2 to t–1). Accordingly, nine matching variables will be used. In detail, the rationale of our chosen characteristics is that ESG ratings ensure both groups have similar environmental performance before green bond issuance. Using ROA and Tobin's Q alleviates concerns that the treated firms may be more profitable and have a higher value. Using size and debt capacity (leverage) further rules out the chance that the treated group may have better access to capital markets.

Moreover, as Cai et al. (2016) and Ioannou and Serafeim (2012) argue, firms domiciled in a more prosperous country may have better environmental performance. Therefore, I match firms based on country, industry to ensure that treated and matched control firms face the same conditions in their business environment (including economic, regulatory, and other conditions). More importantly, I select matching firms that also issue non-green corporate bonds in the same year as green bond issuers to alleviate the concern that bond issuance generally will improve sustainability investment.

**Table 33: Propensity Score Matching methods comparison**

| Variables | M0 | M1 | M2 | M3 | M4 | M5 | M6 |
|---|---|---|---|---|---|---|---|
| | Original dataset | Probit model | Logit model | Caliper Neighbor 1 | Caliper Neighbor 2 | Radius Caliper | Kernel |
| **C1: T-test or chi-square test P-values** | | | | | | | |
| SIZE | -31.52 | -1.90 | -3.75 | 0.24 | -2.18 | 1.76 | -0.12 |
| ROA | 8.36 | -2.56 | -1.35 | -1.22 | -2.51 | -0.68 | 0.29 |
| Tobin's Q | 20.83 | 0.2 | 0.51 | 0.37 | -0.32 | -4.26 | -1.96 |
| Lev | -15.98 | -9.89 | -10.00 | -0.74 | -7.10 | 5.03 | 4.11 |
| ESG | 30.41 | -4.70 | -8.71 | 1.10 | -3.47 | -0.34 | 1.40 |
| EnvScore | 16.12 | -6.45 | -5.35 | -1.17 | -6.77 | -5.81 | -5.83 |
| SocScore | 14.42 | -6.24 | -8.49 | 1.17 | -5.48 | -3.31 | -3.35 |
| **C2: The mean difference as a percentage of the average standard deviation** | | | | | | | |
| SIZE | | -4.10 | -8.30 | 0.60 | -4.80 | 4.20 | -0.30 |
| ROA | | -4.40 | -2.20 | -2.40 | -4.40 | -1.20 | 0.50 |
| Tobin's Q | | 0.3 | 0.60 | 0.50 | -0.40 | -6.50 | -2.70 |
| Lev | | -14.50 | -14.40 | -1.30 | -10.80 | 8.40 | 6.70 |
| ESG | | -10.40 | -19.10 | 2.50 | -7.60 | -0.80 | 3.10 |
| EnvScore | | -14.2 | -11.70 | -2.80 | -15.00 | -13.10 | -13.10 |
| SocScore | | -13.70 | -17.70 | 2.90 | -12.40 | -7.70 | -7.70 |
| **C3: Percent reduction bias in means of explantory variables** | | | | | | | |
| SIZE | | 91.40 | 82.30 | 98.70 | 89.80 | 91.10 | 99.40 |
| ROA | | 69.50 | 84.60 | 83.20 | 69.70 | 91.40 | 96.40 |
| Tobin's Q | | 69.5 | 98.40 | 98.60 | 99.00 | 83.40 | 93.00 |
| Lev | | 48.30 | 48.70 | 95.50 | 61.50 | 70.30 | 76.30 |
| ESG | | 76.50 | 56.80 | 94.40 | 82.70 | 98.30 | 93.00 |
| EnvScore | | 42.5 | 52.70 | 88.70 | 39.40 | 47.10 | 47.00 |
| SocScore | | 39.90 | 22.40 | 87.50 | 45.80 | 66.30 | 66.10 |
| **C4: Comparison of treatment and control variance ratio** | | | | | | | |
| SIZE | | 1.01 | 0.88 | 0.76 | 0.93 | 0.70 | 0.71 |
| ROA | | 1.03 | 1.25 | 0.84 | 0.97 | 0.82 | 0.89 |
| Tobin's Q | | 1.23 | 1.39 | 1.08 | 1.18 | 0.60 | 0.81 |
| Lev | | 0.96 | 1.03 | 0.77 | 0.83 | 0.62 | 0.68 |
| ESG | | 0.75 | 0.76 | 0.71 | 0.75 | 0.75 | 0.74 |
| EnvScore | | 0.91 | 0.94 | 0.83 | 0.89 | 0.84 | 0.84 |
| SocScore | | 0.72 | 0.87 | 0.58 | 0.66 | 0.60 | 0.61 |
| **C5: Comparision of the density estimates of the propensity scores of control units with those of the treated units** | | | | | | | |
| B | | 30.30 | 34.90 | 10.60 | 25.80 | 33.3 | 21.10 |
| R | | 0.84 | 0.84 | 1.13 | 0.84 | 0.39 | 0.65 |
| Mean Bias | | 7.7 | 9.1 | 2.0 | 7.3 | 8.00 | 5.2 |
| Median Bias | | 4.4 | 8.3 | 2.4 | 6.2 | 7.7 | 5.5 |

We follow Baser (2006) and apply the following set of guidelines for selecting the best application:

**C1.** Measure two-sample t-statistics between the mean of the green bond issuer for each explanatory variable and the mean of the match firms for each explanatory variable.

**C2.** Measure the mean difference as a percentage of the average standard deviation.

**C3.** Measure the reduction bias percentage in the means of the explanatory variables post matching.

**C4.** Use the variance ratio test to compare the treatment and control F-ratio test or F-test. The F-test demonstrates that whether the variance of two populations is equal or not.

**C5.** Use the Rubins' B (the absolute standardized difference of the means of the linear index of the propensity score in the treatment and control group, and Rubin's R (the ratio of treated to control variances of the propensity score index). Rubin (2001) recommends that B be smaller than 25 and that R be in the range of 0.5 – 2 for the samples to be considered sufficiently balanced.

The main objective of treatment and control group matching is to lower selection bias by improving the balance between the two groups. Therefore, I would like to smaller t-statistic as the more negligible difference (criterion 1); low mean differences measured as a percentage of the average standard deviation (criterion 2); a significant decrease of bias in the explanatory variables' means of (criterion 3); and insignificant differences when comparing the density estimates of the treatment and matched groups (criterion 4 and criterion 5). Therefore, the best matching algorithm for the data is the one that satisfies all five criteria.

After comparing different PSM models in table 33, I choose the model with one neighbour and calliper of 0.01 (model M3). Comparing to the original data set (M0), the t-test of our covariates reduces significantly.

**Table 34: Descriptive statistics comparing treated and matched control firms (monthly variables)**

| | ***Green bonds*** | | | | ***Non-green bonds*** | | | |
|---|---|---|---|---|---|---|---|---|
| Variables | N | Mean | Median | SD | N | Mean | Median | SD |
| ROA | 4,082 | 5.71 | 5.4 | 5.33 | 4,108 | 5.71 | 4.91 | 5.27 |
| SIZE | 4,083 | 18.39 | 18.14 | 2.29 | 4,132 | 18.1 | 17.52 | 2.69 |
| LEV | 4,083 | 61.82 | 68.64 | 1,064.62 | 4,132 | 41.91 | 70.16 | 1479.84 |
| Tobin's Q | 4,071 | 1.13 | 0.93 | 0.69 | 4,119 | 1.21 | 0.94 | 0.85 |
| ESG | 3,629 | 55.23 | 58.69 | 16.2 | 3,699 | 59.02 | 62.24 | 18.68 |
| EnvScore | 3,881 | 48.75 | 45.72 | 27.67 | 3,933 | 57.19 | 68.07 | 29.2 |
| SocScore | 3,881 | 61.44 | 62.28 | 19.59 | 3,933 | 66.02 | 70.99 | 23.93 |
| GovScore | 3,881 | 55.61 | 55 | 18.06 | 3,933 | 57.07 | 63.22 | 22.56 |
| CO2 (mil tonnes) | 2,558 | 7.67 | 0.485 | 32.2 | 2,918 | 4.98 | 0.810 | 12.6 |
| CO2_MV | 2,558 | 0.06 | 0.01 | 0.12 | 2,918 | 0.35 | 0.01 | 1.3 |

Figure 13 compares propensity scores between treatment and control groups before and after matching. It shows that after matching, the gap between the two groups is significantly reduced. Figure 14 shows that propensity score is evenly distributed between treated and control groups. Figure 15 demonstrates that selection biases of measured and tested covariates are reduced by matching. Standardized % bias across covariates after matching is close to 0.

**Figure 13: Comparing treatment and control groups before and after matching.**

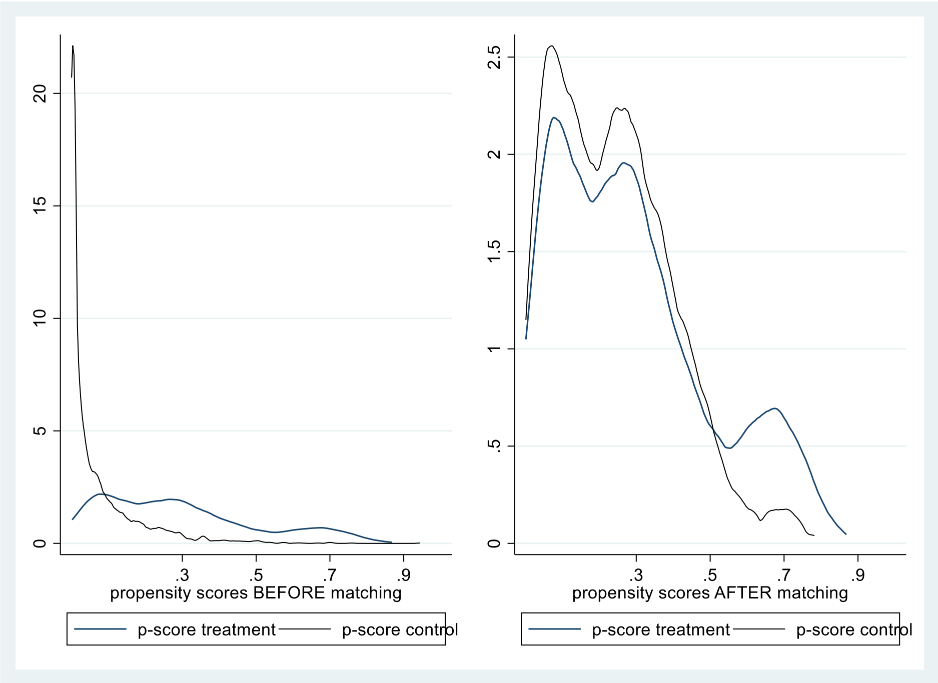



**Figure 14: Histogram of the propensity score in treatment and control groups**

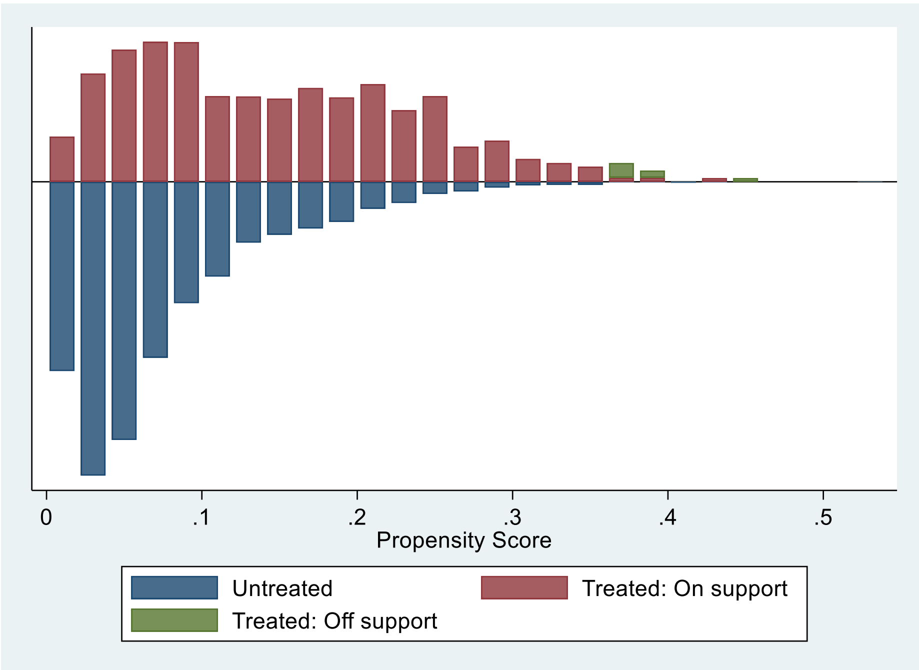
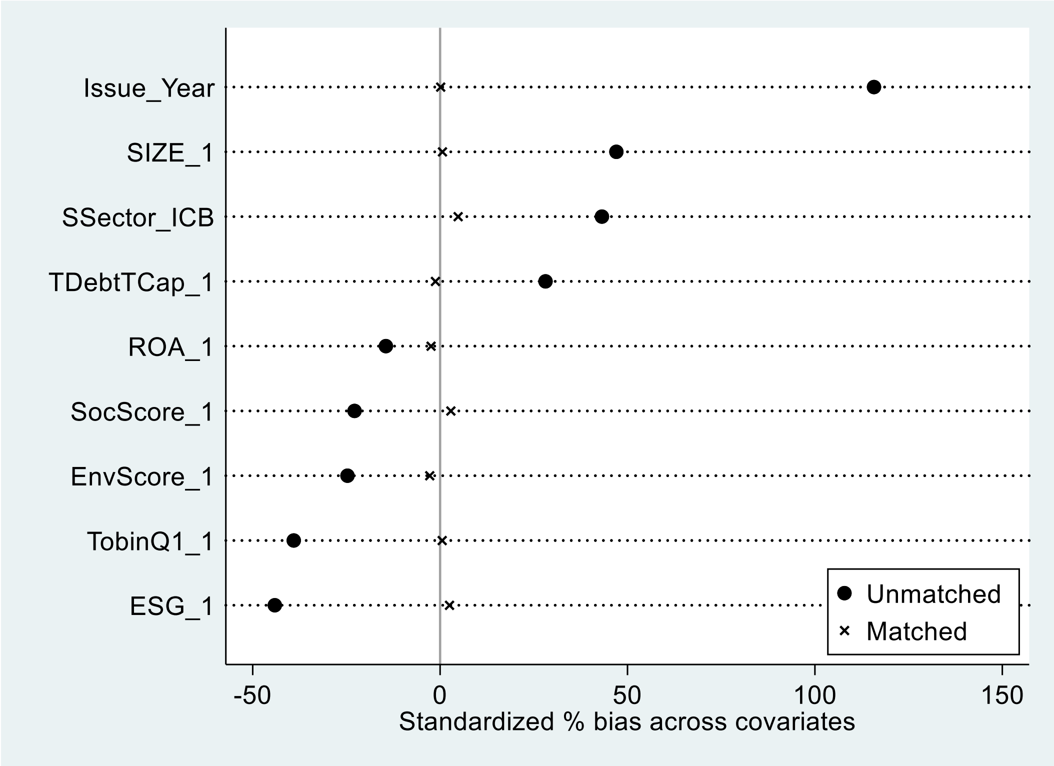


