Ambiguity in Attention to Climate Change and Corporate Bond Returns*

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Abstract

This study examines how ambiguity in news media attention to climate change, capturing variability in how climate-related events are covered across media outlets, affects corporate bond pricing and intertemporal hedging demand. We show that investors prefer bonds with strong potential to hedge against climate risk, thereby accepting lower future returns. This hedging premium is significantly attenuated when media ambiguity is high: during periods of elevated ambiguity, the standard hedging incentive weakens and, for physical climate risks, reverses entirely. Long-term bonds are more sensitive to physical climate risk hedging demand, while transition risk hedging is more pronounced for short-term bonds. When both transition risk and ambiguity are elevated, investors favor bonds issued by firms with low climate exposure, whose reputational resilience preserves their hedging value under uncertain conditions.

JEL classification: C55, D80, D84, G12, G14.

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1. Introduction

Climate change poses a significant and growing economic risk (Stern, 2007; Burke et al., 2015; Alogoskoufis et al., 2021). Investors increasingly use publicly traded assets — including corporate bonds — to hedge against it, since conventional instruments such as futures and insurance contracts are poorly suited for this purpose (Engle et al., 2020; Huynh and Xia, 2021; Alekseev et al., 2022). Yet a fundamental question remains unexplored: what happens to these hedging strategies when investors disagree about the importance of a climate event? Media coverage of climate change is far from uniform — outlets differ substantially in how much attention they devote to the same event on the same day. We call this phenomenon ambiguity in attention to climate change, and we show that it has first-order consequences for bond pricing and hedging demand that are distinct from, and empirically separable from, the effects of climate risk itself.

Our ambiguity measure is grounded in Izhakian (2020)'s expected-volatility framework and validated in Sadoghi and Santi (2026), which introduces a method to quantify perceived risk and ambiguity in attention from news media using the expected volatility of topic probabilities generated by Latent Dirichlet Allocation (LDA) across articles from heterogeneous outlets. This framework has been shown to predict CDS spread dynamics with effects that are empirically distinct from the corresponding risk measure. We apply this approach to the domain of climate change by combining it with climate-specific topic modeling, yielding five disaggregated climate ambiguity measures — one for each of the climate risk categories we identify — alongside their corresponding risk counterparts. This dual decomposition, unavailable in prior bond market studies, allows us to ask not only which type of climate risk investors hedge, but how the credibility of that risk signal, as reflected in media consensus, shapes hedging demand.

Unlike traditional definitions of ambiguity, our measures focus on ambiguity in attention to a recent climate event or the concern of a future one. Ambiguity in the attention to climate change may lead investors to underestimate the importance of climate risks. Thus, climate change hedging strategies may be perceived as less appealing when ambiguity in attention to climate change is high.

The first challenge of our analysis is to measure climate change risk and ambiguity. We use news media articles, as they are one of the most important sources of information about climate change. We first select risk-related news, and then use the list of climate change keywords built by Engle et al. (2020) and Sautner et al. (2023) to identify media articles on climate change. Next, we apply the ClimateBERT language model (Webersinke et al., 2021) to assess the relevance of the selected articles. This model undergoes pre-training on a diverse corpus of texts encompassing climate-related research paper abstracts, corporate and general news articles, and various company reports and documents. Because climate change is a multifaceted phenomenon, we employ Structural Topic Modeling (STM) following the method outlined by Chang et al. (2009) to discern news articles about sustainable investing, climate change transition, chronic physical, acute physical, and environmental degradation surrounding climate change. Each topic identifies a different source of risk.

Sustainable investment aligns financial goals with broader societal and environmental objectives. Climate change transition concerns the current global shift toward a more sustainable net-zero economy. The physical risks of climate change comprise damage to physical assets through extreme weather, reduced agricultural productivity, heat-related illnesses, and death. Such risks can be classified as chronic, driven by longer-term shifts in climate patterns (i.e., sea level rise and temperature increase), or acute, driven by specific extreme weather events (i.e., heat waves, floods, wildfires, and storms). Environmental risks include a wide range of potential threats to the environment and human well-being such as biodiversity loss, pollution, and deforestation.

To appraise climate change risk and ambiguity from media articles, we adopt the approach proposed by Sadoghi and Santi (2026). For risk assessment, we compute the ratio of articles assigned to a specific topic relative to the total number of articles published on a given day. This ratio serves as an indicator of the level of news coverage of a particular topic.

Similar approaches to measuring risk from news have been proposed by Engle et al. (2020); Caldara and Iacoviello (2022); Faccini et al. (2023). By contrast, ambiguity is evaluated by observing the varying degrees of attention that different media outlets allocate to the same topic on any given day. In particular, we calculate ambiguity in media attention as the variance in topic probabilities generated by the LDA algorithm, which reflect the emphasis different media outlets place on climate-related events. This measure captures variability in coverage, not event likelihoods themselves. For instance, in the case of an extreme weather event such as a winter storm, some media outlets may have high coverage of the event, resulting in high LDA probabilities for the topic "acute physical" in those articles, while others may have low coverage of the event. Thus, if there is ambiguity on the importance of the winter storm, LDA probabilities will be more dispersed across different media outlets, increasing the ambiguity in the attention to climate acute physical risks.

Following Huynh and Xia (2021), we estimate a bond's covariance using our climate change metrics to measure its potential to hedge against climate change risk. We use the following notations for climate change risk and ambiguity betas: B_k_risk and B_k_ambg, respectively, where k identifies the topic (sustainable investing, transition, chronic physical, acute physical, or environmental). To estimate the climate change risk and ambiguity betas, we run 60-month rolling regressions of excess bond returns on innovations in monthly climate change risk and ambiguity metrics. Note that the time series B_k_risk measures the sensitivity of corporate bond returns to climate change risk. We find that bonds with higher B_k_risk are significantly associated with lower future returns, except for $B\_sustain\_invs\_risk$ and $B\_environ\_risk$. A one-standard deviation (SD) increase in $B\_transit\_risk$ is related to a decrease in future excess returns of 17.03 basis points (bps) per month. In comparison, a one-SD increase in $B\_acute\_phys\_risk$ is associated with a reduction of future excess returns of 0.85 bps per month, and a one-SD increase in $B\_chro\_phys\_risk$ is associated with a decrease in future excess returns of only 0.62 bps per month. This provides us with strong evidence of hedging against climate transition risk, whereas hedging against physical climate risks is only marginally economically significant. Given the profound impact of climate change on future investment and consumption prospects, investors prefer bonds that demonstrate improved performance as climate change risk metrics increase in value. This preference stems from the recognition that the appreciation in the value of bonds with high B_k_risk can counterbalance the potential decrease in consumption and investment opportunities. Consequently, investors seek greater quantities of these bonds and are willing to accept reduced future returns (Addoum et al., 2019). These findings align with the intertemporal hedging hypothesis, which suggests that investors gravitate towards bonds that offer robust hedging capabilities (Merton, 1973; Campbell, 1993, 1996; Bali et al., 2017; Huynh and Xia, 2021).

We test the intertemporal hedging hypothesis and document two sets of results. First, consistent with Huynh and Xia (2021), during times of heightened climate change risk, bonds with higher climate risk betas earn significantly lower future returns, particularly for transition risk and to a lesser but statistically significant degree for chronic and acute physical risks. Second — and this is the central empirical contribution — we show that this hedging premium is strongly modulated by ambiguity. During periods of heightened ambiguity in attention to climate change, the reduction in future returns associated with higher climate risk betas is substantially attenuated: for chronic and acute physical risks, the premium reverses entirely during high-ambiguity months, with a one-standard-deviation increase in the respective betas associated with positive rather than negative future excess returns of 0.39 bps and 4.20 bps, respectively. This finding is consistent with investors withdrawing from climate hedging strategies when media disagreement about climate event salience makes the expected hedging benefit of high-beta bonds uncertain.

We also study the effects of climate change risk on long-term corporate bonds. We find that the relationship between B_k_risk and future returns on long- and short-term bonds depends on the type of risk analyzed. Specifically, the negative relationship between future returns and corporate bond covariance with chronic and acute physical climate change risk is stronger for long-term bonds. This suggests that investors anticipate physical risks to materialize in the long run. As a result, they seek long-term corporate bonds to hedge against this type of risk. By contrast, the negative relationship between future returns and corporate bond covariance with transition risk is slightly stronger for short-term bonds.

Next, we explore the link between firms' exposure to climate change and B_k_risk. We show that during periods of joint high transition risk and high ambiguity, bonds issued by firms with low climate change exposure have systematically higher transition risk betas, consistent with investors valuing these firms' reputational resilience when the climate risk signal is noisy. The results for physical climate risks are inconclusive because of the lack of measures for a firm's exposure to such risks.