**Figure 15: Graph of reduced bias in covariates after matching.**




### *4.4. Difference-in-difference (DiD) regression*

Our research questions access the differences in firms' environmental performance before and after green bond issuances. Therefore, I examine the effects of green bond issuance on treatment and control groups by running the following regression:

$$Y_{it} = \alpha_i + \alpha_c \times \alpha_t + \alpha_s \times \alpha_t + \beta_1 \times \text{GREEN} + \beta_2 \times \text{POST}_t + \beta_3 \times \text{GREEN} \times \text{POST}_t + \beta_j \times \text{FirmControl}_{jti} + \varepsilon_{it}$$

In which, *i* indexes firms, *t* indexes years, *c* indexes countries, and *s* indexes ICB industries; $Y_{it}$ is the outcome variable of interest (e.g., ESG scores, environments score, or $CO_2$ emissions); $\alpha_i$ are firm fixed effects; $\alpha_c \times \alpha_t$ are country by year fixed effects; $\alpha_s \times \alpha_t$ are industry by year fixed effects; GREEN is a dummy variable ("treatment dummy") that equals one if firm *i* has issued a green bond and zero otherwise. *POST* is a dummy variable that denotes 1 for the year after issuance and zero for years before issuance. $FirmControl_{jti}$ are firm-level control variables of firm *i* at time $t$, including ROA (Return on Asset), LEV (Total debt over total equity), SIZE (logarithm of the total asset), and Tobin's Q.

The coefficient of interest is $\beta_3$ which measures the difference-in-differences in the outcome variable $Y_{it}$ between treated and matched control firms. In other words, $\beta_3$ measures the change in $Y_{it}$ following the green bond issue accounting for contemporaneous changes in y at otherwise comparable firms that do not issue green bonds.

## 5. Results

### *5.1. Green bond issuance and environmental performance*

First, I evaluate whether green bond issuance is a credible signal that informs investors about firms' long-term sustainability. According to signaling theory, green bonds also serve as a more critical factor in bridging the information gap between companies and investors regarding companies' sustainability engagement. This section uses two environmental performance measures as dependent variables: $CO_2$ consumption and ESG score.

**Table 35: Green bond issuance DID regression (dependent variable: CO2 consumption)**

| VARIABLES | (1)<br>CO2 | (2)<br>CO2_MV | (3)<br>CO2 | (4)<br>CO2_MV |
|---|---|---|---|---|
| GREEN | -0.3378 | -0.199*** | 0.2542 | -0.277*** |
| | (-0.587) | (-7.602) | (0.426) | (-10.25) |
| POST | -9.699*** | 0.318*** | -7.960*** | 0.346*** |
| | (-8.930) | (6.412) | (-7.249) | (6.967) |
| GREEN×POST | 24.23*** | -0.161** | 22.36*** | -0.161** |
| | (14.45) | (-2.101) | (13.32) | (-2.119) |
| ROA | | | 0.2869*** | -0.000579 |
| | | | (4.731) | (-0.211) |
| LEV | | | 0.006032 | 0.00599*** |
| | | | (0.399) | (8.755) |
| SIZE | | | 1.327*** | -0.0503*** |
| | | | (9.671) | (-8.096) |
| Tobin's Q | | | -0.5218** | -0.0511*** |
| | | | (-2.400) | (-5.195) |
| Constant | 6.450*** | 0.482*** | -19.34*** | 1.331*** |
| | (4.369) | (7.165) | (-5.460) | (8.301) |
| Year_Industry FE | Yes | Yes | Yes | Yes |
| Year_Country FE | Yes | Yes | Yes | Yes |
| Observations | 5,476 | 5,476 | 5,476 | 5,476 |
| R-squared | 0.440 | 0.281 | 0.454 | 0.309 |

This table shows the results of the model:

$$\mathrm{CO2_{it}} = \alpha_i + \alpha_c \times \alpha_t + \alpha_s \times \alpha_t + \beta_1 \times \mathrm{GREEN} + \beta_2 \times \mathrm{POST_t} + \beta_3 \times \mathrm{GREEN} \times \mathrm{POST_t} + \beta_{jti} \times \mathrm{FirmControl_{jti}} + \varepsilon_{it}$$

In which, $\mathrm{CO2_{it}}$ is the measures for $CO_2$ consumption of firm *i* in month *t*; I used two measures: one raw $CO_2$ consumption in tonnes and $CO_2$ over firm's market value measure; $\alpha_i$ are firm fixed effects; $\alpha_c \times \alpha_t$ are country by year fixed effects; $\alpha_s \times \alpha_t$ are industry by year fixed effects; *GREEN* is a dummy variable ("treatment dummy") that equals one if firm *i* has issued a green bond and zero otherwise*; POST* is a dummy variable which denotes 1 for the year after issuance and zero for years before issuance. *FirmControl a*re firm-level control variables, including *ROA* (Return on Asset), *LEV* (Total debt over total equity), *SIZE* (logarithm of the total asset), and *Tobin's Q*. The data set is in monthly frequency, t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and *, respectively. The sample period is from January 2007 to December 2019.

The use of CO2 consumption as a proxy for environmental performance is motivated by Flammer (2021). However, Flammer (2021)'s study measures CO2 consumption by the ratio of CO2 in tonnes over the firms' book value of assets. I extend this specification and use both the actual amount of CO2 in a million tonnes and an objective measure of CO2 divided by firms' market value. I argue that only relative measures of CO2 over firms' books or market values may not reflect a clear picture of firms' environmental performance. It may be the case that the amount of CO2 consumption still increases after green bond issuance, but it increases slower than the firm's book values, thus, leading to a lower $CO_2$ over book values measures.

Table 35 shows a positive and significant estimated coefficient of *GREEN×POST* interaction term in the model of raw CO2, which indicates that firms still increase their CO2 consumption after issuing green bonds. On average, firms that issued green bonds increased their total raw $CO_2$ consumption by 22.3 million tonnes after the green bond issuance more than non-green bond-issuers. This is in line with our previous screening that firms who issue green bonds have the environment as the core to the firms' operations (e.g., utilities, energy, transportation). It is likely that working in industries that are heavily dependent on exploiting natural resources, and these firms will find it difficult to cut their overall emissions. Also, according to Flammer (2021), green bonds amount in general is far smaller than firms' asset sizes; thus, the green bond is less likely to lead to better environmental performance. I argue whether green bond issuance gives investors an accurate signal on firms' sustainability commitment. Furthermore, for our sample, the DiD regression on raw $CO_2$ consumption indicates that this signal does not accurately reflect firms' environmental activities.

On the other hand, I observe that CO2 consumption relative to firms' market value significantly declined after issuing green bonds. From column 4 of Table 35, green bond issuers' emission over market value is reduced by 16.1% post-issuance, corresponding to 9,660 tonnes per 1 million dollars in market value (given the mean of 0.06 in table 34). While raw CO2 increases, as I find previously, the measure of CO2 over market value reduced most likely because of more rapid growth in firms' market capitalization. The increase in stock prices could cause an increase in market values after the issuance of green bonds. The CO2 emissions divided by market value (*CO2_MV*) reduced because the changes in *CO2_MV* could be caused by 'positive impact of the stock market as Tang and Tang (2016) and Flammer (2021) find that stock prices positively respond to green bond issuance. Therefore, reducing *CO2_MV* could be unlikely that firms have better environmental performance, but those investors are likely interested in firms that issue green bonds. Thus, to further examine whether green bond issuance is a credible signal for firms' eco-commitment, I run DiD model with firms' ESG scores as our dependent variables. I report results for both total ESG scores and separated environmental and social scores in table 36.

**Table 36: Green bond issuance DID regression (dependent variable: ESG scores)**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | ESG | EnvScore | SocScore | ESG | EnvScore | SocScore |
| GREEN | 1.504*** | -5.059*** | -3.367*** | -2.321*** | -4.388*** | -3.269*** |
| | (3.409) | (-6.518) | (-5.619) | (-7.366) | (-5.537) | (-5.361) |
| POST | 6.911*** | 9.841*** | 2.056* | 4.550*** | 10.98*** | 3.339*** |
| | (8.956) | (7.057) | (1.91) | (8.209) | (7.681) | (3.037) |
| GREEN×POST | 0.784 | 4.975** | 10.74*** | -0.35 | 4.600* | 9.830*** |
| | (0.605) | (2.074) | (5.796) | (-0.383) | (1.91) | (5.303) |
| ROA | | | | 0.0428 | 0.154** | 0.0333 |
| | | | | (1.424) | (2.083) | (-0.586) |
| LEV | | | | -0.000161 | -0.000177 | -0.000687*** |
| | | | | (-1.429) | (-0.692) | (-3.502) |
| SIZE | | | | 2.727*** | -2.128*** | -1.037*** |
| | | | | (21.89) | (-6.870) | (-4.351) |
| Tobin's Q | | | | 1.582*** | -2.578*** | -3.224*** |
| | | | | (7.318) | (-4.703) | (-7.643) |
| ESG (t-1) | | | | 0.397*** | 0.00376 | 0.0498*** |
| | | | | (69.14) | (0.26) | (4.465) |
| Constant | 51.50*** | 42.92*** | 56.12*** | -20.30*** | 86.80*** | 79.69*** |
| | (44.28) | (20.72) | (35.09) | (-7.858) | (13.62) | (16.25) |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 7,328 | 7,814 | 7,814 | 7,316 | 7,722 | 7,722 |
| R-squared | 0.259 | 0.066 | 0.048 | 0.635 | 0.081 | 0.061 |

This table reports the results of the mode:

$$\mathrm{ESG_{it}} = \alpha_\mathrm{i} + \alpha_\mathrm{c} \times \alpha_\mathrm{t} + \alpha_\mathrm{s} \times \alpha_\mathrm{t} + \beta_1 \times \mathrm{GREEN} + \beta_2 \times \mathrm{POST_t} + \beta_3 \times \mathrm{GREEN} \times \mathrm{POST_t} + \beta_{jti} \times \mathrm{FirmControl}_{jti} + \varepsilon_\mathrm{it}$$

In which, $\mathrm{ESG_{it}}$ is the measures for ESG performance of firm *i* in month *t*; I run the model for both total ESG scores as well as separated Environment and Social scores; $\alpha_i$ are firm fixed effects; $\alpha_c \times \alpha_t$ are country by year fixed effects; $\alpha_s \times \alpha_t$ are industry by year fixed effects; *GREEN* is a dummy variable ("treatment dummy") that equals one if firm *i* has issued a green bond and zero otherwise*; POST* is a dummy variable which denotes 1 for the year after issuance and zero for years before issuance. *FirmControl a*re firm-level control variables, including *ROA* (Return on Asset), *LEV* (Total debt over total equity), *SIZE* (logarithm of the total asset), and *Tobin's Q*. The data set is in monthly frequency, t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and *, respectively. The sample period is from January 2007 to December 2019.

As shown in Columns 5 and 6 of Table 36, the coefficient of the treatment variable, *GREEN* variables, is negative. This indicates that before issuance, the mean in environment score and the social score of green bond issuers are 4.38 points, 3.27 points lower than non-green bond issuers. One rationale for this difference is that green bond issuers in our sample mainly operate in environment-dependent industries, such as general material, utilities, or transportation. These firms often exploit natural resources for their business while creating higher emission than other. However, I find that post-issuance environment and social scores are improving, and green bond issuers' environment and social scores respectively increase 4.6 and 9.8 points more than match firms following issuance. The overall ESG score, however, reports no significant change after green bond issuance. These results demonstrate a substantial improvement in the environmental footprint and social engagement of firms with green bonds. As demonstrated in signaling theory, firms genuinely commit to a better sustainable operation when issuing green bonds.

One specific note is that the findings do not imply a causal effect of green bonds issuance on environmental practices. Instead, it demonstrates that green bonds serve as a credible signal for companies' commitment to the environment. Furthermore, although Attig et al. (2013) find that credit rating agencies give firms with good social performance a higher rating, the issuance of green bonds does not enter the assessment grid used by ASSET4 to determine the rating (Eikon, 2017). As such, there is no mechanical link between the issuance of green bonds and higher environmental ratings. Therefore, I can eliminate the situation where ASSET4 analysts perceive the issuance of green bonds as good environmental practice and upgrade the company's environmental rating accordingly.

Overall, I can find that after issuing green bonds, although firms' $CO_2$ consumption still increased, firms' Environmental scores significantly increase. This evidence is inconsistent with the green washing theory that firms issue green bonds while not genuinely engaging in sustainability activities properly. This finding supports the work of Flammer (2021).

### *5.2. Impact of external uncertainties on environmental performance*

Although I observe an upturn in the environmental performance of firms after issuing green bonds (as shown in section 5.1), I would want to explore further any external countable factors that may affect firms' sustainability performance post-issuance. In order to answer this question, I consider the impact of two types of uncertainty: climate change news uncertainty and external uncertainties.