This study contributes to the climate finance literature by examining climate risk mitigation strategies. Engle et al. (2020) implemented a procedure to dynamically hedge climate change risk using stocks of firms with good environmental scores. Alekseev et al. (2022) has suggested a quantity-based approach to building portfolios to hedge against climate risk. Huynh and Xia (2021) found that bonds issued by firms with better environmental performance are used to hedge against climate change risks. Therefore, investors are willing to pay higher prices and accept lower returns for these bonds. Ilhan et al. (2021) showed that uncertainty about climate policy is priced in the option market. Moreover, uncertainty about the impacts of climate change and climate model uncertainty can affect the social cost of carbon (Barnett et al., 2020). Our study differs from extant literature along two dimensions. First, in terms of measurement, we use five topically disaggregated risk measures derived from 145,752 articles across more than a dozen international outlets, enabling us to separately identify transition, chronic physical, acute physical, sustainable investment, and environmental risk channels — each with distinct pricing implications that a single-index approach cannot detect. Second, and most critically, we introduce an ambiguity dimension. Our ambiguity measure, proposed by Sadoghi and Santi (2026), captures not the level of climate news attention but the cross-outlet dispersion in how outlets weight a given climate topic. This is a second-order uncertainty — not 'how bad is climate change?' but 'how salient is this event right now?' — and it has asset pricing consequences that risk measures alone cannot capture.

Our findings carry concrete practical implications. Aggregate media ambiguity about climate change weakens climate risk hedging and may cause mispricing in the bond market, providing an empirical argument for policies that improve the clarity and consistency of climate risk communication. For investors, high-ambiguity periods represent a systematic risk to climate hedging strategies, as portfolios constructed to hedge climate risk may underperform precisely when ambiguity is elevated. The five-topic decomposition we introduce enables portfolio managers to differentiate between transition and physical risk hedges — a distinction single-index approaches cannot provide. Finally, bonds issued by firms with low climate exposure carry a pricing advantage that is strongest when climate risk and ambiguity are high, providing a financial incentive for genuine emissions reduction beyond regulatory compliance.

2. Hypothesis development

We begin by clarifying the conceptual distinction between climate change risk and ambiguity in attention to climate change. Climate change risk captures the aggregate level of media coverage devoted to a specific climate topic on a given day — how prominent flood risk or transition policy is in the news. This concept is related to measures used in prior work (Engle et al., 2020; Huynh and Xia, 2021), though we disaggregate it into five distinct topics: sustainable investing, transition, chronic physical, acute physical, and environmental risks. Ambiguity in attention captures the dispersion of that coverage across outlets: do all outlets agree that a given climate event is salient, or do some report it extensively while others largely ignore it? This reflects not uncertainty about the event itself, but disagreement about its relevance and importance.

The distinction matters for asset pricing. When outlets converge on the salience of a climate event, investors can form reliable expectations about the hedging value of bonds that co-move with that event. When outlets diverge, investors receive conflicting signals about the event's importance, discount their assessment of climate risk severity, and reduce their demand for climate hedges accordingly. Importantly, the two measures are constructed to capture independent dimensions of media coverage, and Sadoghi and Santi (2026) confirm empirically that they exhibit insignificant correlation, ensuring that we separately identify their effects on bond returns in the analysis that follows.

Following Merton (1973) and Huynh and Xia (2021), we assume that climate change risk affects investors' investment opportunities and influences future returns on corporate bonds through intertemporal hedging demands. Investors seek bonds with higher covariance with climate change risk metrics to offset potential losses in consumption and investment opportunities and are willing to accept lower future returns on these bonds. We extend this framework by examining five distinct sources of climate change risk — transition, chronic physical, acute physical, sustainable investing, and environmental — each captured by separate covariance measures for both risk and ambiguity.

Specifically, for each bond and each topic k, we estimate B_k_risk as the slope coefficient from monthly rolling regressions of excess bond returns on innovations in the corresponding climate change risk metric, and B_k_ambg as the analogous coefficient on innovations in the corresponding ambiguity metric, controlling for standard bond market factors in both cases. A bond with a high B_k_risk exhibits returns that increase with climate change risk on topic k, making it an effective hedge against that particular source of risk. A bond with a high B_k_ambg exhibits returns that increase with ambiguity in attention to topic k, capturing the bond's sensitivity to media disagreement about that climate event. Consequently, investors demand more bonds with high B_k_risk and are willing to accept lower future returns on them. We do not expect hedging of sustainable investment risk, as it is not systematic and can be mitigated through diversification.

H1. *There is a negative relationship between a bond's B_k_risk and future returns* *with* $k = \{transit, chro\_phy, acute\_phys, environ\}$.

Asset pricing theory predicts that this relationship should be time-varying and more pronounced during periods of heightened climate risk (Bloom, 2009; Bali et al., 2017), consistent with Huynh and Xia (2021).

H2. *The negative relationship between a bond's* B_k_risk *and future returns is relatively stronger in times of heightened climate change risk.*

The central and novel hypothesis of this study concerns the role of ambiguity. When media outlets disagree substantially about the salience of a climate event, investors may underestimate the importance of climate risks and their potential impact on future consumption and investment opportunities. Consequently, the demand for bonds with high B_k_risk weakens during high-ambiguity periods, yielding a weaker — or in some cases reversed — negative relationship between B_k_risk and future returns.

H3. *The negative relationship between a bond's* B_k_risk *and future returns is relatively weaker in times of heightened ambiguity in the attention to climate change.*

Next, we examine whether the pricing of climate change risk depends on a bond's term structure. Huynh and Xia (2021) document that the negative relationship between B_k_risk and future returns is stronger for long-term bonds. We provide further evidence by considering the different sources of climate change risk.

Prices of long-term bonds could be more sensitive to chronic physical climate change risk than short-term bonds because the consequences of climate change risk will be more intense, affecting a firm's resilience in the long run. For instance, Painter (2020) showed that long-term municipal bonds are more sensitive to hedging demands to mitigate exposure to sea level rise risk. Furthermore, Goldsmith-Pinkham et al. (2023) found that sea-level-rise risk exposure is priced in the municipal bond market, and the effect is larger for long-term bonds. By contrast, the realization of climate change risks, such as natural disasters, regulatory changes, and technological advances in a transitioning economy, can affect the current investment opportunity set (Black Rock, 2016). Thus, we propose the fourth hypothesis.

H4a. *The negative relationship between future returns and the covariance of corporate bonds with chronic physical climate change risk is relatively stronger for long-term bonds.*

H4b. *The negative relationship between future returns and the covariance of corporate bonds with transition and acute physical climate change risk is relatively stronger for short-term bonds.*

The above hypotheses imply that bonds with high B_k_risk tend to be issued by firms with low exposure to climate change risk. Huynh and Xia (2021) document this relationship and show that it strengthens during periods of heightened climate risk, as investors actively seek out environmentally resilient issuers for hedging purposes.

H5. *The negative relationship between a bond's* B_k_risk *and the issuer's exposure to climate change risk is relatively stronger in times of high climate change risk.*

The novel question we ask is how ambiguity modulates this relationship. When media outlets disagree about the salience of a climate event, the aggregate climate risk signal becomes noisy, and investors are less certain about the severity of the threat to their future consumption and investment opportunities. In this environment, they place greater weight on firm-level climate credentials as a direct indicator of resilience: bonds issued by firms with low climate exposure offer a reliable hedge regardless of how the media narrative resolves, because these firms are fundamentally less vulnerable to climate-related shocks. Their reputational credibility and perceived resilience become particularly valuable precisely when the aggregate signal is unclear (Lins et al., 2017). This suggests that the negative relationship between B_k_risk and issuer climate exposure should strengthen — or at minimum persist — during high-ambiguity periods.

H6. *The negative relationship between a bond's* B_k_risk *and the issuer's exposure to climate change risk is relatively stronger in times of high ambiguity in the attention to climate change.*

3. Data and variable constructions

3.1. Corporate bond data

We use corporate bond transaction data from the Financial Industry Regulatory Authority's Trade Reporting and Compliance Engine (TRACE) enhanced database (Bessembinder et al., 2006) covering July 2002 to December 2020. The TRACE database provides detailed information on intraday bond-trading prices and volumes. All bond transactions in the U.S. dating back to July 2002 when TRACE was set up are included in the database. We apply an algorithm developed by Dick-Nielsen (2014) to exclude transactions previously flagged as errors. We exclude transactions documented after the original transaction date and corrections or cancellations of the reported transactions. We filter out all mortgage-backed, asset-backed, and agency-backed securities, and convertible bonds. We remove bonds with less than one year of maturity and those traded at less than \$5. We also exclude bonds issued under Rule 144A that are not traded in the U.S. market or in U.S. dollars. Following the literature, we eliminate these transactions as conceivable outliers and not regular transactions.

We follow Bessembinder et al. (2008) and Huynh and Xia (2021) in estimating the monthly corporate bond return as

$$r_{it} = \frac{(P_{it} + AI_{it}) + C_{it} - (P_{it-1} + AI_{it-1})}{(P_{it-1} + AI_{it-1})}, \tag{1}$$

where P_{it} is the last monthly transaction price at which bond i was traded in month t, computed as the trading volume-weighted average of all the intraday transaction prices (Bessembinder et al., 2008). AI_{it} is the accrued interest, and C_{it} is the coupon payment. We use the one-month Treasury bill rate as risk-free (r_{ft}) to estimate the excess returns on corporate bonds, as: $EBR_{it} = r_{it} - r_{ft}$.

3.2. *Climate change risk and ambiguity in attention*

News media serve as a vital conduit for information on climate change. We use news articles focused on risk from the LexisNexis database. This involved compiling a list of risk-related terms and keywords from reputable sources such as the 2018 Society for Risk Analysis glossary, the foundational principles of risk analysis from 2018, and various white papers from risklibrary.net. This ensures that our measures are not influenced by "certain" or predictable content—such as scheduled earnings announcements, policy releases, or standard corporate updates—which could bias the perception of uncertainty. Additionally, we use the metadata provided by LexisNexis, including subjects, keywords, and geographical information, to identify the main themes of these articles. The metadata were identified using an automated process within the LexisNexis database.

We use the list of climate change keywords built by Engle et al. (2020) and Sautner et al. (2023) to detect news media articles about climate change. Moreover, we used the ClimateBERT language model (Webersinke et al., 2021) to assess the relevance of the selected articles. This model is pre-trained on a diverse corpus of texts, encompassing climate-related research paper abstracts, general news articles, corporate reports, and various company documents.[1]

Our dataset comprises 145,752 English news articles sourced from leading international publications, both print and online, from January 2005 through July 2020. These articles come from a wide range of respected sources, including The New York Times, The Washington Post, The Los Angeles Times, BBC, Financial Times, and The Guardian. Using a heterogeneous set of media sources to estimate climate change risk and ambiguity, we can mitigate the effects of opinionated and biased messages or outliers in the media.

Given the multifaceted nature of climate change, we employ STM, following the approach delineated by Chang et al. (2009), to identify distinct topics within news articles related to climate change. These topics include sustainable investing, climate change tran-

[1]The results of the analysis with the ClimateBERT language model are presented in Table 10.

sitions, chronic physical risks, acute physical risks, and environmental risks. Sustainable investing aligns financial goals with broader societal and environmental objectives. Climate change transition pertains to the global movement towards a more sustainable, net-zero economy. Chronic physical risks of climate change encompass long-term impacts on physical assets due to shifts in climate patterns, such as sea level rise and temperature increases. Acute physical risks involve damages caused by specific extreme weather events such as heatwaves, floods, wildfires, and storms. Environmental risks cover a wide range of potential threats to the environment and human well-being such as biodiversity loss, pollution, and deforestation.[2]

To compute climate change risk and ambiguity, we follow Sadoghi and Santi (2026), who uses the probability distribution of topics across documents obtained with LDA, denoted by $\theta(x)$. For risk assessment, we compute the ratio of articles assigned to a specific topic relative to the total number of articles published on a given day. This ratio serves as an indicator of the level of news coverage for a particular topic (similar approaches were proposed by Engle et al., 2020; Caldara and Iacoviello, 2022; Faccini et al., 2023). Specifically, we assign each news article d to the news topic k with the largest value of $\theta(x)$, denoted by $\theta_{d,t}^{max}$. On any given day, more than one article could be assigned to a particular topic. We aggregate the monthly risk $Risk_{k,t}$ on topic k as:

$$Risk_{k,t} = \frac{\sum_{d=1}^{D_t} I(\theta_{k,d,t} = \theta_{d,t}^{max})}{D_t}, \tag{2}$$

where $I(\theta_{k,d,t} = \theta_{d,t}^{max})$ is an indicator function that is equal to one when the marginal probability of document d on day t discussing topic k ($\theta_{k,d,t}$) is equal to $\theta_{d,t}^{max}$, and the number of documents on day t is denoted by D_t. Notably, we do not use average LDA probability as a measure of risk because we want to build independent measures of risk and ambiguity to allow for an independent examination of their impacts.

Ambiguity is evaluated by observing the varying degrees of attention different media

[2]Table 9 contains a list of the 15 terms that are associated with each topic with the highest probability.

outlets allocate to the same topic on any given day. To measure ambiguity, we use the expected volatility of the probability of a certain topic across news articles (Izhakian, 2020; Sadoghi and Santi, 2026). In the presence of ambiguity, media outlets exhibit heterogeneous attention to a climate event, reflecting uncertainty about its importance. While some outlets emphasize the event and provide extensive coverage, leading to a high $\theta_{k,d,t}$, others devote limited attention, resulting in a low $\theta_{k,d,t}$. This divergence in coverage does not stem from conflicting information, but from ambiguity in attention, which generates dispersion in the probability that different media outlets report on the event. For practical implementation, we aggregate the monthly ambiguity ($Ambg_{k,t}$) on topic k as:

$$Ambg_{k,t} = \bar{\theta}_{k,t} \times \frac{\sum_{d=1}^{D_t} (\theta_{k,d,t} - \bar{\theta}_{k,t})^2}{D_t}, \tag{3}$$

where D_t denotes the number of documents on day t, and $\bar{\theta}_{k,t}$ is the average probability that on day t an article will discuss topic k, $\bar{\theta}_{k,t} = \frac{\sum_{d=1}^{D_t} \theta_{k,d,t}}{D_t}$.

One could, in principle, measure ambiguity as the within-day standard deviation of a binary indicator recording whether each outlet's articles are classified as belonging to a given topic. However, this approach treats all assignments equally, losing the intensity of coverage: an article that is overwhelmingly about flood risk (high LDA probability $\theta_{k,d,t}$) and an article that briefly mentions floods alongside many other topics (low $\theta_{k,d,t}$) would receive the same binary indicator value. LDA probabilities, by contrast, capture the degree to which a given article's content is concentrated on a specific topic, reflecting the actual editorial emphasis an outlet places on that climate event. Our ambiguity measure exploits the variance of these probabilities across outlets: when some outlets assign high probabilities and others low probabilities to the same topic on the same day, this reflects genuine disagreement in editorial emphasis — ambiguity in attention — rather than mere absence or presence of coverage. This approach was introduced and formally validated in Sadoghi and Santi (2026), who show using a CDS spread application that LDA-based ambiguity has effects that are empirically distinct from the corresponding risk measure and from simpler variance alternatives.

3.3. *Climate change news betas*

For each bond i in each month t, we estimate the climate change risk and ambiguity betas (B_k_risk and B_k_ambg) from the monthly rolling regression of excess bond returns on innovations in the monthly climate change risk and ambiguity metrics over a 60-month window with a minimum of 30 valid monthly return observations (Huynh and Xia, 2021). We control for excess market returns, bond market illiquidity, term spread, default spread, and TED spread as follows:

$$\begin{aligned} EBR_{i,t} =& \alpha_{i,t} + B\_k\_risk * I\_Risk_{k,t} + B\_k\_ambg * I\_Ambg_{k,t} + \\ & B\_Term * Term\_Spread_t + B\_Default * Default\_Spread_t + \\ & B\_Market * Market\_Exc_t + B\_TED * TED\_Spread_t + \\ & B\_Illiq * Market\_Illiquidity_t + \epsilon_{i,t}, \end{aligned} \tag{4}$$

where $I\_Risk_{k,t}$ and $I\_Ambg_{k,t}$ represent the innovations in the monthly climate change risk and ambiguity metrics, respectively. Following Ardia et al. (2023), we compute $I\_Risk_{k,t}$ and $I\_Ambg_{k,t}$ as the residuals from the first-order autoregressive model augmented by the following controls: excess market return, TED spread, default spread, and HML (high-minus-low) and SMB (small-minus-big) risk factors.

$Term\_Spread$ is the difference between the monthly returns on the Ibbotson U.S. long-term government bond index and the one-month Treasury bill rate. The term spread reflects investors' expectations of future economic activities. $Default\_Spread$ is computed as the difference between BAA- and AAA-rated corporate bond monthly yields.[3] $Market\_Exc$ is the excess equity market return obtained from the Kenneth French data library (`https://`

[3]The data to compute the term spread and default spread as in Welch and Goyal (2008) are available on Amit Goyal's website.

mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). The TED spread (TED_Spread), retrieved from the Federal Reserve Bank of St. Louis, is the difference between the 3-month London Interbank Offered Rate (LIBOR) and the 3-month Treasury bill rate. The TED spread controls for the corporate bond market's sensitivity to credit risk. Bond market illiquidity ($Market\_Illiquidity$) is the market illiquidity for all listed corporate bonds in the U.S. (Dick-Nielsen et al., 2012).[4]

The estimates of B_k_risk from Equation (4) capture a bond's covariance with innovations in the climate change risk metric for topic k. Thus, positive values of B_k_risk indicate that the bond value increases with the climate change risk metric. Similarly, the estimates of B_k_ambg capture a bond's covariance with innovations in the ambiguity in the attention to climate change metric for topic k. Thus, the positive values of B_k_ambg indicate that the bond value increases with the ambiguity in the attention to climate change metric.