#### *5.2.1 Impact of news sentiment on environmental performance*

We first investigate whether sentiments in the news have any significant impact on green bond issuers. As I observe from data screening in section 2.1, most green bond issuers are industries that heavily depend on natural resources. Therefore, it is expected that when the media displays unfavourable or uncertain information about climate change, it implies general uncertainties around climate movements, which may affect firms' operation, relocation as well as firm's relationship with their social-political stakeholders.

**Table 37: Moderating effect of News sentiments on the relationship between green issuance and Environment score performance**

| VARIABLES | (1)<br>CO2_MV | (2)<br>EnvScore | (3)<br>CO2_MV | (4)<br>EnvScore |
|---|---|---|---|---|
| GREEN | -0.564*** | -1.227 | -0.143*** | -3.847*** |
| | (-4.73) | (-0.33) | (-4.59) | (-4.678) |
| POST | 0.710*** | 8.849 | 0.2835*** | 9.894*** |
| | (3.16) | (1.23) | (7.69) | (6.796) |
| GREEN×POST | -0.454 | 29.61*** | -0.1200** | 4.113 |
| | (-1.30) | (2.42) | (-1.81) | (1.634) |
| DoS_LM | -0.1015 | -11.34*** | | |
| | (-1.10) | (-4.07) | | |
| GREEN×POST×DoS_LM | 0.185 | -24.21** | | |
| | (0.53) | (-2.00) | | |
| Unc_LM | | | -0.3194*** | -16.97*** |
| | | | (-4.00) | (-7.347) |
| GREEN×POST×Unc_LM | | | -0.5667** | -6.750 |
| | | | (-2.46) | (-0.668) |
| Constant | -0.699** | 123.95*** | -0.756** | 112.1*** |
| | (-2.348) | (6.21) | (-2.027) | (15.95) |
| Controls | Included | Included | Included | Included |
| Year FE | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes |
| Observations | 5,078 | 6,966 | 5,078 | 6,966 |
| R-squared | 0.294 | 0.096 | 0.539 | 0.111 |

This table reports the results of the models:

$$\mathrm{Y_{it}} = \alpha_\mathrm{i} + \alpha_\mathrm{c} \times \alpha_\mathrm{t} + \alpha_\mathrm{s} \times \alpha_\mathrm{t} + \beta_1 \times \mathrm{GREEN} + \beta_2 \times \mathrm{POST_t} + \beta_3 \times \mathrm{NewsSent_t} + \beta_4 \times \mathrm{GREEN} \times \mathrm{POST_t} \times \mathrm{NewsSent_t} + \beta_{jti} \times \mathrm{FirmControl_{jti}} + \varepsilon_\mathrm{it}$$

This model is the extended model for the one in tables 35 and 36, $NewsSent_t$ denotes for the disagreement (*DoS_LM)* and (*UnC_LM*) and uncertainty variables, obtained from LM (Loughran and McDonalds). The data set is in monthly frequency, t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and *, respectively. The sample period is from January 2007 to December 2019.

We further explore whether this negative effect of sentiments in climate change news affects firms more after they issue green bonds. I interact disagreement and uncertainty sentiments with GREEN×POST term and report results in table 37. Column 2 of Table 37 shows that firms' environment scores can increase significantly by 29.61 points after green bond issuance. However, this improvement is reduced by 24.21 points more than match bond issuers because of the disagreement sentiment in climate change news. These results are significant at a 5% level. In contrast, I observe that the impacts of disagreement sentiments to *CO2_MV* are insignificant (Column 1 of Table 37).

On the other hand, column 3 of Table 37 shows that uncertainty sentiment reduces post-issuance emission improvement. Our model outcomes indicate that disagreement sentiment in climate news induces a reduction in firms' environmental performance. Researches in climate communication suggest that extreme weather or climate change highlighted in media will help elicit public concern and promote protective actions. However, many researchers also warn against fear appeals that it may trigger counter-productive responses like denial, avoidance, and disagreement because solutions are uncertain, unknown, or undesirable[13]. Our results support the real options theory, suggesting that when firms face uncertain news regarding climate change, they are discouraged from investing in sustainability.

### *5.2.2 Impact of national-level uncertainties on environmental performance*

To further investigate the impact of uncertainty, I take into account three types of national-level uncertainty: *EPU* – an economic policy uncertainty index – is developed by Baker et al. (2016); *PSU* – an index of political stability and absence of violence – is developed by the Worldwide Governance Indicators project; and *CCU* is climate change uncertainty which was measured as the vulnerability dimension of the Notre Dame Global Adaptation Index.

The moderating effects of three sources of national-level uncertainties are reported in Table 38. As columns 1 and 4 present, climate change-induced uncertainty (*CCU*) is negatively related to firms' CO2 consumption post-issuance. For example, in Column 4, emissions are reduced by 241,380 tons of CO2 per one million dollars of market value, a reduction by 4.023 times (given the mean of 0.06 from table 6); however, in a period of a high level of climate change-induced uncertainty (*CCU*), this emission reduction will be 2.48 times less (corresponding to the consumption of more 148,800 tons CO2 per one million of dollar of market value). Similarly, CO2 reduction post-issuance will also be lessened by 1.8 times and 1.4% in times of high economic policy uncertainty and political uncertainty, respectively. It suggests that all three national-level uncertainties examined in our models reduce firm sustainability engagement. Our results are consistent with prior studies, including Gulen and Ion (2015), Jens (2017), Bonaime et al. (2018), and Jia and Li (2020), which demonstrate that external uncertainties hinder firms' long-term investment. From a theoretical standpoint, these results support the real options theory that national-level uncertainty negatively affects firms' long-term investment.

[13] See, e.g., LAZARUS, R. S. 1999. Hope: An Emotion and a Vital Coping Resource Against Despair. *Social Research,* 66**,** 653-678.; HASTINGS, G., STEAD, M. & WEBB, J. 2004. Fear appeals in social marketing: Strategic and ethical reasons for concern. *Psychology and Marketing,* 21**,** 961-986.

**Table 38: Moderating effect of national-level uncertainty on the relationship between green issuance and CO2 consumption**

| VARIABLES | (1)<br>CO2_MV | (2)<br>CO2_MV | (3)<br>CO2_MV | (4)<br>CO2_MV |
|---|---|---|---|---|
| GREEN | -0.299*** | -0.602*** | -0.660*** | -1.151*** |
| | (-3.301) | (-11.07) | (-12.80) | (-10.15) |
| POST | 0.127 | 0.686*** | -1.621*** | -4.942*** |
| | (1.396) | (6.618) | (-16.49) | (-29.32) |
| GREEN×POST | -0.0222 | -0.431*** | -1.572*** | -4.023*** |
| | (0.171) | (-3.316) | (9.603) | (16.01) |
| CCU | 88.98*** | 90.35*** | 83.32*** | -28.61*** |
| | (8.863) | (8.863) | (8.758) | (-3.488) |
| EPU | 12.18*** | 12.39*** | 11.17*** | -6.535*** |
| | (8.333) | (8.197) | (8.102) | (-5.444) |
| PSU | -0.0160*** | -0.0166*** | -0.0209*** | -0.00548*** |
| | (-8.835) | (-8.992) | (-12.05) | (-3.722) |
| GREEN×POST×CCU | -1.354*** | | | -2.488*** |
| | (-2.644) | | | (-6.215) |
| GREEN×POST×EPU | | 0.497** | | -1.821*** |
| | | (2.320) | | (-8.762) |
| GREEN×POST×PSU | | | -0.00920*** | -0.0140*** |
| | | | (-15.85) | (-24.87) |
| Constant | -19.59*** | -19.28*** | -15.79*** | 10.58*** |
| | (-8.018) | (-7.809) | (-6.823) | (5.168) |
| Controls | Included | Included | Included | Included |
| Year_Industry FE | Yes | Yes | Yes | Yes |
| Year_Country FE | Yes | Yes | Yes | Yes |
| Observations | 5,476 | 5,476 | 5,476 | 5,476 |
| R-squared | 0.246 | 0.248 | 0.315 | 0.734 |

This table reports the results for the model:

$$\mathrm{CO2_{it}} = \alpha_i + \alpha_c \times \alpha_t + \alpha_s \times \alpha_t + \beta_1 \times \mathrm{GREEN} + \beta_2 \times \mathrm{POST_t} + \beta_3 \times \mathrm{UNC_t} + \beta_4 \times \mathrm{GREEN} \times \mathrm{POST_t} \times \mathrm{UNC_t} + \beta_{jti} \times \mathrm{FirmControl_{jti}} + \varepsilon_{it}$$

This model is the extended model for the one in table 35, $UNC_t$ denotes for the three sources of external uncertainties: Economic Policy Uncertainty (*EPU*) was developed by Baker et al. (2016); Climate change-induced uncertainty (*CCU*) is collected from The Notre Dame Global Adaptation Index, and political system stability (*PSU)* are retrieved from World Bank's Worldwide Governance Indicators Project. The data set is in monthly frequency, t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and *, respectively. The sample period is from January 2007 to December 2019.

**Table 39: Moderating effect of national-level uncertainty on the relationship between green issuance and environmental score**

| VARIABLES | (1) EnvScore | (2) EnvScore | (3) EnvScore | (4) EnvScore |
|---|---|---|---|---|
| GREEN | -2.503 | -9.278*** | -3.776*** | -8.300** |
| | (-1.087) | (-6.972) | (-3.809) | (-2.327) |
| POST | 6.116** | 8.158*** | 8.675*** | 26.67*** |
| | (-2.561) | (3.339) | (-3.422) | (-4.428) |
| GREEN×POST | -0.509 | -4.825 | 5.755* | 34.85*** |
| | (-0.150) | (-1.115) | (1.802) | (3.876) |
| CCU | 90.09*** | 104.7*** | 68.99** | 77.31** |
| | (2.812) | (3.243) | (2.216) | (2.353) |
| PSU | 0.0240*** | 0.0205*** | 0.0340*** | 0.0171** |
| | (4.555) | (2.937) | (6.484) | (2.391) |
| EPU | -5.214** | -7.638*** | -8.325*** | -8.417*** |
| | (-2.112) | (-3.071) | (-3.105) | (-3.047) |
| GREEN×POST×CCU | -27.41** | | | -46.11*** |
| | (-2.161) | | | (-3.310) |
| GREEN×POST×PSU | | 0.00237 | | -0.0659*** |
| | | (0.160) | | (-3.352) |
| GREEN×POST×EPU | | | -16.45*** | -31.13*** |
| | | | (-3.005) | (-4.231) |
| Controls | Included | Included | Included | Included |
| Year FE | Yes | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes |
| Observations | 7,722 | 7,722 | 7,722 | 7,723 |
| R-squared | 0.469 | 0.468 | 0.468 | 0.471 |

This table shows the results for the model:

$$\mathrm{EnvScore_{it}} = \alpha_i + \alpha_c \times \alpha_t + \alpha_s \times \alpha_t + \beta_1 \times \mathrm{GREEN} + \beta_2 \times \mathrm{POST_t} + \beta_3 \times \mathrm{UNC_t} + \beta_4 \times \mathrm{GREEN} \times \mathrm{POST_t} \times \mathrm{UNC_t} + \beta_{jti} \times \mathrm{FirmControl_{jti}} + \varepsilon_{it}$$

This model is the extended model for the one in table 36 for environment score, $UNC_t$ denotes for the three sources of external uncertainties: Economic Policy Uncertainty (*EPU*) was developed by Baker et al. (2016); Climate change-induced uncertainty (*CCU*) is collected from The Notre Dame Global Adaptation Index, and political system stability (*PSU)* are retrieved from World Bank's Worldwide Governance Indicators Project. The data set is in monthly frequency, t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and *, respectively. The sample period is from January 2007 to December 2019.

Similarly, I run a triple DID regression with environment score as another proxy for firms' sustainability performance. I interact three national sources of uncertainties with the *GREEN_POST* term. As presented in table 39, similar to the model of $CO_2$, firms' environment score is also negatively affected by uncertainty in the external environment. As shown in Column 4 of Table 39, firms' environment score can increase by 34.85 points after issuing green bonds; however, uncertainty induced by climate change and economic policy will decrease this improvement by 46 points and 31 points, respectively. Similarly, the impact of political uncertainty on firms' environment score is also negative but at a smaller rate (6.6%). All are significant at a 1% level. With substantial and significant negative impact, the three sources of national-level uncertainties, including climate uncertainty, economic uncertainty, and political uncertainty, can counter the positive effect of green bond issuance on firms' environmental performance. Significantly, these external uncertainty factors have a more substantial impact on firms with green bonds. This difference results from the fact that most of the green bond issuers in our sample operate in environmentally sensitive industries. These firms, therefore, find it essential to maintain their relationships with several stakeholders, such as natural environment stakeholders (e.g., environment protection groups), economic groups (e.g., investors) as well as socio-political stakeholders (e.g., government). Therefore, they are more sensitive to these uncertainties than other firms. These results are in line with the works of Jia and Li (2020), Bonaime et al. (2018), and Jens (2017) that external uncertainties interrupt firms' sustainability investment, especially for green bond issuers. Although green bonds are not exposed to long-term climate change risk, they often carry specific risks originated from uncertainties relating to the development of green technologies (e.g., renewable energy investment or clean technology development). Therefore, external uncertainty, especially those related to climate change, will likely discourage firms' long-term sustainability investment.

In summary, in this section, I find strong evidence that the disagreement in climate change news, climate change-induced uncertainty, economic policy uncertainty, and political uncertainty are negatively related to firms' environmental performance following green bond issuance. The results support real options theory that firms are discouraged to invest when there is a higher level of uncertainties.

### *5.3. Climate change topics in the news and environmental performance*

Next, I examine whether media communication prompt companies to tackle their pollution issues. News topics are classified based on WMatrix corpus analysis. *PHY* is physical climate change topics, SOC is the social topic, and *POL* is government and policy topics.

As shown in Column 1 and 3 of Table 40, the $CO_2$ consumption relative to market value decrease after green bond issuance. Furthermore, physical climate (*PHY*) and climate policy (*POL*) help increase this reduction by 2.42 times and 0.55 times more, respectively. These results indicate that, different from the impact of uncertainties on sustainability engagement of green bond issuers, topics mentioned in climate change news encourage firms to step up in their green investments. In column 4, when I control all triple DID interactions of the three topics in the same model, physical climate topics remain strong and significant. The more physical climate mentioned in climate change news shows, the more effort companies put in reducing $CO_2$ consumption after green bond issuance.