3.4. Control variables

In the regression analysis, we include several control variables to account for known determinants of corporate bond returns.

To control for a bond's exposure to economic conditions, market risk, and market illiquidity, we include B_Term, $B\_Default$, B_TED, B_Market, and B_Illiq, respectively, estimated from Equation (4).

Our regression also includes bond-level control variables, such as corporate bond illiquidity (Chen et al., 2007), trading volume ($Volume$), number of transactions (No_Transc), and time to maturity ($Maturity$). Bond illiquidity ($Illiquidity$) is computed at the end of each month as the covariance of the change in the natural logarithm of the bond price on a given day and on the following day (Bao et al., 2011). $Volume$ is the natural logarithm of the average daily volume of bonds traded in a month, No_Transc is the natural logarithm of

[4] The data on the bond market illiquidity are available on Peter Feldhutter's website.

the average number of daily transactions in a month, and $Maturity$ is the natural logarithm of the number of years until bond maturity.

We further control for firm characteristics and risks. We integrate the Enhanced TRACE dataset with stock data from the CRSP and COMPUSTAT datasets, which include details about the bond-issuing firms. We control for stock return volatility ($Volatility$) computed as 6-month rolling standard deviations of stock returns (Ang et al., 2006); stock downside risk ($Downside\_risk$), which is the average of the four lowest bond returns below value-at-risk at the 10% threshold computed using rolling windows of 36 months; and firm-specific ambiguity ($AmbiguityStock$), which is the expected volatility of intraday stock returns (Izhakian, 2020).[5] We use the previous month's bond returns to measure short-term reversals ($Reversal$) as in Jegadeesh (1990). Moreover, we include the natural logarithm of the market value of the issuer's common equity ($Size$), and return on equity ($Profitability$), computed as net income divided by shareholder equity. $Profitability$ accounts for the differences in firms' ability to generate earnings. We also control for a firm's ability to meet long-term obligations ($Solvency$), computed as total debt divided by shareholder equity.

3.5. Environmental data

We consider quarterly data on firm-level exposure to climate change risk measured by performing a textual analysis of earnings calls (Sautner et al., 2023). *cc_expo* captures the exposures related to opportunity, physical, and regulatory shocks associated with climate change.[6] Moreover, we use information on firms carbon emissions retrieved from the Carbon Disclosure Project (CDP) and Refinitiv ESG. These emission data adhere to the greenhouse gas (GHG) protocol. Specifically, we use the natural logarithm of carbon intensity, that is, the firm's total annual emissions scaled by its annual average market capitalization, denoted by $Scope(1 + 2 + 3)$.

[5] We thank Yehuda Izhakian for providing us with the monthly time series of firm-specific ambiguity.

[6] The data on firm-level climate change exposure is obtained from https://osf.io/fd6jq/

Table 1: **Summary statistics**
This table presents the summary statistics for the key variables used in the baseline analysis. The summary statistics include the mean (Mean), standard-deviation (S.D.), minimum (Min), maximum (Max), median (Median), and the number of observations (N). See Table 8 for descriptions of the variables.

Variable	Mean	S.D.	Min	Median	Max	N
EBR (%)	0.462	0.414	-0.692	0.480	1.306	1,189,973
Market_Exc	0.000	0.002	-0.005	0.001	0.004	168
Term_Spread	0.343	0.222	0.139	0.280	1.796	168
TED_Spread	0.356	0.337	0.110	0.240	2.250	168
Default_Spread	2.088	1.634	0.747	1.756	20.398	168
Market_Illiquidity	-1.009	0.828	-1.856	-1.297	3.271	168
B_transit_risk	-1.351	2.531	-6.754	-0.962	5.963	466,092
B_sustain_invs_risk	-0.524	1.455	-4.001	-0.614	2.165	466,092
B_chro_phy_risk	0.072	0.484	-1.162	0.19	1.018	466,092
B_acute_phy_risk	-0.390	0.265	-0.988	-0.443	0.245	466,092
B_environ_risk	0.516	0.384	-0.240	0.511	1.507	466,092
B_transit_ambg	0.968	1.323	-1.111	0.629	4.571	466,092
B_sustain_invs_ambg	0.187	0.771	-1.158	0.090	2.667	466,092
B_chro_phy_ambg	1.302	0.789	-0.06	1.145	3.305	466,092
B_acute_phy_ambg	-0.007	0.53	-1.201	-0.053	2.608	466,092
B_environ_ambg	0.589	0.475	-0.253	0.558	1.739	466,092
B_Term	-0.006	0.548	-7.913	0.049	7.003	466,092
B_Default	-0.109	0.136	-0.83	-0.127	0.584	466,092
B_Market	-3.027	28.983	-199.603	1.299	215.06	466,092
B_TED	0.755	0.751	-6.521	0.808	9.275	466,092
B_Illiq	-0.157	0.310	-2.301	-0.163	1.462	466,092
Illiquidity	1.616	1.272	0.000	1.281	18.500	1,121,930
Volume	13.796	2.503	6.908	14.358	19.001	1,334,268
No_Trasc	1.291	0.778	0.000	1.172	4.174	1,334,268
Maturity	2.148	0.820	0.693	2.079	7.600	1,328,651
Reversal	0.498	0.160	0.218	0.496	0.806	1,165,699
Volatility	0.227	0.236	0.001	0.184	1.245	1,187,472
Downside_risk	0.461	0.175	-0.746	0.457	1.331	1,245,449
AmbiguityStock	0.013	0.010	0.000	0.011	0.049	1,152,041
Size	9.351	2.498	0.000	9.956	12.968	1,197,877
Profitability	0.058	0.360	-3.736	0.000	3.036	1,079,062
Solvency	2.392	4.886	-25.036	0.002	31.126	1,101,100

3.6. *Summary Statistics*

The sample covers the period from January 2005 to July 2020 and is composed of data from the intersection of the TRACE database, CRSP, and Compustat. To mitigate the impact of outliers, we winsorize all continuous variables at the 1st and 99th percentiles.

Table 1 reports the summary statistics of the main variables used in this analysis. Average monthly excess return on corporate bonds over the sample period is 0.462%, with a standard deviation of 0.41. The average corporate bond has a climate change transition, sustainable investing, chronic physical, and acute physical and environmental risk betas of -1.351, -0.524, 0.072, -0.390, and 0.516, respectively. Furthermore, the average bond is sold almost four times a day for an average of approximately $ 980,000; it has around eight years to maturity, an illiquidity measure of 1.616, and short-term reversal returns of 0.498%. The average firm in the sample has volatility of 0.227, downside risk of 0.461, an ambiguity level of 0.013, a market value of equity of $ 11.5 million, a profitability of 0.058, and a solvency

Table 2: **Correlation matrix of climate change risk and ambiguity betas**
This table presents the Pearson correlation coefficients of climate change risk and ambiguity betas. Panel I reports the correlation matrix of climate change risk betas. Panel II reports the correlation matrix of ambiguity in the attention to climate change betas, and Panel III reports the correlations between climate change risk and ambiguity betas. P-values are in parentheses. Variables are defined in Table 8.

Panel I: Correlations between risk betas

Variables	B_transit_risk	B_sustain_invs_risk	B_chro_phy_risk	B_acute_phy_risk	B_environ_risk
B_transit_risk	1.00				
B_sustain_invs_risk	0.12	1.00			
	(0.00)				
B_chro_phy_risk	0.09	-0.70	1.00		
	(0.00)	(0.00)			
B_acute_phy_risk	0.07	0.02	-0.21	1.00	
	(0.00)	(0.00)	(0.00)		
B_environ_risk	-0.27	-0.60	0.25	-0.51	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	

Panel II: Correlations between ambiguity betas

Variables	B_transit_ambg	B_sustain_invs_ambg	B_chro_phy_ambg	B_acute_phy_ambg	B_environ_ambg
B_transit_ambg	1.00				
B_sustain_invs_ambg	0.04	1.00			
	(0.00)				
B_chro_phy_ambg	0.36	0.50	1.00		
	(0.00)	(0.00)			
B_acute_phy_ambg	-0.27	0.35	0.12	1.00	
	(0.00)	(0.00)	(0.00)		
B_environ_ambg	0.17	0.29	0.61	0.03	1.00
	(0.00)	(0.00)	(0.00)	(0.00)	

Panel III: Correlations between risk and ambiguity betas

Variables	B_transit_ambg	B_sustain_invs_ambg	B_chro_phy_ambg	B_acute_phy_ambg	B_environ_ambg
B_transit_risk	0.01	-0.42	-0.60	-0.19	-0.68
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
B_sustain_invs_risk	0.06	-0.07	0.07	0.17	-0.13
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
B_chro_phy_risk	-0.25	-0.07	-0.38	0.05	-0.05
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
B_acute_phy_risk	0.11	-0.07	-0.30	-0.16	-0.31
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
B_environ_risk	0.18	0.15	0.39	-0.28	0.40
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

ratio of 2.39.

Table 2 shows the correlation between climate change risk and the ambiguity betas. We observe that bond returns have different sensitivities to different sources of uncertainty stemming from climate change. Moreover, bond returns react differently to climate change risks and ambiguity.[7]

4. Empirical analysis

We examine the relationship between a bond's climate change risk beta and future excess returns at the bond-month level. We control for bond- and firm-level variables (Bessem-

[7] By construction, the risk and ambiguity measures capture independent dimensions of media coverage. Sadoghi and Santi (2026) confirm empirically that their correlation is negligible, reporting a correlation of -0.04 between the climate risk and ambiguity in attention measures.

binder and Maxwell, 2008; Lin et al., 2011; Huynh and Xia, 2021), and consider bond, month, and year fixed effects to control for unobserved heterogeneity (Patton and Verardo, 2012; Ben-Rephael et al., 2021; Huynh and Xia, 2021). Specifically, we estimate the following regression.

$$EBR_{i,t+1} = \alpha + \beta B\_k\_risk_{i,t} + \delta B\_k\_ambg_{i,t} + \gamma' X_{i,t} + \eta' Z_{j,t} + \psi_i + \mu + \tau + \epsilon_{i,t}, \tag{5}$$

where, for bond i, month t, and firm j, $X_{i,t}$ represents a vector of bond-level control variables, $Z_{j,t}$ is a set of firm-level control variables, and ψ_i, μ, and τ are vectors of bond, month, and year fixed effects, respectively. $X_{i,t}$ includes term spread beta, default spread beta, market beta, TED spread beta, market illiquidity beta, bond illiquidity, trading volume, number of transactions, time to maturity, and short-term reversal. $Z_{j,t}$ includes stock volatility, downside risk, stock return ambiguity, market capitalization, profitability, and the solvency ratio.

Table 3 presents the results of the panel regressions of the 1-month-ahead corporate bond excess returns on B_k_risk and B_k_ambg with and without the control variables. We find that the coefficients of B_k_risk are negative and significant for transition, chronic physical, and acute physical risks. These coefficients are economically significant, particularly for the transition risk. A one-standard-deviation (SD) increase in $B\_transit\_risk$ is associated with a decrease in future excess returns of 17.03 bps per month, while a one-SD increase in $B\_chro\_phys\_risk$ is associated with a decrease in future excess returns of only 0.62 bps per month and a one-SD increase in $B\_acute\_phys\_risk$ is associated with a decrease in future excess returns of 0.85 bps per month. Hence, we find no strong evidence of investors hedging against physical risks.

These findings align with H1, which suggests investors prefer bonds with strong hedging capabilities (Merton, 1973; Campbell, 1993, 1996; Bali et al., 2017; Huynh and Xia, 2021). As climate change increasingly affects future investment and consumption prospects,

Table 3: **Climate change risk and ambiguity betas and future excess returns on corporate bonds**
The table reports the results from the monthly panel regression of one-month-ahead bond excess return $EBR_{i,t+1}$ and bond climate change risk and ambiguity betas ($B\_k\_risk_{i,t}, B\_k\_ambg_{i,t}$) of corporate bond i with and without control variables as follows $EBR_{i,t+1} = \alpha + \beta B\_k\_risk_{i,t} + \delta B\_k\_ambg_{i,t} + Controls_{i,j,t} + \epsilon_{i,t}$. We consider several control variables at the bond level: B_Term, B_Default, B_Market, B_TED, B_Illiq, Illiquidity, Volume, No_Trasc, Maturity, Reversal, and at the firm level: Volatility, Downside_Risk, AmbiguityStock, Size, Profitability, Solvency. The sample covers the period from January 2005 to July 2020. All regression models include year, month, and bond fixed effects. The robust standard errors are clustered at the bond level and they are reported in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$ indicate statistical significance at the 1%, 5%, and 10% level, respectively. Variables are defined in Table 8.

Dependent Variable:	Future corporate bond excess returns									
	Transit		Sustain_invs		Chro_phy		Acute_phy		Environ	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
B_transit_risk	-0.0500***	-0.0673***								
	(0.0006)	(0.0010)								
B_transit_ambg	0.1045***	0.1250***								
	(0.0011)	(0.0015)								
B_sustain_invs_risk			0.0435***	0.0287***						
			(0.0011)	(0.0013)						
B_sustain_invs_ambg			-0.0116***	-0.0111***						
			(0.0010)	(0.0012)						
B_chro_phy_risk					-0.0182***	-0.0129***				
					(0.0019)	(0.0027)				
B_chro_phy_ambg					-0.0979***	-0.0847***				
					(0.0014)	(0.0016)				
B_acute_phy_risk							-0.0792***	-0.0319***		
							(0.0036)	(0.0038)		
B_acute_phy_ambg							-0.0082***	0.0169***		
							(0.0014)	(0.0024)		
B_environ_risk									-0.0194***	0.0208***
									(0.0029)	(0.0040)
B_environ_ambg									0.2422***	0.2427***
									(0.0030)	(0.0033)
B_Term		-0.0379***		-0.0425***		-0.0393***		-0.0418***		-0.0280***
		(0.0018)		(0.0014)		(0.0015)		(0.0016)		(0.0015)
B_Default		0.3997***		0.3015***		0.2695***		0.3279***		0.1833***
		(0.0116)		(0.0101)		(0.0085)		(0.0101)		(0.0096)
B_Market		-0.0020***		-0.0011***		-0.0013***		-0.0015***		-0.0010***
		(0.0000)		(0.0000)		(0.0000)		(0.0000)		(0.0000)
B_TED		-0.0368***		-0.0339***		-0.0209***		-0.0343***		-0.0301***
		(0.0019)		(0.0016)		(0.0016)		(0.0018)		(0.0015)
B_Illiq		0.0832***		0.0241***		0.0610***		0.0642***		0.0645***
		(0.0040)		(0.0033)		(0.0031)		(0.0032)		(0.0036)
Illiquidity		-0.0094***		-0.0124***		-0.0139***		-0.0116***		-0.0113***
		(0.0010)		(0.0009)		(0.0009)		(0.0009)		(0.0010)
Volume		-0.0028***		-0.0030***		-0.0032***		-0.0030***		-0.0031***
		(0.0005)		(0.0005)		(0.0005)		(0.0005)		(0.0005)
No_Trasc		-0.0046**		-0.0049***		-0.0042**		-0.0048***		-0.0024
		(0.0015)		(0.0015)		(0.0015)		(0.0015)		(0.0015)
Maturity		0.0021		0.0126***		0.0054		0.0070*		-0.0072*
		(0.0034)		(0.0028)		(0.0028)		(0.0028)		(0.0030)
Reversal		0.6038***		0.6607***		0.6583***		0.6461***		0.7013***
		(0.0148)		(0.0148)		(0.0149)		(0.0147)		(0.0154)
Volatility		-0.0879***		-0.0731***		-0.0738***		-0.0704***		-0.0580***
		(0.0050)		(0.0041)		(0.0040)		(0.0040)		(0.0044)
Downside_Risk		0.4971***		0.2209***		0.2833***		0.3069***		0.2364***
		(0.0437)		(0.0299)		(0.0343)		(0.0333)		(0.0329)
AmbiguityStock		-1.0261***		-1.4890***		-1.3380***		-1.5349***		-1.5227***
		(0.0655)		(0.0629)		(0.0624)		(0.0638)		(0.0642)
Size		-0.0000		0.0005		-0.0024		0.0000		0.0007
		(0.0018)		(0.0016)		(0.0016)		(0.0016)		(0.0017)
Profitability		-0.0068***		-0.0070***		-0.0073***		-0.0070***		-0.0069***
		(0.0013)		(0.0014)		(0.0015)		(0.0014)		(0.0014)
Solvency		0.0000		-0.0001		-0.0000		-0.0000		-0.0001
		(0.0001)		(0.0001)		(0.0001)		(0.0001)		(0.0001)
Constant	0.2216***	-0.2582***	0.2874***	-0.0908***	0.3099***	-0.0407	0.2771***	-0.1078***	0.2939***	-0.0592*
	(0.0034)	(0.0326)	(0.0030)	(0.0260)	(0.0036)	(0.0271)	(0.0032)	(0.0276)	(0.0032)	(0.0290)
FE:Month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE:Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE:Bond	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	373903	272270	373903	272270	373903	272270	373903	272270	373903	272270
adj. R^2	0.333	0.351	0.310	0.314	0.315	0.319	0.307	0.313	0.325	0.328

investors are more likely to choose bonds that perform better when climate risk metrics increase. This preference is based on the understanding that an increase in the value of bonds with high B_k_risk can help offset the potential declines in consumption and investment opportunities. Consequently, investors actively seek bonds, even with lower future returns potential (Addoum et al., 2019).