**Table 40: Moderating effect of News topics on the relationship between green issuance and CO2 consumption**

| VARIABLES | (1)<br>CO2_MV | (2)<br>CO2_MV | (3)<br>CO2_MV | (4)<br>CO2_MV |
|---|---|---|---|---|
| GREEN | -0.516** | -0.319*** | -0.233 | -1.665*** |
| | (-2.019) | (-3.075) | (-1.197) | (-2.679) |
| POST | 6.851*** | -0.212* | 1.447*** | 7.733*** |
| | (13.48) | (-1.959) | (5.083) | (5.841) |
| GREEN×POST | -6.705*** | 0.381** | -1.839*** | -6.681*** |
| | (-7.893) | (2.516) | (-4.096) | (-2.751) |
| PHY | 0.00855 | -0.0401 | -0.0350 | -0.0525 |
| | (0.0998) | (-0.571) | (-0.496) | (-0.551) |
| SOC | -0.0334 | -0.0516* | -0.0164 | -0.0602* |
| | (-1.390) | (-1.858) | (-0.674) | (-1.908) |
| POL | -0.0203 | -0.00777 | 0.00779 | -0.131 |
| | (-0.350) | (-0.133) | (0.108) | (-1.596) |
| GREEN×POST×PHY | 2.421*** | | | 2.806*** |
| | (7.519) | | | (4.553) |
| GREEN×POST×SOC | | -0.227*** | | -0.0202 |
| | | (-5.514) | | (-0.178) |
| GREEN×POST×POL | | | 0.556*** | -0.353 |
| | | | (3.335) | (-1.056) |
| Constant | -0.0192 | 0.266 | 0.117 | 0.534 |
| | (-0.0426) | (0.595) | (0.260) | (0.978) |
| Controls | Included | Included | Included | Included |
| Year_Industry FE | Yes | Yes | Yes | Yes |
| Year_Country FE | Yes | Yes | Yes | Yes |
| Observations | 5,078 | 5,078 | 5,078 | 5,078 |
| R-squared | 0.516 | 0.505 | 0.500 | 0.518 |

This table reports results for the model:

$$\mathrm{CO2\_MV_{it}} = \alpha_i + \alpha_c \times \alpha_t + \alpha_s \times \alpha_t + \beta_1 \times \mathrm{GREEN} + \beta_2 \times \mathrm{POST_t} + \beta_3 \times \mathrm{UNC_t} + \beta_4 \times \mathrm{GREEN} \times \mathrm{POST_t} \times \mathrm{NewsTopics_t} + \beta_{jti} \times \mathrm{FirmControl_{jti}} + \varepsilon_{it}$$

This model is the extended model for the one in table 35, $\mathrm{NewsTopics_t}$ are classified based on WMatrix corpus analysis. *PHY* is physical climate change topics (related to the environment, food, and housing), *SOC* is the social topic, and *POL* is government and policy topics. The data set is in monthly frequency, t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and *, respectively. The sample period is from January 2007 to December 2019.

Similar to the model of $CO_2$ consumption, when I use the Environment score as a proxy for firms' sustainability performance, news topics also show a significant impact in our models. As shown in Table 41, in columns 1 and 3, green bond issuance signals an increase in firms' environmental engagement, and climate change topics related to physical climate and climate policy help to boost this development by 25.07 times and 10.79 times, respectively. Interestingly, however, social topic in climate change news has an opposite effect compared to the other two topics. When the social topic increases by one index point, it will reduce firms' environmental performance improvement after green bond issuance by 3.3 times. Our results support the research stream that focuses on the impact of climate news on environmental investment (Tang and Zhang, 2020, Kassinis and Vafeas, 2006). News media, thus, play an important role in displaying the fact about climate change and encouraging firms to commit better to sustainability. After issuing green bonds when facing higher stakeholder pressure, firms continued to invest in improving their environmental footprint.

**Table 41: Moderating effect of News topics on the relationship between green issuance and ESG performance**

| VARIABLES | (1)<br>EnvScore | (2)<br>EnvScore | (3)<br>EnvScore |
|---|---|---|---|
| GREEN | -2.661 | -5.103 | -0.979 |
| | (-0.360) | (-1.546) | (-0.168) |
| POST | 97.81*** | -15.66*** | 36.13*** |
| | (6.524) | (-4.548) | (4.188) |
| GREEN×POST | 66.72*** | 9.837** | 30.31** |
| | (-2.609) | (1.985) | (-2.185) |
| PHY | 2.111 | 0.297 | 0.524 |
| | (0.821) | (0.150) | (0.264) |
| SOC | -1.163 | -1.873** | -1.054 |
| | (-1.588) | (-2.183) | (-1.435) |
| POL | -0.259 | 0.138 | 1.658 |
| | (-0.150) | (0.0803) | (0.758) |
| GREEN×POST×PHY | 25.07** | | |
| | (2.565) | | |
| GREEN×POST×SOC | | -3.365*** | |
| | | (-2.602) | |
| GREEN×POST×POL | | | 10.79** |
| | | | (2.069) |
| Constant | 103.0*** | 109.9*** | 101.9*** |
| | (7.334) | (8.052) | (7.323) |
| Controls | Included | Included | Included |
| Year_Industry FE | Yes | Yes | Yes |
| Year_Country FE | Yes | Yes | Yes |
| Observations | 6,966 | 6,966 | 6,966 |
| R-squared | 0.507 | 0.507 | 0.505 |

This table reports the results of the models:

$$\mathrm{EnvScore_{it}} = \alpha_i + \alpha_c \times \alpha_t + \alpha_s \times \alpha_t + \beta_1 \times \mathrm{GREEN} + \beta_2 \times \mathrm{POST_t} + \beta_3 \times \mathrm{UNC_t} + \beta_4 \times \mathrm{GREEN} \times \mathrm{POST_t} \times \mathrm{NewsTopics_t} + \beta_{jti} \times \mathrm{FirmControl_{jti}} + \varepsilon_{it}$$

This model is the extended model for the one in table 36, $NewsTopics_t$ are classified based on WMatrix corpus analysis. *PHY* is physical climate change topics (related to the environment, food, and housing), *SOC* is the social topic, and *POL* is government and policy topics. The data set is in monthly frequency, t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and *, respectively. The sample period is from January 2007 to December 2019.

## 6. Robustness test

### *6.1 Subsample tests*

Subsample tests are performed for the robustness test to ensure that our results are not driven by sample composition. Since financial institutions' financial data and leverage ratios have different meanings than non-financial firms, I exclude financial firms in our sample and run the baseline model. Table 42 indicates that green bond issuance remains positively related to firms' environment score and raw $CO_2$ consumption while negatively associated with $CO_2$ consumption scaled by market value.

**Table 42: Subsample test – excluding financial firms.**

| | (1) | (2) | (3) |
|---|---|---|---|
| VARIABLES | CO2 | CO2_MV | EnvScore |
| | | | |
| GREEN | -4.416*** | -0.324*** | -4.272*** |
| | (-7.157) | (-10.89) | (-5.047) |
| POST | -4.523*** | 0.404*** | 13.52*** |
| | (-4.054) | (7.498) | (9.172) |
| GREEN×POST | 19.36*** | -0.210*** | 4.298* |
| | (11.55) | (-2.598) | (1.666) |
| Constant | -104.4*** | 0.287 | 80.58*** |
| | (-18.32) | (1.043) | (11.67) |
| | | | |
| Controls | Included | Included | Included |
| Year FE | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes |
| Observations | 5,206 | 5,206 | 7,243 |
| R-squared | 0.516 | 0.305 | 0.090 |

We run baseline regressions, excluding financial firms, to examine whether green bond issuance relates to corporate sustainability performance. The data set is in monthly frequency, t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and *, respectively. The sample period is from January 2007 to December 2019.

Furthermore, I run the baseline models with subsample where remove the data of the period in the financial crisis of 2007-2008 is removed. Since our models are run from 2007 to 2019, the historical financial downturn likely drives the results. Results are presented in table 43.

**Table 43: Subsample test – excluding financial crisis.**

| VARIABLES | (1)<br>CO2 | (2)<br>CO2_MV | (3)<br>EnvScore |
|---|---|---|---|
| GREEN | -4.123*** | -0.303*** | -3.233*** |
| | (-6.560) | (-11.19) | (-4.405) |
| POST | -4.592*** | 0.403*** | -1.459 |
| | (-4.188) | (8.521) | (-1.096) |
| GREEN×POST | 19.40*** | -0.235*** | 3.676* |
| | (11.74) | (-3.296) | (1.763) |
| Constant | -87.76*** | -0.900*** | 122.4*** |
| | (-15.81) | (-3.764) | (19.35) |
| Controls | Included | Included | Included |
| Year FE | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes |
| Observations | 4,905 | 4,905 | 6,652 |
| R-squared | 0.512 | 0.259 | 0.332 |

We run baseline regressions, excluding the financial crisis period 2007-2008, to examine whether green bond issuance relates to corporate sustainability performance. The data set is in monthly frequency, t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and *, respectively. The sample period is from January 2009 to December 2019.

As shown in Table 43, I find that the results of our baseline model remain the same even when the financial crisis 2007-2008 is excluded from the sample. As expected, the $CO_2$ emission per million in market value reduced after green bond issuance while the total CO2 emission and environment score increase.

### *6.2 Exogenous shock*

One may argue that movements in climate activities simply cause the improvement in firms' stock performance or environmental performance. Therefore, I perform a robustness test by accounting for an exogenous shock that potentially affects our dependent variables. I choose the exogenous event to be the Paris Agreement 2016. As the legally binding international treaty on climate change, this agreement, which was adopted by 196 countries, is suitable for our quasi-experimental design. DiD analysis can test the consequences of the Paris Agreement 2016 for the green bond issuers compared to non-green bond issuers. Given that this paper is examining the difference over time between two groups, the DID approach could constitute the omitted factors that impact the two groups alike, also rules out omitted trends that correlate with stock liquidity, abnormal returns, and environmental performance in the treatment and control groups.

As presented in table 44, for all three dependent variables representing CO2 consumption and environment score, the estimated coefficient of *POST* and *GREEN* variables are not significant, indicating that exogenous shocks do not affect green bond issuer and non-green bond issuers differently. In other words, there is no difference in terms of stock market reactions and firms' sustainability engagement between green and non-green bond issuers from before to after the Paris Agreement 2016. Therefore, I can reject the hypothesis that there are omitted factors that correlate with our target variables.

**Table 44: Robustness test for exogenous shock (Paris Agreement 2016)**

| VARIABLES | (1)<br>CO2 | (2)<br>CO2_MV | (3)<br>EnvScore |
|---|---|---|---|
| GREEN | -2.5e+06 | -0.0804*** | -10.29*** |
| | (-1.19) | (-2.579) | (-5.653) |
| POST_PARIS | -4,7e+06*** | -0.01858 | 6.633*** |
| | (-2.86) | (-1.53) | (4.083) |
| GREEN×POST_PARIS | 2,999,651 | 0.00336 | 2.145 |
| | (1.18) | (0.18) | (0.934) |
| Constant | -1.44e+08*** | 0.0738 | 187.3*** |
| | (-10.30) | (0.909) | (14.48) |
| Controls included | Yes | Yes | |
| Year FE | Yes | Yes | Yes |
| Industry FE | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes |
| Observations | 1,103 | 1,103 | 1,491 |
| R-squared | 0.579 | 0.397 | 0.316 |

We examine the effects of exogenous shock on treatment and control groups by running the following regression:

$$Y_{it} = \alpha_i + \alpha_i \times \alpha_t + \alpha_s \times \alpha_t + \beta_1 \times \mathrm{GREEN} + \beta_2 \times POST\_PARIS_i + \beta_3 \times \mathrm{GREEN} \times POST\_PARIS_i + \beta_{jti} \times \mathrm{FirmControl}_{\mathrm{jti}_t} + \varepsilon_{t+1}$$

In which, *i* indexes firms, *t* indexes years, and *s* indexes ICB industries; *y* is the outcome variable of interest (e.g., abnormal return, stock liquidity, environmental performance); $\alpha_i$ are firm fixed effects; $\alpha_i \times \alpha_t$ are firm by year fixed effects; $\alpha_s \times \alpha_t$ are industry by year fixed effects; *GREEN* is a dummy variable ("treatment dummy") that equals one if firm *i* is the green bond issuer and zero otherwise. *POST_PARIS* is a dummy variable that denotes 1 for 2015 (one year before the Paris Agreement entered into forced 2016) and zero for 2017 (one year after). The data set is in monthly frequency, t-statistics are reported in parentheses, and significance at the 1%, 5%, or 10% level is indicated by an ***, **, and *, respectively. The sample period is from January 2015 to December 2017.

Overall, the results of robustness tests demonstrate that our main results were not affected by sample composition (sub-sample tests) and external shock.

## 7. Summary of the chapter

Being motivated by a growing discussion around green investments and bridging the literature gap, I examine the green bond's role in reducing information asymmetry and potential factors that may impact firms' environmental performance post-issuance. The findings reveal that after issuing green bonds, firms still increase their CO2 consumption. This is because most green bond issuers have the environment as the core to the firms' operations (e.g., utilities, energy, transportation). On the other hand, I observe that $CO_2$ per one million in marker value significantly declined 12.9% after issuing green bonds. Consistently, after issuing green bonds, the issuers' environment and social score increase significantly by 4.6 and 9.8 points, respectively. Our results are consistent with the signaling argument that firms issue green bonds to signal the market that they intend to improve their environmental footprint.

Furthermore, I use disagreement sentiment in climate change news, climate change-induced uncertainty, economic policy uncertainty, and political uncertainty to show that national-level uncertainty is negatively related to firms' environmental performance following green bond issuance. From a theoretical standpoint, these findings support the real options theory.

Last, I discover strong evidence that climate communication plays an essential role in firms' commitment to improving their environmental footprint. Especially, climate news related to physical climate change and climate policy encourages firms to commit better to sustainability.

We bring in four practical implications for green bond issuance based on our results. First, these findings are valuable to investors who are sensitive to the environment. Our findings suggest that when firms issue green bonds, they genuinely signal investors their real intention in improving environmental engagement. Second, for directors and managers, I also analyze a set of dynamic national-level uncertainties that can drive firms' sustainability performance. Third, our results should be of interest to policymakers. Since external uncertainties have adverse effects on a firm's sustainability performance, such policy or political uncertainties can be reduced by introducing appropriate public policies. Lastly, climate communication can also be benefited from this paper. As firms can be encouraged to solve environmental issues by specific climate change topics mentioned in the news, news media can display more climate facts, especially ones that are related to physical climate change and climate policies.

Neverthless, this chapter encounters some limitations. The paper only considers environmental score and $CO_2$ assumption as indicators for firms' sustainability investments. However, several data points can be taken into account, such as GHG emmision, renewable energy or waste management scores. We leave this space for future research.

**Appendix: List of variables**

| VARIABLES | ABBREVIATION | MEASUREMENT | SOURCE |
|---|---|---|---|
| **DEPENDENT VARIABLES** | | | |
| ESG score | ESG | Refinitiv's ESG Score is an overall company score based on the self-reported information in the environmental, social, and corporate governance pillars. | DataStream |
| Environmental Score | EnvScore | Refinitiv's environmental score pillar based on the self-reported information | DataStream |
| Social Score | SocScore | Refinitiv's social score pillar based on the self-reported information | DataStream |
| Governance Score | GovScore | Refinitiv's governance score pillar based on the self-reported information | DataStream |
| CO2 consumption | CO2 | Total Carbon dioxide (CO2) and CO2 equivalents emission in a million tonnes. Following gases are relevant: carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), hydrofluorocarbons (HFCS), perfluorinated compound (PFCS), sulfur hexafluoride (SF6), nitrogen trifluoride (NF3) | DataStream |
| CO2 over market value | CO2_MV | Total Carbon dioxide (CO2) and CO2 equivalents emission in tonnes divided firms’ market value. | DataStream |

| INDEPENDENT VARIABLES | | | |
|---|---|---|---|
| Disagreement sentiment | DoS_LM/ DoS_WM | $$DoS_t = \left\| \frac{x_{p,t} - x_{p,all}}{\sigma_{p,all}} + \frac{x_{n,t} - x_{n,all}}{\sigma_{n,all}} \right\|$$ $x_{p,t}$ and $x_{n,t}$ are positive and negative probabilities based on Loughran and McDonald's (2011) classification and WMatrix corpus analysis tool. $x_{p,all}$ and $x_{n,all}$ are the average percentage of positive and negative probabilities detected during the time frame of the data set. $\sigma_{p,all}$ and $\sigma_{n,all}$ are standard deviation for positive and negative sentiments | News collected from ProQuest. |
| Uncertainty sentiment | UNC_LM/UNC_ WM | $$UNC_t = \left\| \frac{x_{u,t} - x_{u,all}}{\sigma_{u,all}} \right\|$$ $x_{u,t}$ is uncertainty probability based on Loughran and McDonald's (2011) classification and WMatrix corpus analysis tool. $x_{u,all}$ is average percentage uncertainty probability detected during the time frame of the dataset. $\sigma_{p,all}$ and $\sigma_{n,all}$ are standard deviation for uncertainty probability. | News collected from ProQuest. |

| | | | |
|---|---|---|---|
| Economic Policy Uncertainty | EPU | National-level economic policy uncertainty | Baker et al.(2016) |
| Climate change uncertainty | CCU | Climate change-induced uncertainty | The Notre Dame Global Adaptation Index |
| Political uncertainty | PSU | Political system stability, I multiplied minus one with the political system stability index to calculate PSU to make that the higher PSU index, the more politically unstable, and vice versa | World Bank's Worldwide Governance Indicators Project |
| Physical climate topics | PHY | The climate change news topics are classified using a corpus analysis and comparison tool developed by Lancaster University (Rayson, 2008).<br><br>For content analysis, I get the most mentioned categories: ENV (environment), HOU (house), FOOD (food), SOC (social), and POL (government and policy). For this research, I categorize the PHY index (physical climate change and its impact on climate news) equals to sum relative frequency of ENV, HOU, and FOOD | Calculated by authors, WMatrix |
| Social climate topics | SOC | | |
| Climate policy topics | POL | | |
| **CONTROL VARIABLES** | | | |
| Return on Asset | ROA | Firms' return on asset | DataStream |
| Company size | SIZE | The natural logarithm of total assets in local currency. | DataStream |

| | | | |
|---|---|---|---|
| Leverage | LEV | $$Leverage = \frac{Long - term\ debt}{total\ equity}$$ | DataStream |
| Tobin's Q | TobinQ | $$Tobin's\ Q = \frac{Enterprise\ Value}{Total\ Asset}$$ | Calculated by authors, DataStream |

# Conclusion

This thesis studies the impact of climate change risks on investors' behaviours as well as companies' practices.

I demonstrate that disagreement and uncertainty sentiments in climate change news affect trading behaviours and asset returns on the stock market. I describe the effect in a daily panel data model (Chapter 1). The results show that an increase (decrease) of disagreement and uncertainty sentiments in news leads to an increase (decrease) in stock volatility and trading volumes. When a piece of news is published, investors interpret it differently, leading to diverged beliefs. Investors' trading activities in the stock market will reflect this difference, thus leading to higher stock trading volumes and stock volatility. Disagreement and uncertainty sentiments improve approximately 15% of firms' stock trading volumes. I also show that disagreement sentiment impacts abnormal stock returns differently than the impact of uncertainty sentiment on abnormal stock returns. These different effects on abnormal stock returns justify our rationale to examine disagreement and uncertainty sentiment separately. Results suggest that disagreement and uncertainty sentiment share similar characters but do not entirely amount to the same scale. There may be disagreement among people regarding the extent of climate change uncertainty, resulting in a different impact on asset returns.

I also examine the effectiveness of firms' environmental performance in hedging against various climate risks (Chapter 2). Since disagreement and uncertainty sentiments are shown to affect stock performance in chapter 1, I use these sentiments together with national-level climate change-induced uncertainty and physical climate change topics covered in the news as four climate risk hedge targets. Using mimicking portfolio approach, I document that both environment performance scores and reporting scores can construct well-mixed portfolios that can hedge against climate change risks from several sources, both in and out of sample. In some cases, portfolios based on ESG disclosure scores outperform those constructed using ESG performance scores. This result suggests that it would be necessary for studies that focus on portfolios construction to consider both environmental performance and reporting scores to build hedge portfolios.

Finally, I also document firms' sustainability practices when they promise to improve their environmental footprint by focusing on green bonds and the green bond market (Chapter 3). To do so, I match green bond issuers with non-green bond issuers by using propensity matching scores then run the difference-in-difference model with a matching data set. The difference-in-difference models compare the $CO_2$ consumptions, ESG score, and environment scores of the treatment group (green bond issuers) with the matched control group (non-green bond issuers) before and after issuance. I observe that firms' $CO_2$ per one million in marker value significantly declined 12.9% post green bond issuance. Consistently, the results show that after issuing green bonds, the issuers' environment and social score increases significantly by 4.6 and 9.8 points. Note that these results do not indicate a causal effect of green bonds issuance on environmental practices. Instead, it demonstrates that green bonds serve as a credible signal for companies' commitment to the environment. In addition, I discover that national-level uncertainties, including disagreement sentiment in climate change news, climate change-induced uncertainty, economic policy uncertainty, and political uncertainty discourages firms' long-term investment. Furthermore, I observe strong evidence that climate communication plays an essential role in firms' commitment to improving their environmental footprint. Notably, climate news related to physical climate change and climate policy urges firms to commit better to sustainability.

The results of this thesis have several implications. First, for investors, (i) the results in this thesis show that sentiments derived from daily climate news would be an essential climate change risk that investors should consider when investing. The thesis also demonstrates that it is financially profitable to use companies' environment scores to protect investors' portfolios from climate change risks and uncertainties. Furthermore, (ii) for investors who are sensitive to the environment, our findings suggest that green bonds are a credible signal regarding companies' commitment to improving their environmental footprint. Since this commitment materializes in eco-friendly practices, firms invest more and improve their sustainability performance.

Secondly, for managers and directors, the findings in this thesis show that (i) firms' environmental performance and disclosure information can mitigate climate change risks from several sources. For example, in the presence of disagreement and uncertainty sentiment in climate news, ESG performance and disclosure scores weaken the positive effect of these sentiments on stock volatility and trading volume. It allows formulating managerial recommendations regarding firms' environmental data. For example, it suggests that firms can make environmental information available to investors to reduce the impact of climate change uncertainties on stock prices. In addition, (ii) I also analyze a set of dynamic national-level uncertainties that can negatively drive firms' sustainability performance, including disagreement sentiment in climate change news, climate change-induced uncertainty, economic policy uncertainty, and political uncertainty. Developing appropriate policies and considering climate change impact as part of the company's risk profile will help companies act timely and ensure consistent investment in improving their environmental footprint.

Lastly, from policymakers' point of view, since external uncertainties have undesirable effects on a firm's sustainability performance, such policy or political uncertainties can be lessened by introducing appropriate public policies. Moreover, as firms can be encouraged to solve environmental issues by specific climate change topics stated in the news, the media should present specific facts regarding global warming to fully understand the issues, especially news related to physical climate change or climate policies. Lastly, public support of green finance should be enhanced, primarily through uniform environmental performance ratings and green investment classification. These standards will offer investors more truthful information on the environmental impacts of firms in which they seek to invest.

This thesis sheds light on several possible research in the future. Firstly, as I only studied individual investors' reactions by examining the movement in stock markets, thus the practices of shareholders participating in companies' sustainability engagements and reforming the decisions are left untouched. Within the impact investing approach of climate finance, the shareholder engagement approach aims to increase the participation in polluting companies to push for the cut in their environmental impacts. These shareholder engagement practices have potential interaction with ESG integration and divestment decisions that have not been examined in literature as far as the author is aware of. Therefore, it represents an exciting line of research in the future. Secondly, as more data becomes available, especially environment performance rating scores or green bond standards, future research could deliver larger-scale evidence on the extensive benefits of corporate green bonds. In addition, our findings also highlight that our mimicking portfolio approach performs the worst against innovations in climate change-induced uncertainty. Future research can examine a better set of characteristics to adequately capture cross-sectional variation in exposure to this type of climate change risk. Lastly, the relationship between asset pricing and climate finance is examined more and more in the literature. Future researches can continue to shed light on how finance could assist and encourage the ecological transition.

# Reference


AARTS, H. & DIJKSTERHUIS, A. 2003. The silence of the library: environment, situational norm, and social behavior. *Journal of Personality and Social Psychology,* 84**,** 18-28.

ABREU, M. & MENDES, V. 2012. Information, overconfidence and trading: Do the sources of information matter? *Journal of Economic Psychology,* 33**,** 868-881.

AKERLOF, G. A. 1970. The Market for "Lemons": Quality Uncertainty and the Market Mechanism*. *The Quarterly Journal of Economics,* 84**,** 488-500.

ALIZADEH, S., BRANDT, M. W. & DIEBOLD, F. X. 2002. Range-Based Estimation of Stochastic Volatility Models. *The Journal of Finance,* 57**,** 1047-1091.

ALLAIS, M. 1953. Le comportement de l'homme rationnel devant le risque: Critique des postulats et axiomes de l'ecole Americaine. [Rational man's behavior in the presence of risk: critique of the postulates and axioms of the American school.]. *Econometrica,* 21**,** 503-546.

ANDERSEN, T. G. 1996. Return Volatility and Trading Volume: An Information Flow Interpretation of Stochastic Volatility. *The Journal of Finance,* 51**,** 169-204.

ANDERSSON, M., BOLTON, P. & SAMAMA, F. 2016. Hedging Climate Risk. *Financial Analysts Journal,* 72**,** 13-32.

ANTONIOU, C., HARRIS, R. D. F. & ZHANG, R. 2015. Ambiguity aversion and stock market participation: An empirical analysis. *Journal of Banking & Finance,* 58**,** 57-70.

ANTWEILER, W. & FRANK, M. 2004. Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards. *Journal of Finance,* 59**,** 1259-1294.

ARNELL, N. W. & GOSLING, S. N. 2016. The impacts of climate change on river flood risk at the global scale. *Climatic Change,* 134**,** 387-401.

ASHWIN KUMAR, N. C., SMITH, C., BADIS, L., WANG, N., AMBROSY, P. & TAVARES, R. 2016. ESG factors and risk-adjusted performance: a new quantitative model. *Journal of Sustainable Finance & Investment,* 6**,** 292-300.

ATMAZ, A. & BASAK, S. 2018. Belief Dispersion in the Stock Market. *The Journal of Finance,* 73**,** 1225-1279.

ATTIG, N., EL GHOUL, S., GUEDHAMI, O. & SUH, J. 2013. Corporate Social Responsibility and Credit Ratings. *Journal of Business Ethics,* 117**,** 679-694.

AUDRINO, F., SIGRIST, F. & BALLINARI, D. 2020. The impact of sentiment and attention measures on stock market volatility. *International Journal of Forecasting,* 36**,** 334-357.

AUGUSTIN, P. & IZHAKIAN, Y. 2019. Ambiguity, Volatility, and Credit Risk. *The Review of Financial Studies,* 33**,** 1618-1672.

AYBARS, A., ATAÜNAL, L. & GÜRBÜZ, A. 2018. ESG and Financial Performance: Impact of Environmental, Social and Governance Issues on Corporate Performance.

BAKER, M. & WURGLER, J. 2006. Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance,* 61**,** 1645-1680.

BAKER, S. R., BLOOM, N. & DAVIS, S. J. 2016. Measuring Economic Policy Uncertainty*. *The Quarterly Journal of Economics,* 131**,** 1593-1636.

BAMBER, L. S., BARRON, O. E. & STEVENS, D. E. 2011. Trading Volume Around Earnings Announcements and Other Financial Reports: Theory, Research Design, Empirical Evidence, and Directions for Future Research*. *Contemporary Accounting Research,* 28**,** 431-471.