As expected, we find no evidence of hedging of sustainable investment risk, as diversification can mitigate these risks. Surprisingly, the coefficient of $B\_environ\_risk$ is significantly negative only in the model without controls. Once the control variables are included, the coefficient becomes significantly positive. Moreover, the sign of the coefficient of B_k_ambg depends on the type of risk analyzed.

The coefficients of the control variables are consistent with previous findings. We find that bonds with lower trading volume and number of transactions, lower liquidity, higher default spread beta, smaller TED spread beta, greater downside risk, and lower profitability have higher future returns.

4.1. Nonlinearity in the climate change risk premium

Next, we examine H2 and H3, which posit that the effect of the climate change risk beta on future bond returns changes over time, and is relatively more pronounced during times of heightened climate change risk and weaker during times of heightened ambiguity in the attention to climate change. We define a month as having high climate change risk (ambiguity) if the innovation in the monthly climate change risk (ambiguity) metric is greater than the 50th percentile. Accordingly, we construct the dummy variables H_k_risk and H_k_ambg, which are equal to one for months with high climate change risk or ambiguity and 0 otherwise. We re-estimate two new specifications of the regression equation (5) that include $H\_k\_risk \times B\_k\_risk$ and H_k_risk, and $H\_k\_ambg \times B\_k\_risk$ and H_k_ambg. The results are reported in Table 4. We focus on climate change transition and chronic and acute physical risks, as shown in Table 3 and do not find any evidence of hedging of sustainable

Table 4: **Nonlinear relationship between climate change risk beta and future excess returns on corporate bonds** The table reports the results from the regression tests of the nonlinear effect of climate change risk beta on future excess return on corporate bonds, conditional on high and low periods of the climate change risk (Columns 1, 3, and 5) and ambiguity (Columns 2, 4, and 6) metrics. H_k_risk and H_k_ambg are dummy variables equal to 1 for months with innovation in climate change risk or ambiguity above the 50th percentile of the sample period, and 0 otherwise. $H\_k\_risk \times B\_k\_risk$ is an interaction term between high climate change risk and climate change risk beta. $H\_k\_ambg \times B\_k\_risk$ is an interaction term between high ambiguity in the attention to climate change and climate change risk beta. We add several control variables at the bond level: B_Term, B_Default, B_Market, B_TED, B_Illiq, Illiquidity, Volume, No_Trasc, Maturity, Reversal, and at the firm level: Volatility, Downside_Risk, AmbiguityStock, Size, Profitability, Solvency. The sample covers the period from January 2005 to July 2020. All regression models include year, month, and bond fixed effects. The robust standard errors are clustered at the bond level and they are reported in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$ indicate statistical significance at the 1%, 5%, and 10% level, respectively. Variables are defined in Table 8.

Dependent Variable:	Future excess returns					
	Transit		Chro_phy		Acute_phy	
Interaction with high climate change	Risk	Ambiguity	Risk	Ambiguity	Risk	Ambiguity
	(1)	(2)	(3)	(4)	(5)	(6)
B_transit_risk	-0.0559***	-0.0661***				
	(0.0010)	(0.0009)				
H_transit_risk	-0.0000					
	(0.0009)					
H_transit_risk×B_transit_risk	-0.0326***					
	(0.0005)					
B_transit_ambg	0.1225***	0.1117***				
	(0.0015)	(0.0014)				
H_transit_ambg		-0.0981***				
		(0.0011)				
H_transit_ambg×B_transit_risk		0.0214***				
		(0.0005)				
B_chro_phy_risk			-0.0081**	-0.0582***		
			(0.0026)	(0.0031)		
H_chro_phy_risk			-0.0321***			
			(0.0007)			
H_chro_phy_risk×B_chro_phy_risk			-0.0144***			
			(0.0017)			
B_chro_phy_ambg			-0.0835***	-0.0829***		
			(0.0016)	(0.0016)		
H_chro_phy_ambg				0.0013		
				(0.0010)		
H_chro_phy_ambg×B_chro_phy_risk				0.0663***		
				(0.0020)		
B_acute_phy_risk					0.0685***	-0.2228***
					(0.0048)	(0.0045)
H_acute_phy_risk					-0.2082***	
					(0.0027)	
H_acute_phy_risk×B_acute_phy_risk					-0.2726***	
					(0.0058)	
B_acute_phy_ambg					0.0096***	0.0081***
					(0.0022)	(0.0023)
H_acute_phy_ambg						0.1195***
						(0.0018)
H_acute_phy_ambg×B_acute_phy_risk						0.3815***
						(0.0051)
Control:Bond	Yes	Yes	Yes	Yes	Yes	Yes
Control:Firm	Yes	Yes	Yes	Yes	Yes	Yes
FE:Month	Yes	Yes	Yes	Yes	Yes	Yes
FE:Year	Yes	Yes	Yes	Yes	Yes	Yes
FE:Bond	Yes	Yes	Yes	Yes	Yes	Yes
N	272270	272270	272270	272270	272270	272270
adj. R^2	0.366	0.381	0.321	0.320	0.336	0.329

investing and environmental risks.

Consistent with H2, Table 4 shows that the coefficient of the interaction term $H\_k\_risk \times B\_k\_risk$ is negative and significant at the 1% level for all types of risk, which suggests that during times of heightened climate change risk, the impact of the climate change risk beta on future bond returns is significantly greater than that in low climate change risk periods. Furthermore, in line with H3, the interaction term $H\_k\_ambg \times B\_k\_risk$ is positive, and significant at the 1% level for all types of risk, which suggests during times of heightened ambiguity in the attention to climate change, the impact of the climate change risk beta on future bond returns is significantly lower than that in low ambiguity in the attention to climate change periods.

The total premium for B_k_risk is also economically significant. The coefficient estimates suggest that, during times of high climate change risk ($H\_k\_risk = 1$), a one-SD increase in climate change transition beta is associated with a total reduction of 22.40 bps in future bond excess returns, while a one-SD increase in climate change chronic physical beta is associated with a total reduction of 1.09 bps in future bond excess returns, and a one-SD increase in acute physical beta is associated with a total reduction of 5.41 bps in future bond excess returns. However, during times of high ambiguity in the attention to climate change ($H\_k\_ambg = 1$), a one-SD increase in climate change transition beta is associated with a total reduction of 11.31 bps in future bond excess returns, while a one-SD increase in chronic physical beta is associated with a total increase of 0.39 bps in future bond excess returns, and a one-SD increase in acute physical beta is associated with a total increase of 4.20 bps in future bond excess returns. These results suggest that investors no longer gravitate towards bonds that offer hedging capabilities for acute and chronic physical risks during times of high ambiguity in the attention to climate change.

Table 5: **Time-to-maturity and climate change risk premium**

The table reports the results from the monthly panel regression of one-month-ahead bond excess return $EBR_{i,t+1}$ and bond climate change risk and ambiguity betas $(B\_k\_risk_{i,t}, B\_k\_ambg_{i,t})$ of corporate bond i with control variables as follows $EBR_{i,t+1} = \alpha + \beta B\_k\_risk_{i,t} + \delta B\_k\_ambg_{i,t} + Controls_{i,j,t} + \epsilon_{i,t}$ separately for short-term and long-term bonds, where long-term bonds are those with a time to maturity longer than 20 years. We consider several control variables at the bond level: B_Term, B_Default, B_Market, B_TED, B_Illiq, Illiquidity, Volume, No_Trasc, Maturity, Reversal, and at the firm level: Volatility, Downside_Risk, AmbiguityStock, Size, Profitability, Solvency. Columns 1, 3, and 5 present the results for the short-term bond subsample, while columns 2, 4, and 6 report the results for the long-term bond subsample. The sample covers the period from January 2005 to July 2020. All regression models include year, month, and bond fixed effects. The robust standard errors are clustered at the bond level and they are reported in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$ indicate statistical significance at the 1%, 5%, and 10% level, respectively. Variables are defined in Table 8.