BANCEL, F. & GLAVAS, D. 2018. Are Agency Problems a Determinant of Green Bond Issuance? *SSRN Electronic Journal*.

BANERJEE, S., DAVIS, J. & GONDHI, N. 2019. Choosing to Disagree in Financial Markets. *SSRN Electronic Journal*.

BANERJEE, S. & KREMER, I. 2010. Disagreement and Learning: Dynamic Patterns of Trade. *The Journal of Finance,* 65**,** 1269-1302.

BARBER, B., MORSE, A. & YASUDA, A. 2020. Impact Investing. *Journal of Financial Economics,* 139.

BARBER, B. & ODEAN, T. 2001. Boys Will Be Boys: Gender, Overconfidence, And Common Stock Investment. *The Quarterly Journal of Economics,* 116**,** 261-292.
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**,** 785-818.
BARBERIS, N. & THALER, R. 2002. A Survey of Behavioral Finance. *Advances in Behavioral Finance,* 2.
BARLEVY, G. & VERONESI, P. 2003. Rational panics and stock market crashes. *Journal of Economic Theory,* 110**,** 234-263.
BARNEA, A. & RUBIN, A. 2010. Corporate Social Responsibility as a Conflict Between Shareholders. *Journal of Business Ethics,* 97**,** 71-86.
BASER, O. 2006. Too Much Ado about Propensity Score Models? Comparing Methods of Propensity Score Matching. *Value in Health,* 9**,** 377-385.
BAUER, R., KOEDIJK, K. & OTTEN, R. 2005. International evidence on ethical mutual fund performance and investment style. *Journal of Banking & Finance,* 29**,** 1751-1767.
BAULKARAN, V. 2019. Stock market reaction to green bond issuance. *Journal of Asset Management,* 20**,** 331-340.
BEACH, L. R. & STROM, E. 1989. A toadstool among the mushrooms: Screening decisions and image theory's compatibility test. *Acta Psychologica,* 72**,** 1-12.
BEBBINGTON, K., MACLEOD, C., ELLISON, T. M. & FAY, N. 2016. The sky is falling: Evidence of a negativity bias in the social transmission of information. *Evolution and Human Behavior,* 38.
BENABOU, R. & TIROLE, J. 2010. Individual and Corporate Social Responsibility. *Economica,* 77**,** 1-19.
BENARTZI, S. & THALER, R. H. 1995. Myopic Loss Aversion and the Equity Premium Puzzle. *The Quarterly Journal of Economics,* 110**,** 73-92.
BERKMAN, H., DIMITROV, V., JAIN, P., KOCH, P. & TICE, S. 2009. Sell on the News: Differences of Opinion, Short-Sales Constraints, and Returns Around Earnings Announcements. *Journal of Financial Economics,* 92**,** 376-399.
BERNANKE, B. S. 1983. Nonmonetary Effects of the Financial Crisis in the Propagation of the Great Depression. *The American Economic Review,* 73**,** 257-276.
BERNOULLI, D. 1954. Exposition of a New Theory on the Measurement of Risk. *Econometrica,* 22**,** 23.
BIRD, R., CHOI, D. F. S. & YEUNG, D. 2013. Market uncertainty, market sentiment, and the post-earnings announcement drift. *Review of Quantitative Finance and Accounting,* 43**,** 45-73.
BLACK, F. & SCHOLES, M. 1973. The Pricing of Options and Corporate Liabilities. *Journal of Political Economy,* 81**,** 637-54.
BLOOMBERG, M. 2017. Bloomberg says London will remain Europe's financial capital.
BOLTON, D. & LANDELLS, T. 2015. Reconceptualizing Power Relations as Sustainable Business Practice. *Business Strategy and the Environment,* 24**,** 604-616.
BOLTON, P. & KACPERCZYK, M. 2020a. Do Investors Care about Carbon Risk? *NBER Working Papers 26968*.
BOLTON, P. & KACPERCZYK, M. T. 2020b. Do Investors Care About Carbon Risk? *NBER Working Paper Series*.
BONAIME, A., GULEN, H. & ION, M. 2018. Does policy uncertainty affect mergers and acquisitions? *Journal of Financial Economics,* 129**,** 531-558.
BRAMMER, S., BROOKS, C. & PAVELIN, S. 2006. Corporate Social Performance and Stock Returns: UK Evidence from Disaggregate Measures. *Financial Management,* 35**,** 97-116.
BRENNER, M. & IZHAKIAN, Y. 2018. Asset Pricing and Ambiguity: Empirical Evidence. *Journal of Financial Economics,* 130.
BROADSTOCK, D. C. & CHENG, L. T. W. 2019. Time-varying relation between black and green bond price benchmarks: Macroeconomic determinants for the first decade. *Finance Research Letters,* 29**,** 17-22.
BURKE, M., HSIANG, S. M. & MIGUEL, E. 2015. Global non-linear effect of temperature on economic production. *Nature,* 527**,** 235-239.

CAI, Y., JUDD, K. L., LENTON, T. M., LONTZEK, T. S. & NARITA, D. 2015. Environmental tipping points significantly affect the cost−benefit assessment of climate policies. *Proceedings of the National Academy of Sciences,* 112**,** 4606-4611.
CAI, Y. & LONTZEK, T. S. 2019. The Social Cost of Carbon with Economic and Climate Risks. *Journal of Political Economy,* 127**,** 2684-2734.
CAI, Y., PAN, C. H. & STATMAN, M. 2016. Why do countries matter so much in corporate social performance? *Journal of Corporate Finance,* 41**,** 591-609.
CAO, H., WANG, T. & ZHANG, H. 2005a. Model Uncertainty, Limited Market Participation, and Asset Prices. *Review of Financial Studies,* 18**,** 1219-1251.
CAO, H. H., WANG, T. & ZHANG, H. H. 2005b. Model Uncertainty, Limited Market Participation, and Asset Prices. *Review of Financial Studies,* 18**,** 1219-1251.
CARHART, M. M. 1997. On Persistence in Mutual Fund Performance. *The Journal of Finance,* 52**,** 57-82.
CARLIN, B. I., LONGSTAFF, F. A. & MATOBA, K. 2014. Disagreement and asset prices. *Journal of Financial Economics,* 114**,** 226-238.
CARNEY, M. 2015. *RE: Breaking the tragedy of the horizon - climate change and financial stability*
CHAN, G. 2019a. 'Action now': the farmers standing up against 'wilful ignorance' on climate. *The Guardian*.
CHAN, G. 2019b. 'Action now': the farmers standing up against 'wilful ignorance' on climate.
CHAN, K. 1998. Mass communication and pro-environmental behaviour: waste recycling in Hong Kong. *Journal of Environmental Management,* 52**,** 317-325.
CHAN, L. & LIEN, D. 2001. Using high, low, open, and closing prices to estimate the effects of cash settlement on futures prices. *International Review of Financial Analysis,* 12**,** 35-47.
CHANG, S.-C., CHEN, S.-S., CHOU, R. & LIN, Y.-H. 2008. Weather and intraday patterns in stock returns and trading activity. *Journal of Banking & Finance,* 32**,** 1754-1766.
CHAVA, S. 2014. Environmental Externalities and Cost of Capital. *Management Science,* 60**,** 2223-2247.
CHEN, M.-P., CHEN, P.-F. & LEE, C.-C. 2013. Asymmetric effects of investor sentiment on industry stock returns: Panel data evidence. *Emerging Markets Review,* 14**,** 35–54.
CHEN, Y., GHOSH, M., LIU, Y. & ZHAO, L. 2019. Media Coverage of Climate Change and Sustainable Product Consumption: Evidence from the Hybrid Vehicle Market. *Journal of Marketing Research,* 56**,** 995-1011.
CHOI, D., GAO, Z. & JIANG, W. 2018. Attention to Global Warming. *SSRN Electronic Journal*.
CHRISTIANSEN, C., SCHMELING, M. & SCHRIMPF, A. 2012. A comprehensive look at financial volatility prediction by economic variables. *Journal of Applied Econometrics,* 27**,** 956-977.
CLAXTON, J. D., FRY, J. N. & PORTIS, B. 1974. A taxonomy of prepurchase information gathering patterns. *Journal of consumer research,* 1**,** 35-42.
COHEN, L. 2009. Loyalty-Based Portfolio Choice. *Review of Financial Studies,* 22**,** 1213-1245.
CONNAKER, A. & MADSBJERG, S. 2019. *The State of Socially Responsible Investing* [Online]. Havard Business Review. Available: https://hbr.org/2019/01/the-state-of-socially-responsible-investing [Accessed 2020].
COOPER, M. J., MCCONNELL, J. J. & OVTCHINNIKOV, A. V. 2005. The Other January Effect. *Journal of Financial Economics,* 82**,** 315-341.
COUDERT, V. & GEX, M. 2008. Does risk aversion drive financial crises? Testing the predictive power of empirical indicators. *Journal of Empirical Finance,* 15**,** 167-184.
COVAL, J. D. & SHUMWAY, T. 2005. Do Behavioral Biases Affect Prices? *The Journal of Finance,* 60**,** 1-34.
CRANE, A., MATTEN, D. & SPENCE, L. 2013. *Corporate Social Responsibility: Readings and Cases in a Global Context*, Routledge.
D'AMICO, S. & ORPHANIDES, A. 2008. Uncertainty and disagreement in economic forecasting. Board of Governors of the Federal Reserve System (U.S.).

DA, Z., ENGELBERG, J. & GAO, P. 2015. The Sum of All FEARS Investor Sentiment and Asset Prices. *Review of Financial Studies,* 28**,** 1-32.
DANIEL, K. D., HIRSHLEIFER, D. & SUBRAHMANYAM, A. 2001. Overconfidence, Arbitrage, and Equilibrium Asset Pricing. *The Journal of Finance,* 56**,** 921-965.
DAVIS, A., GE, W., MATSUMOTO, D. & ZHANG, J. L. 2015. The effect of manager-specific optimism on the tone of earnings conference calls. *Review of Accounting Studies,* 20**,** 639-673.
DE VILLIERS, C., NAIKER, V. & VAN STADEN, C. J. 2011. The Effect of Board Characteristics on Firm Environmental Performance. *Journal of Management,* 37**,** 1636-1663.
DERWALL, J., GUENSTER, N., BAUER, R. & KOEDIJK, K. 2005. The Eco-Efficiency Premium Puzzle. *Financial Analysts Journal,* 61**,** 51-63.
DERYUGINA, T. & HSIANG, S. 2014. *Does the Environment Still Matter? Daily Temperature and Income in the United States*.
DHALIWAL, D. S., LI, O. Z., TSANG, A. & YANG, Y. G. 2011. Voluntary Nonfinancial Disclosure and the Cost of Equity Capital: The Initiation of Corporate Social Responsibility Reporting. *The Accounting Review,* 86**,** 59-100.
DHALIWAL, D. S., RADHAKRISHNAN, S., TSANG, A. & YANG, Y. G. 2012. Nonfinancial Disclosure and Analyst Forecast Accuracy: International Evidence on Corporate Social Responsibility Disclosure. *The Accounting Review,* 87**,** 723-759.
DIAZ-RAINEY, I., ROBERTSON, B. & WILSON, C. 2017. Stranded research? Leading finance journals are silent on climate change. *Climatic Change,* 143**,** 243-260.
DONG, R., FISMAN, R., WANG, Y. & XU, N. 2019. Air pollution, affect, and forecasting bias: Evidence from Chinese financial analysts. *Journal of Financial Economics*.
DRECHSLER, I. 2013. Uncertainty, Time-Varying Fear, and Asset Prices. *The Journal of Finance,* 68**,** 1843-1889.
EASLEY, D. & O'HARA, M. 2009. Ambiguity and Nonparticipation: The Role of Regulation. *Review of Financial Studies,* 22**,** 1817-1843.
ECCLES, R., IOANNOU, I. & SERAFEIM, G. 2014a. The Impact of Corporate Sustainability on Organizational Processes and Performance. *Management Science,* 60**,** 2835-2857.
ECCLES, R. G., IOANNOU, I. & SERAFEIM, G. 2014b. The Impact of Corporate Sustainability on Organizational Processes and Performance. *Management Science,* 60**,** 2835-2857.
EIKON 2017. Thomson Reuters ESG Scores.
EL GHOUL, S., GUEDHAMI, O., KWOK, C. C. Y. & MISHRA, D. 2011. Does corporate social responsibility affect the cost of capital? *Journal of Banking & Finance,* 35**,** 2388-2406.
ELKINGTON, J. 1994. Towards the Sustainable Corporation: Win-Win-Win Business Strategies for Sustainable Development. *California Management Review,* 36**,** 90-100.
ELLSBERG, D. 1961a. Risk, Ambiguity, and the Savage Axioms. *The Quarterly Journal of Economics,* 75**,** 643.
ELLSBERG, D. 1961b. Risk, Ambiguity, and the Savage Axioms. *The Quarterly Journal of Economics,* 75**,** 643-669.
ENGLE, R. F., GIGLIO, S., KELLY, B., LEE, H. & STROEBEL, J. 2020. Hedging Climate Change News. *The Review of Financial Studies,* 33**,** 1184-1216.
EPSTEIN, L. G. & SCHNEIDER, M. 2008. Ambiguity, Information Quality, and Asset Pricing. *The Journal of Finance,* 63**,** 197-228.
EPSTEIN, L. G. & SCHNEIDER, M. 2010. Ambiguity and Asset Markets. *Annual Review of Financial Economics,* 2**,** 315-346.
ESCRIG-OLMEDO, E., FERNÁNDEZ-IZQUIERDO, M. Á., FERRERO-FERRERO, I., RIVERA-LIRIO, J. M. & MUÑOZ-TORRES, M. J. 2019. Rating the Raters: Evaluating how ESG Rating Agencies Integrate Sustainability Principles. *Sustainability,* 11**,** 915.
FAMA, E. F. & FRENCH, K. 2007. Disagreement, tastes, and asset prices. *Journal of Financial Economics,* 83**,** 667-689.

FAMA, E. F. & FRENCH, K. R. 1992. The Cross-Section of Expected Stock Returns. *The Journal of Finance,* 47**,** 427-465.
FAMA, E. F. & FRENCH, K. R. 1996. Multifactor explanations of asset pricing anomalies. *Journal of Finance,* 51**,** 55-84.
FESSLER, D. M. T., PISOR, A. C. & NAVARRETE, C. D. 2014. Negatively-Biased Credulity and the Cultural Evolution of Beliefs. *PLoS ONE,* 9**,** e95167.
FESTINGER, L. 1962. Cognitive dissonance. *Scientific American,* 207**,** 93-107.
FLAMMER, C. 2021. Corporate green bonds. *Journal of Financial Economics*.
FLAMMER, C. & BANSAL, P. 2017. Does a long-term orientation create value? Evidence from a regression discontinuity. *Strategic Management Journal,* 38**,** 1827-1847.
FRIEDE, G., BUSCH, T. & BASSEN, A. 2015. ESG and financial performance: aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance & Investment,* 5**,** 210-233.
FRIEDMAN, M. 1970. The Social Responsibility of Business Is to Increase Its Profits. *Corporate Ethics and Corporate Governance.* Springer Berlin Heidelberg.
GALEMA, R., PLANTINGA, A. & SCHOLTENS, B. 2008. The stocks at stake: Return and risk in socially responsible investment. *Journal of Banking & Finance,* 32**,** 2646-2654.
GALLANT, A. R., HSU, C.-T. & TAUCHEN, G. 1999a. Using Daily Range Data to Calibrate Volatility Diffusions and Extract the Forward Integrated Variance. *Review of Economics and Statistics,* 81**,** 617-631.
GALLANT, A. R., HSU, C.-T. & TAUCHEN, G. 1999b. Using Daily Range Data to Calibrate Volatility Diffusions and Extract the Forward Integrated Variance. *The Review of Economics and Statistics,* 81**,** 617-631.
GARCÍA, D. 2013. Sentiment during Recessions. *The Journal of Finance,* 68**,** 1267-1300.
GIANNINI, R., IRVINE, P. & SHU, T. 2019. The convergence and divergence of investors' opinions around earnings news: Evidence from a social network. *Journal of Financial Markets,* 42**,** 94-120.
GILBOA, I. & SCHMEIDLER, D. 1989. Maxmin expected utility with non-unique prior. *Journal of Mathematical Economics,* 18**,** 141-153.
GILLIS, J. 2012. Clouds' Effect on Climate Change Is Last Bastion for Dissenters.
GIORDANI, P. & SÖDERLIND, P. 2003. Inflation forecast uncertainty. *European Economic Review,* 47**,** 1037-1059.
GLAS, A. & HARTMANN, M. 2016a. Inflation uncertainty, disagreement and monetary policy: Evidence from the ECB Survey of Professional Forecasters. *Journal of Empirical Finance,* 39**,** 215-228.
GLAS, A. & HARTMANN, M. 2016b. Inflation uncertainty, disagreement and monetary policy: Evidence from the ECB Survey of Professional Forecasters. University of Heidelberg, Department of Economics.
GODFREY, P. C. 2005. The Relationship Between Corporate Philanthropy And Shareholder Wealth: A Risk Management Perspective. *Academy of Management Review,* 30**,** 777-798.
GOMEZ-CARRASCO, P. & MICHELON, G. 2017. The Power of Stakeholders' Voice: The Effects of Social Media Activism on Stock Markets. *Business Strategy and the Environment,* 26**,** 855-872.
GONCALVES, S. & MEDDAHI, N. 2011. Box-Cox transforms for realized volatility. *Journal of Econometrics,* 160**,** 129-144.
GREGORY, A., THARYAN, R. & CHRISTIDIS, A. 2013. Constructing and Testing Alternative Versions of the Fama-French and Carhart Models in the UK. *Journal of Business Finance & Accounting,* 40**,** 172-214.
GREGORY, R. P. 2021. The pricing of global temperature shocks in the cost of equity capital. *Journal of International Financial Markets, Institutions and Money,* 72**,** 101319.
GRIFFIN, P., LONT, D. & LUBBERINK, M. 2019. Extreme high surface temperature events and equity-related physical climate risk. *Weather and Climate Extremes,* 26**,** 100220.
GRIFFITH, S. J. & REISEL, N. 2019. Dead Hand Proxy Puts and Hedge Fund Activism. *Journal of Financial and Quantitative Analysis,* 54**,** 1615-1642.

GUENSTER, N., BAUER, R., DERWALL, J. & KOEDIJK, K. 2011. The Economic Value of Corporate Eco-Efficiency. *European Financial Management,* 17, 679-704.

GULEN, H. & ION, M. 2015. Policy Uncertainty and Corporate Investment. *Review of Financial Studies*, hhv050.

HAMBEL, C., KRAFT, H. & SCHWARTZ, E. S. 2018. The Carbon Abatement Game. *Macroeconomics: Aggregative Models eJournal*.

HANSEN, J., SATO, M. & RUEDY, R. 2012. Perception of climate change. *Proceedings of the National Academy of Sciences,* 109, E2415-E2423.

HANSSON, S. O. 2005. Decision Theory: A Brief Introduction.

HARJOTO, M. A. & JO, H. 2015. Legal vs. Normative CSR: Differential Impact on Analyst Dispersion, Stock Return Volatility, Cost of Capital, and Firm Value. *Journal of Business Ethics,* 128, 1-20.

HASTINGS, G., STEAD, M. & WEBB, J. 2004. Fear appeals in social marketing: Strategic and ethical reasons for concern. *Psychology and Marketing,* 21, 961-986.

HEAL, G. & PARK, J. 2013. Feeling the Heat: Temperature, Physiology & the Wealth of Nations. National Bureau of Economic Research, Inc.

HENDERSON, G., COX, F., GANESH, S., JONKER, A., YOUNG, W. & JANSSEN, P. H. 2015. Rumen microbial community composition varies with diet and host, but a core microbiome is found across a wide geographical range. *Scientific Reports,* 5, 14567.

HENDERSON, R. M., REINERT, S. A., DEKHTYAR, P. & MIGDAL, A. 2018. Climate Change in 2018: Implications for Business.

HESTON, S. L. & SINHA, N. R. 2017. News vs. Sentiment: Predicting Stock Returns from News Stories. *Financial Analysts Journal,* 73, 67-83.

HISANO, R., SORNETTE, D., MIZUNO, T., OHNISHI, T. & WATANABE, T. 2013. High Quality Topic Extraction from Business News Explains Abnormal Financial Market Volatility. *PLoS ONE,* 8.

HOLT, D. & BARKEMEYER, R. 2012. Media coverage of sustainable development issues - attention cycles or punctuated equilibrium? *Sustainable Development,* 20, 1-17.

HONG, H. & KACPERCZYK, M. 2009. The price of sin: The effects of social norms on markets. *Journal of Financial Economics,* 93, 15-36.

HONG, H., LI, F. W. & XU, J. 2019. Climate risks and market efficiency. *Journal of Econometrics,* 208, 265-281.

HONG, H. & SRAER, D. A. 2016. Speculative Betas. *The Journal of Finance,* 71, 2095-2144.

HONG, H. & STEIN, J. C. 2007. Disagreement and the Stock Market. *Journal of Economic Perspectives,* 21, 109-128.

HSIANG, S. M. & JINA, A. S. 2014. The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence From 6,700 Cyclones. *National Bureau of Economic Research Working Paper Series,* No. 20352.

HSU, P.-H., LI, K. & TSOU, C.-Y. 2019. The Pollution Premium. *Environmental Justice & Sustainability eJournal*.

HUBERMAN, G. 2001. Familiarity Breeds Investment. *The Review of Financial Studies,* 14, 659–680.

HUMPHREY, J. E. & TAN, D. T. 2014. Does it Really Hurt to be Responsible? *Journal of Business Ethics,* 122, 375-386.

ILLEDITSCH, P. K. 2011. Ambiguous Information, Portfolio Inertia, and Excess Volatility. *The Journal of Finance,* 66, 2213-2247.

IMF. 2020. *World Uncertainty Index* [Online]. International Monetary Fund. Available: https://worlduncertaintyindex.com/data/ [Accessed 2020].

IOANNOU, I. & SERAFEIM, G. 2012. What drives corporate social performance? The role of nation-level institutions. *Journal of International Business Studies,* 43, 834-864.

IPCC 2014. Climate Change 2014 Synthesis Report. *In:* TEAM, T. C. W., PACHAURI, R. K. & MEYER, L. (eds.).

JAKOB, M. & HILAIRE, J. 2015. Unburnable fossil-fuel reserves. *Nature,* 517, 150-151.

JEGADEESH, N. & WU, D. 2013. Word power: A new approach for content analysis. *Journal of Financial Economics,* 110**,** 712-729.
JENS, C. E. 2017. Political uncertainty and investment: Causal evidence from U.S. gubernatorial elections. *Journal of Financial Economics,* 124**,** 563-579.
JENSEN, S. & TRAEGER, C. 2014. Optimal climate change mitigation under long-term growth uncertainty: Stochastic integrated assessment and analytic findings. *European Economic Review,* 69**,** 104-125.
JIA, J. & LI, Z. 2020. Does external uncertainty matter in corporate sustainability performance? *Journal of Corporate Finance,* 65**,** 101743.
JIAO, P., VEIGA, A. & WALTHER, A. 2020. Social media, news media and the stock market. *Journal of Economic Behavior & Organization,* 176**,** 63-90.
JO, H. & NA, H. 2012. Does CSR Reduce Firm Risk? Evidence from Controversial Industry Sectors. *Journal of Business Ethics,* 110**,** 441-456.
JONES, L. 2020. $1Trillion Mark Reached in Global Cumulative Green Issuance: Climate Bonds Data Intelligence Reports: Latest Figures.
JULIO, B. & YOOK, Y. 2012. Political Uncertainty and Corporate Investment Cycles. *The Journal of Finance,* 67**,** 45-83.
KAHNEMAN, D. & TVERSKY, A. 1979. Prospect Theory: An Analysis of Decision under Risk. *Econometrica,* 47**,** 263-291.
KARNANI, A. 2010. *The Case Against Corporate Social Responsibility* [Online]. MIT Sloan Management Review. Available: https://www.wsj.com/articles/SB10001424052748703338004575230112664504890 [Accessed].
KARPOFF, J. M. 1986. A Theory of Trading Volume. *The Journal of Finance,* 41**,** 1069-1087.
KASSINIS, G. & VAFEAS, N. 2006. Stakeholder Pressures And Environmental Performance. *Academy of Management Journal,* 49**,** 145-159.
KATORI, T. 2018. The Financial Potential of Green Bonds: Comparing the Three Issuing Schemes. *SSRN Electronic Journal*.
KEARNEY, C. & LIU, S. 2014. Textual sentiment in finance: A survey of methods and models. *International Review of Financial Analysis,* 33**,** 171-185.
KEMPF, A. & OSTHOFF, P. 2007. The Effect of Socially Responsible Investing on Portfolio Performance. *European Financial Management,* 13**,** 908-922.
KIEL, G. C. & LAYTON, R. A. 1981. Dimensions of Consumer Information Seeking Behavior. *Journal of Marketing Research,* 18**,** 233-239.
KING, B. G. & SOULE, S. A. 2007. Social Movements as Extra-Institutional Entrepreneurs: The Effect of Protests on Stock Price Returns. *Administrative Science Quarterly,* 52**,** 413-442.
KLEIN, L. & FORD, G. 2003. Consumer Search for Information in the Digital Age: An Empirical Study of Prepurchase Search for Automobiles. *Journal of Interactive Marketing,* 17**,** 29-49.
KOLSTAD, I. 2007. Why Firms Should Not Always Maximize Profits. *Journal of Business Ethics,* 76**,** 137-145.
KOSTOPOULOS, D., MEYER, S. & UHR, C. 2020. Google search volume and individual investor trading. *Journal of Financial Markets,* 49**,** 100544.
KRUEGER, P., SAUTNER, Z. & STARKS, L. T. 2020. The Importance of Climate Risks for Institutional Investors. *The Review of Financial Studies,* 33**,** 1067-1111.
KRÜGER, P. 2015. Corporate goodness and shareholder wealth. *Journal of Financial Economics,* 115**,** 304-329.
KRUTTLI, M., TRAN, B. & WATUGALA, S. 2019. Pricing Poseidon: Extreme Weather Uncertainty and Firm Return Dynamics. *Finance and Economics Discussion Series,* 2019.
KUMAR, K., BOESSO, G. & MICHELON, G. 2016. How Do Strengths and Weaknesses in Corporate Social Performance Across Different Stakeholder Domains Affect Company Performance? *Business Strategy and the Environment,* 25**,** 277-292.