Dependent Variable:	Future excess returns					
	Transit		Chro_phy		Acute_phy	
Time to Maturity (years)	(< 20)	(≥ 20)	(< 20)	(≥ 20)	(< 20)	(≥ 20)
	(1)	(2)	(3)	(4)	(5)	(6)
B_transit_risk	-0.0692***	-0.0660***				
	(0.0011)	(0.0024)				
B_transit_ambg	0.1289***	0.1206***				
	(0.0017)	(0.0035)				
B_chro_phy_risk			-0.0122***	-0.0206**		
			(0.0031)	(0.0064)		
B_chro_phy_ambg			-0.0844***	-0.0930***		
			(0.0018)	(0.0037)		
B_acute_phy_risk					-0.0284***	-0.0391***
					(0.0043)	(0.0095)
B_acute_phy_ambg					0.0188***	0.0112
					(0.0027)	(0.0058)
Control:Bond	Yes	Yes	Yes	Yes	Yes	Yes
Control:Firm	Yes	Yes	Yes	Yes	Yes	Yes
FE:Month	Yes	Yes	Yes	Yes	Yes	Yes
FE:Year	Yes	Yes	Yes	Yes	Yes	Yes
FE:Bond	Yes	Yes	Yes	Yes	Yes	Yes
N	222412	49858	222412	49858	222412	49858
adj. R^2	0.353	0.341	0.319	0.312	0.313	0.305

4.2. *Time-to-maturity and the climate change risk premium*

To test H4a and H4b, we estimate the regression equation (5) separately for the subsamples of long-term and short-term bonds, where long-term bonds are those with a time to maturity longer than 20 years.

Table 5 presents the estimation results. Columns 1, 3, and 5 present the results for the short-term bonds subsample, whereas columns 2, 4, and 6 report the results for the long-term bonds subsample. The results in Columns 3 and 4 align with H4a, suggesting that long-term bonds are more sensitive to hedging demands to mitigate the exposure to chronic physical climate change risk. Moreover, we show that the prices of both short- and long-term bonds are affected by demand to hedge against climate change transition and acute physical risk. However, the coefficients of *B_transit_risk* are only slightly higher in absolute terms in the short-term bond subsample, whereas those of *B_acute_phy_risk* are higher in absolute terms in the long-term bond subsample. Thus, the results are only partially consistent with

H4b.

The findings suggest that long-term bonds are more sensitive to hedging demands for mitigating physical climate risks. A possible explanation is that businesses expect such physical risks to materialize in the long run, when hence, hedging against such risks considered more valuable. By contrast, climate change policies might affect the current investment opportunity set (Black Rock, 2016) which may lead investors to consider hedging climate transition risk more valuable in the short run.

4.3. Determinants of the climate change risk beta

Huynh and Xia (2021) document that bonds with high B_k_risk tend to be issued by firms with low climate change exposure, proxied by environmental performance scores, where higher scores indicate lower exposure. We extend this analysis by testing whether this relationship strengthens during periods of high climate change risk and high ambiguity in attention, consistent with H5 and H6.

We proxy firm-level climate exposure using two measures, both defined such that higher values indicate greater exposure to climate risk. The first is the textual measure of Sautner et al. (2023), which captures exposures related to opportunity, physical, and regulatory climate shocks (cc_expo). The second is carbon emissions intensity ($Scope(1+2+3)$), which more narrowly reflects exposure to transition risk. We note that despite cc_expo being designed to capture physical climate exposure alongside transition exposure, it likely reflects the latter more strongly in practice: the number of firms disclosing positive physical risk exposure is considerably lower than those disclosing transition exposure, consistent with Bolstad et al. (2020) who find that climate disclosures remain heavily skewed toward transition-related valuation risks.

During periods of high climate risk, we expect B_k_risk to be higher for firms with low cc_expo and low $Scope(1+2+3)$, as their bonds are actively sought for hedging. During periods of high ambiguity, we expect the same relationship to hold or strengthen, as investors

Table 6: **Determinants of climate change risk beta - Climate change exposure**
The table reports in Columns 1, 3, and 5 the estimates of the regression of one-month-ahead *B_k_risk* on *cc_expo*, *H_k_risk*, and an interaction term between *H_k_risk* and *cc_expo*, and in Columns 2, 4 and 6 the estimates of the regression of one-month-ahead *B_k_risk* on *cc_expo*, *H_k_ambg*, and an interaction term between *H_k_ambg* and *cc_expo*. *cc_expo* is a firm's exposure to climate change risk estimated by Sautner et al. (2023). We consider several control variables at the bond level: B_Term, B_Default, B_Market, B_TED, B_Illiq, Illiquidity, Volume, No_Trasc, Maturity, Reversal, and at the firm level: Volatility, Downside_Risk, AmbiguityStock, Size, Profitability, Solvency. The sample covers the period from January 2005 to July 2020. All regression models include year, month and bonds fixed effects. The robust standard errors are clustered at the bond level and they are reported in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$ indicate statistical significance at the 1%, 5%, and 10% level, respectively. Variables are defined in Table 8.

Dependent Variable:	Future Beta risk					
	Transit		Chro_phy		Acute_phy	
Interaction with high climate change	Risk (1)	Ambiguity (2)	Risk (3)	Ambiguity (4)	Risk (5)	Ambiguity (6)
cc_expo	4.9828*** (3092)	2.9148* (1830)	0.4914 (0.4878)	-0.1346 (0.4749)	0.2787 (0.3216)	0.2306 (0.3040)
H_transit_risk	-0.0922*** (0.0039)					
H_transit_risk×cc_expo	-5.5396*** (0.8638)					
H_transit_ambg		0.2288*** (0.0031)				
H_transit_ambg×cc_expo		-4.8377*** (0.5756)				
H_chro_phy_risk			-0.0032*** (0.0006)			
H_chro_phy_risk×cc_expo			0.2651 (0.1402)			
H_chro_phy_ambg				0.0224*** (0.0008)		
H_chro_phy_ambg×cc_expo				1.8510*** (0.1614)		
H_acute_phy_risk					-0.0378*** (0.0006)	
H_acute_phy_risk×cc_expo					0.0449 (0.1568)	
H_acute_phy_ambg						-0.0187*** (0.0005)
H_acute_phy_ambg×cc_expo						0.3289* (0.1628)
Control:Bond	Yes	Yes	Yes	Yes	Yes	Yes
Control:Firm	Yes	Yes	Yes	Yes	Yes	Yes
FE:Month	Yes	Yes	Yes	Yes	Yes	Yes
FE:Year	Yes	Yes	Yes	Yes	Yes	Yes
FE:Bond	Yes	Yes	Yes	Yes	Yes	Yes
N	256767	256767	256767	256767	256767	256767
adj. R^2	0.865	0.867	0.663	0.665	0.416	0.410

gravitate toward low-exposure firms whose reputational resilience provides a reliable anchor when the aggregate climate signal is noisy (Lins et al., 2017). In both cases, we expect a negative and significant coefficient on the interaction term between the high-risk or high-ambiguity dummy and the exposure proxy.

Table 6 reports in Columns 1, 3, and 5 the estimates of the regression of one-month-ahead *B_k_risk* on *cc_expo*, *H_k_risk*, and an interaction term between *H_k_risk* and *cc_expo* in Columns 2, 4 and 6 the estimates of the regression of one-month-ahead *B_k_risk* on *cc_expo*, *H_k_ambg*, and an interaction term between *H_k_ambg* and *cc_expo*. We include

Table 7: **Determinants of climate change risk beta - Carbon emissions intensity**
The table reports in Columns 1, 3, and 5 the estimates of the regression of one-month-ahead *B_k_risk* on $Scope(1+2+3)$, *H_k_risk*, and an interaction term between *H_k_risk* and $Scope(1+2+3)$, and in Columns 2, 4 and 6 the estimates of the regression of one-month-ahead *B_k_risk* on $Scope(1+2+3)$, *H_k_ambg*, and an interaction term between *H_k_ambg* and $Scope(1+2+3)$. $Scope(1+2+3)$ is a firm's total carbon emission intensity (Scope 1, 2, and 3). We consider several control variables at the bond level: B_Term, B_Default, B_Market, B_TED, B_Illiq, Illiquidity, Volume, No_Trasc, Maturity, Reversal, and at the firm level: Volatility, Downside_Risk, AmbiguityStock, Size, Profitability, Solvency. The sample covers the period from January 2005 to July 2020. All regression models include year, month and bonds fixed effects. The robust standard errors are clustered at the bond level and they are reported in parentheses. $^{***}p<0.01$; $^{**}p<0.05$; $^{*}p<0.1$ indicate statistical significance at the 1%, 5%, and 10% level, respectively. Variables are defined in Table 8.