LAKONISHOK, J. & MABERLY, E. 1990. The Weekend Effect: Trading Patterns of Individual and Institutional Investors. *Journal of Finance,* 45**,** 231-43.
LAZARUS, R. S. 1999. Hope: An Emotion and a Vital Coping Resource Against Despair. *Social Research,* 66**,** 653-678.
LEE, B., ROSENTHAL, L., VELD, C. & VELD-MERKOULOVA, Y. 2015. Stock market expectations and risk aversion of individual investors. *International Review of Financial Analysis,* 40**,** 122-131.
LI, F. 2006. Do Stock Market Investors Understand the Risk Sentiment of Corporate Annual Reports? *SSRN Electronic Journal*.
LI, G. & LI, D. 2011. Belief Dispersion Among Household Investors and Stock Trading Volume. *SSRN Electronic Journal*.
LI, Z., TANG, Y., WU, J., ZHANG, J. & LV, Q. 2020. The Interest Costs of Green Bonds: Credit Ratings, Corporate Social Responsibility, and Certification. *Emerging Markets Finance and Trade,* 56**,** 2679-2692.
LINSELL, K. 2017. The $123 Billion Question Hanging Over Renewable Energy.
LOUGHRAN, T. & MCDONALD, B. 2011. When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. *The Journal of Finance,* 66**,** 35-65.
LUSTIG, H., ROUSSANOV, N. & VERDELHAN, A. 2014. Countercyclical currency risk premia. *Journal of Financial Economics,* 111**,** 527-553.
LYON, T. P. & MONTGOMERY, A. W. 2015. The Means and End of Greenwash. *Organization & Environment,* 28**,** 223-249.
MACHINA, M. 1982. "Expected Utility" Analysis without the Independence Axiom. *Econometrica,* 50**,** 277-323.
MACKINTOSH, J. 2018. Is Tesla or Exxon More Sustainable? It Depends Whom You Ask.
MAENHOUT, P. J. 2004a. Robust Portfolio Rules and Asset Pricing. *The Review of Financial Studies,* 17**,** 951-983.
MAENHOUT, P. J. 2004b. Robust Portfolio Rules and Asset Pricing. *Review of Financial Studies,* 17**,** 951-983.
MAFFIOLETTI, A. & SANTONI, M. 2005. Do Trade Union Leaders Violate Subjective Expected Utility? Some Insights From Experimental Data. *Theory and Decision,* 59**,** 207-253.
MALIK, M. 2015. Value-Enhancing Capabilities of CSR: A Brief Review of Contemporary Literature. *Journal of Business Ethics,* 127**,** 419-438.
MANDELBROT, B. 1963. The Variation of Certain Speculative Prices. *The Journal of Business,* 36.
MARKOWITZ, H. 1952. PORTFOLIO SELECTION*. *The Journal of Finance,* 7**,** 77-91.
MARQUIS, C., TOFFEL, M. W. & ZHOU, Y. 2016. Scrutiny, Norms, and Selective Disclosure: A Global Study of Greenwashing. *Organization Science,* 27**,** 483-504.
MATSUMURA, E. M., PRAKASH, R. & VERA-MUNOZ, S. 2014. Firm-Value Effects of Carbon Emissions and Carbon Disclosure. *The Accounting Review,* 89**,** 695-724.
MERTON, R. C. 1973. An Intertemporal Capital Asset Pricing Model. *Econometrica,* 41**,** 867.
MIAO, J., WEI, B. & ZHOU, H. 2012. Ambiguity Aversion and Variance Premium. *SSRN Electronic Journal*.
MILLER, E. M. 1977. Risk, Uncertainty, and Divergence of Opinion. *The Journal of Finance,* 32**,** 1151-1168.
MISKA, C., SZŐCS, I. & SCHIFFINGER, M. 2018. Culture’s effects on corporate sustainability practices: A multi-domain and multi-level view. *Journal of World Business,* 53**,** 263-279.
MITTNIK, S., ROBINZONOV, N. & SPINDLER, M. 2015. Stock Market Volatility: Identifying Major Drivers and the Nature of Their Impact. *Journal of Banking & Finance,* 58**,** 1-14.
MORONEY, R., WINDSOR, C. & AW, Y. T. 2012. Evidence of assurance enhancing the quality of voluntary environmental disclosures: an empirical analysis. *Accounting & Finance,* 52**,** 903-939.

NONEJAD, N. 2017. Forecasting aggregate stock market volatility using financial and macroeconomic predictors: Which models forecast best, when and why? *Journal of Empirical Finance,* 42**,** 131-154.

NORDHAUS, W. D. 2017. Revisiting the social cost of carbon. *Proceedings of the National Academy of Sciences,* 114**,** 1518-1523.

ODEAN, T. 1998. Are Investors Reluctant to Realize Their Losses? *The Journal of Finance,* 53**,** 1775-1798.

OECD 2017. *Investing in Climate, Investing in Growth*.

ORLITZKY, M. 2013. Corporate Social Responsibility, Noise, and Stock Market Volatility. *Academy of Management Perspectives,* 27**,** 238-254.

ORLITZKY, M. & SHEN, J. 2013. Corporate Social Responsibility, Industry, and Strategy. *Industrial and Organizational Psychology,* 6**,** 346-350.

OZSOYLEV, H. & WERNER, J. 2011. Liquidity and asset prices in rational expectations equilibrium with ambiguous information. *Economic Theory,* 48**,** 469.

PARK, C. 2005. Stock Return Predictability and the Dispersion in Earnings Forecasts*. *The Journal of Business,* 78**,** 2351-2376.

PASTOR, L., STAMBAUGH, R. F. & TAYLOR, L. A. 2019. Sustainable Investing in Equilibrium. *SSRN Electronic Journal*.

PAYE, B. S. 2012. 'Déjà vol': Predictive regressions for aggregate stock market volatility using macroeconomic variables. *Journal of Financial Economics,* 106**,** 527-546.

PEETERS, G. 1971. The positive-negative asymmetry: On cognitive consistency and positivity bias. *European Journal of Social Psychology,* 1**,** 455-474.

PERESS, J. 2004. Wealth, Information Acquisition, and Portfolio Choice. *Review of Financial Studies,* 17**,** 879-914.

PETERSEN, M. A. 2009. Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *Review of Financial Studies,* 22**,** 435-480.

PHAN, D. H. B., SHARMA, S. S. & TRAN, V. T. 2018. Can economic policy uncertainty predict stock returns? Global evidence. *Journal of International Financial Markets, Institutions and Money,* 55**,** 134-150.

PIÑEIRO, J., LÓPEZ-CABARCOS, M., ROMERO-CASTRO, N. & PÉREZ-PICO, A. M. 2019. Innovation, entrepreneurship and knowledge in the business scientific field: Mapping the research front. *Journal of Business Research,* 115.

PLANTINGA, A., GALEMA, R. & SCHOLTENS, B. 2008. The Stocks at Stake: Return and Risk in Socially Responsible Investment. *Journal of Banking & Finance,* 32**,** 2646-2654.

PORTER, M. & KRAMER, M. 2003. The Competitive Advantage of Corporate Philanthropy. *Harvard business review,* 80**,** 56-68, 133.

PWC 2019. 22nd Annual Global CEO Survey.

RABIN, M. & THALER, R. H. 2001. Anomalies: Risk Aversion. *Journal of Economic Perspectives,* 15**,** 219-232.

RAYSON, P. 2008. From key words to key semantic domains. *International Journal of Corpus Linguistics,* 13**,** 519-549.

REICHELT, H. Green bonds : a model to mobilize private capital to fund climate change mitigation and adaptation projects. 2010.

REINHARDT, F. L. & STAVINS, R. N. 2010. Corporate social responsibility, business strategy, and the environment. *Oxford Review of Economic Policy,* 26**,** 164-181.

RENNEBOOG, L., TER HORST, J. & ZHANG, C. 2008. Socially responsible investments: Institutional aspects, performance, and investor behavior. *Journal of Banking & Finance,* 32**,** 1723-1742.

RICH, R. & TRACY, J. 2010. The Relationships among Expected Inflation, Disagreement, and Uncertainty: Evidence from Matched Point and Density Forecasts. *The Review of Economics and Statistics,* 92**,** 200-207.

RICH, R. & TRACY, J. 2018. A Closer Look at the Behavior of Uncertainty and Disagreement: Micro Evidence from the Euro Area. *Federal Reserve Bank of Dallas, Working Papers,* 2018.

RILEY, J. G. 1979. Informational Equilibrium. *Econometrica,* 47**,** 331.

ROZIN, P. 2001. Social Psychology and Science: Some Lessons From Solomon Asch. *Personality and Social Psychology Review,* 5**,** 2-14.

RUBIN, D. B. 2001. *Health Services and Outcomes Research Methodology,* 2**,** 169-188.

RUPANDE, L., MUGUTO, H. T., MUZINDUTSI, P.-F. & YANG, Z. 2019. Investor sentiment and stock return volatility: Evidence from the Johannesburg Stock Exchange. *Cogent Economics & Finance,* 7**,** 1600233.

SALZMAN, J. E. & HUNTER, D. B. 2007. Negligence in the Air: The Duty of Care in Climate Change Litigation. *University of Pennsylvania Law Review,* 155**,** 101-154.

SAVAGE, L. J. 1954. *The Foundations of Statistics*, Wiley Publications in Statistics.

SCHIERMEIER, Q. 2018a. Droughts, heatwaves and floods: How to tell when climate change is to blame. *Nature,* 560**,** 20-22.

SCHIERMEIER, Q. 2018b. Droughts, heatwaves and floods: How to tell when climate change is to blame. *Nature,* 560**,** 20-22.

SELDEN, G. C. 1912. *Psychology of the Stock Market: Human Impulses Lead To Speculative Disasters,* New York, Ticker Publishing.

SHEN, J., YU, J. & ZHAO, S. 2017. Investor sentiment and economic forces. *Journal of Monetary Economics,* 86**,** 1-21.

SHILLER, R. 1999. Human behavior and the efficiency of the financial system. *In:* TAYLOR, J. B. & WOODFORD, M. (eds.) *Handbook of Macroeconomics.* Elsevier.

SHLEIFER, A. & VISHNY, R. W. 1997. The Limits of Arbitrage. *The Journal of Finance,* 52**,** 35-55.

SHMIDT, G. A. 2015. Thoughts on 2014 and ongoing temperature trends. *RealClimate*.

SIGANOS, A., VAGENAS-NANOS, E. & VERWIJMEREN, P. 2014. Facebook's daily sentiment and international stock markets. *Journal of Economic Behavior & Organization,* 107.

SIGANOS, A., VAGENAS-NANOS, E. & VERWIJMEREN, P. 2017. Divergence of sentiment and stock market trading. *Journal of Banking & Finance,* 78**,** 130-141.

SLOAN, R. G. 1996. USING EARNINGS AND FREE CASH FLOW TO EVALUATE CORPORATE PERFORMANCE. *Journal of Applied Corporate Finance,* 9**,** 70-79.

SPENCE, M. 1973. Job Market Signaling. *The Quarterly Journal of Economics,* 87**,** 355.

SPENCE, M. 2002. Signaling in Retrospect and the Informational Structure of Markets. *The American Economic Review,* 92**,** 434-459.

STATMAN, M. & GLUSHKOV, D. 2008. The Wages of Social Responsibility. *Financial Analysts Journal,* 65.

STATMAN, M. & GLUSHKOV, D. 2016. Classifying and Measuring the Performance of Socially Responsible Mutual Funds. *The Journal of Portfolio Management,* 42**,** 140-151.

STERN, N. 2013. The Structure of Economic Modeling of the Potential Impacts of Climate Change: Grafting Gross Underestimation of Risk onto Already Narrow Science Models. *Journal of Economic Literature,* 51**,** 838-859.

SUN, L., NAJAND, M. & SHEN, J. 2016. Stock return predictability and investor sentiment: A high-frequency perspective. *Journal of Banking & Finance,* 73**,** 147-164.

TANG, D. & ZHANG, Y. 2020. Do shareholders benefit from green bonds? *Journal of Corporate Finance,* 61.

TANG, Z. & TANG, J. 2016. Can the Media Discipline Chinese Firms' Pollution Behaviors? The Mediating Effects of the Public and Government. *Journal of Management,* 42**,** 1700-1722.

TETLOCK, P. 2007. Giving Content to Investor Sentiment: The Role of Media in the Stock Market. *Journal of Finance,* 62**,** 1139-1168.

TOLLIVER, C., KEELEY, A. R. & MANAGI, S. 2020. Drivers of green bond market growth: The importance of Nationally Determined Contributions to the Paris Agreement and implications for sustainability. *Journal of Cleaner Production,* 244**,** 118643.

TRINKS, P. J. & SCHOLTENS, B. 2017. The Opportunity Cost of Negative Screening in Socially Responsible Investing. *Journal of Business Ethics,* 140**,** 193-208.

TRUEMAN, B. 1988. A Theory of Noise Trading in Securities Markets. 43**,** 83.

TRUMPP, C., ENDRIKAT, J., ZOPF, C. & GUENTHER, E. 2015. Definition, Conceptualization, and Measurement of Corporate Environmental Performance: A Critical Examination of a Multidimensional Construct. *Journal of Business Ethics,* 126**,** 185-204.

TVERSKY, A. & KAHNEMAN, D. 1992. Advances in Prospect Theory: Cumulative Representation of Uncertainty. *Journal of Risk and Uncertainty,* 5**,** 297-323.

VENEZIA, I. & SHAPIRA, Z. 2007. On the behavioral differences between professional and amateur investors after the weekend. *Journal of Banking & Finance,* 31**,** 1417-1426.

VISCUSI, W. K. & CHESSON, H. 1999. Hopes and fears: The conflicting effects of risk ambiguity. *Theory and Decision,* 47**,** 153-178.

VON NEUMANN, J. & MORGENSTERN, O. 1944. *Theory of games and economic behavior,* Princeton, NJ, US, Princeton University Press.

WAKKER, P., TIMMERMANS, D. & MACHIELSE, I. 2007a. The Effects of Statistical Information on Risk- and Ambiguity-Attitudes, and on Rational Insurance Decisions. *Management Science,* 53**,** 1770-1784.

WAKKER, P. P., TIMMERMANS, D. R. M. & MACHIELSE, I. 2007b. The Effects of Statistical Information on Risk and Ambiguity Attitudes, and on Rational Insurance Decisions. *Management Science,* 53**,** 1770-1784.

WANG, T. & BANSAL, P. 2012. Social responsibility in new ventures: profiting from a long-term orientation. *Strategic Management Journal,* 33**,** 1135-1153.

WANG, Y., CHEN, C. R. & HUANG, Y. S. 2014. Economic policy uncertainty and corporate investment: Evidence from China. *Pacific-Basin Finance Journal,* 26**,** 227-243.

WELCH, I. & GOYAL, A. 2008. A Comprehensive Look at The Empirical Performance of Equity Premium Prediction. *Review of Financial Studies,* 21**,** 1455-1508.

WHITE, H. 1980. A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica,* 48**,** 817.

YAMAGUCHI, Y. & AHMAD, R. 2021. China's next energy transition plan set to boost green bond issuance in 2021.

YU, J. 2011. Disagreement and return predictability of stock portfolios. *Journal of Financial Economics,* 99**,** 162-183.

YU, J. & YUAN, Y. 2011. Investor sentiment and the mean-variance relation. *Journal of Financial Economics,* 100**,** 367-381.

ZHANG, X. F. 2006. Information Uncertainty and Stock Returns. *The Journal of Finance,* 61**,** 105-137.