Dependent Variable:	Future Beta risk					
	Transit		Chro_phy		Acute_phy	
Interaction with high climate change	Risk (1)	Ambiguity (2)	Risk (3)	Ambiguity (4)	Risk (5)	Ambiguity (6)
Scope(1+2+3)	-0.0117*** (0.0033)	-0.0133*** (0.0032)	0.0071*** (0.0020)	0.0079*** (0.0020)	0.0003 (0.0009)	0.0001 (0.0010)
H_transit_risk	0.0180 (0.0241)					
H_transit_risk×Scope(1+2+3)	-0.0041** (0.0013)					
H_transit_ambg		0.2532*** (0.0209)				
H_transit_ambg×Scope(1+2+3)		-0.0022 (0.0011)				
H_chro_phy_risk			-0.0025 (0.0044)			
H_chro_phy_risk×Scope(1+2+3)			0.0000 (0.0002)			
H_chro_phy_ambg				0.0465*** (0.0056)		
H_chro_phy_ambg×Scope(1+2+3)				-0.0014*** (0.0003)		
H_acute_phy_risk					-0.0493*** (0.0060)	
H_acute_phy_risk×Scope(1+2+3)					0.0006 (0.0003)	
H_acute_phy_ambg						-0.0330*** (0.0058)
H_acute_phy_ambg×Scope(1+2+3)						0.0009** (0.0003)
Control:Bond	Yes	Yes	Yes	Yes	Yes	Yes
Control:Firm	Yes	Yes	Yes	Yes	Yes	Yes
FE:Month	Yes	Yes	Yes	Yes	Yes	Yes
FE:Year	Yes	Yes	Yes	Yes	Yes	Yes
FE:Bond	Yes	Yes	Yes	Yes	Yes	Yes
N	163888	163888	163888	163888	163888	163888
adj. R^2	0.869	0.871	0.676	0.677	0.300	0.293

the same set of control variables as in the previous regressions.

Firms with low climate change exposure exhibit higher *B_transit_risk* during periods of elevated transition risk, consistent with investors actively seeking out their bonds for hedging purposes. This relationship also strengthens during periods of high ambiguity in attention to climate change: when media outlets disagree about the salience of transition events, investors place greater weight on firm-level climate credentials as a direct indicator of resilience, and the bonds of low-exposure firms attract stronger hedging demand precisely when the aggregate climate signal is noisy. The reputational credibility of these firms (Lins et al., 2017) thus constitutes a distinct source of hedging value under uncertain market conditions, over and above their role as hedges during high-risk periods. Both findings are confirmed in Table 7 using carbon emissions intensity ($Scope(1+2+3)$) as an alternative exposure proxy, with lower-emission firms displaying similarly higher $B\_transit\_risk$.

For chronic and acute physical risks, the interaction term between high risk or ambiguity and climate exposure is either insignificant or positive rather than negative, contrary to the predictions of H5 and H6. We attribute these findings primarily to measurement limitations. Unlike transition risk, which is driven by a firm's carbon footprint and industry classification, physical climate risk exposure depends on the geographical location of a firm's assets — a dimension that neither cc_expo nor carbon emissions intensity captures. Both proxies predominantly reflect transition-related exposure, and their positive interaction with physical risk ambiguity likely reflects the pricing of transition credentials rather than physical hedging motives. We therefore refrain from drawing conclusions about H5 and H6 for physical risk channels.

5. Robustness analysis

This section discusses the several robustness tests used to assess the reliability of the findings; the actual results are reported in detail in the online Appendix.

First, we examine whether B_k_risk has long-term predictive power for future bond returns. We regress the future excess bond returns in months $t+3$ and $t+6$ on B_k_risk measured in month t. The results show that B_k_risk remains significantly negative when predicting 3-month ahead bond excess returns for all types of risk. However, only the coefficient of $B\_chro\_phy\_risk$ is significantly negative when predicting bond excess returns 6-month ahead. These findings indicate that our results are not driven by a short-run reversal effect or a mechanical effect arising from the bid–ask bounce (Jegadeesh, 1990; Lehmann, 1990).

Second, we consider an alternative climate change news index, specifically, the Wall Street Journal climate change news index (EGLKS) developed by Engle et al. (2020), and the media climate change concern index (MCCC), developed by Ardia et al. (2023). We use rolling regressions to estimate equation (4) augmented by innovation in the climate change news indices. We then add the main regression EGLKS beta (B_EGLKS), and MCCC beta (B_MCCC). We find that the coefficient of $B\_k\_risk_{i,t}$ remains significantly negative after including B_EGLKS and B_MCCC for transition and acute physical risk but not for chronic physical risk.

Third, our analysis may be sensitive to differences in trade direction (buy versus sell), trader type (customer versus interdealer), and trade size (above or below \$100,000). We therefore conduct subgroup analyses along these dimensions. The negative relation between B_k_risk risk and future excess bond returns remains broadly robust across the six subsamples. However, for chronic and acute physical risks, the effect does not persist in subsamples restricted to sell trades or to trades with volumes exceeding \$100,000.

Fourth, we investigate whether the results are driven by highly traded bonds. We divide our sample into low- and high-frequency corporate bond transactions, using the first and last quantiles of the average daily number of bond transactions over a month. We find that B_k_risk is negatively associated with future excess bond returns in all subsamples, except for chronic physical risk, for which the results do not hold for bonds with low frequency of exchange and acute physical risk for bonds with high frequency of exchange.

Fifth, we investigate whether the climate change risk premium originates from changes in a firm's default risk. To do so, we estimate the firm's distance to default ($D2D$) following Shumway (2001). The $D2D$ index is based on the Merton model of credit risk; it increases as a firm's asset level exceeds its liabilities, suggesting a lower default probability. We define $SPREAD\_D2D$ as the credit spread divided by one minus the cumulative distribution function of $D2D$ (Kelly et al., 2023). $SPREAD\_D2D$ indicates the value of the credit spread that might be required for each unit of default risk, as estimated by $D2D$. The results show an insignificant relationship between bond climate change risk betas and future default risks, suggesting that corporate bonds' exposure to climate change risk might not have predictive power for firm default risk, and that the effect of B_k_risk is potentially driven by investors' perceptions of a bond's exposure to climate change risk rather than the firm's fundamentals.

Finally, we test the predictive ability of B_k_risk for future abnormal returns for the subsamples of short- and long-term bonds. Future abnormal returns are the difference between corporate bond returns and their expected value, where expected returns are computed as in Bessembinder et al. (2008). We confirm the main results for transition and chronic physical risks but not for acute physical risk.

6. Conclusion

This study examines the impact of climate change risk and ambiguity on corporate bond returns. First, we use news media data to extract the risk and ambiguity levels associated with sustainable investing, climate transition, chronic and acute physical climate changes, and environmental degradation. Then, we compute the covariance between bond returns and innovation using the climate change risk metric (B_k_risk).

We document that investors prefer bonds with a strong potential for hedging against climate risk, as indicated by higher B_k_risk. In particular, B_k_risk predicts lower future returns for transition, chronic and acute physical climate risks. Moreover, this negative association is stronger when climate risk is higher. However, the demand for such bonds decreases as ambiguity in the attention to climate change increases.

Additionally, long-term bonds are more sensitive to hedging demands to mitigate physical climate risks, whereas investors consider hedging climate transition risk more valuable in the short run, as climate change policies might affect their current investment opportunity set (Black Rock, 2016).

Further analysis reveals that when climate change transition risk and ambiguity are high, bonds issued by firms with lower exposure to climate change have a higher $B\_transit\_risk$. This finding is consistent with investors using bonds issued by firms with low exposure to hedge against climate transition risks. The results for physical climate risks are inconclusive because of the lack of measures for a firm's exposure to such risks.

Our findings carry concrete implications for four audiences. For policymakers, our results show that aggregate media ambiguity about climate change — when outlets disagree substantially about the salience of climate events — weakens climate risk hedging and may lead to mispricing in the bond market. This provides an empirical argument for policies that improve the clarity and consistency of climate risk communication, reducing the heterogeneity in how media outlets interpret and report on climate events. For investors, periods of high aggregate media ambiguity about climate change represent a systematic risk to climate hedging strategies: the expected return reduction associated with holding high-beta climate bonds weakens precisely when ambiguity is elevated, meaning that portfolios constructed to hedge climate risk may underperform their intended function during these periods. Investors should therefore account for the prevailing ambiguity regime when assessing the effectiveness of their climate hedges. For institutional bond portfolio managers, the five-topic decomposition we introduce enables a more granular hedging strategy than single-index approaches allow: transition risk is better hedged with short-duration bonds of low-exposure issuers, while chronic and acute physical risks call for longer-dated instruments, a distinction that single-index approaches cannot provide. For firm managers, our results show that bonds issued by firms with low climate exposure carry a pricing advantage that is strongest precisely when climate risk and ambiguity are high, providing a financial incentive for genuine emissions reduction and transparent climate risk management beyond regulatory compliance.

Our study opens several avenues for future research. First, the interaction between media ambiguity and climate hedging documented here for bonds could be examined in equity markets and derivatives (e.g., carbon options), potentially revealing whether the ambiguity premium is systematic across asset classes. Second, as physical climate risk disclosure improves — driven by regulatory mandates and third-party data providers — the physical risk channel identified in our framework should become empirically more tractable, allowing more precise tests of H5 and H6 for chronic and acute risks. Finally, the methodology introduced in Sadoghi and Santi (2026) is domain-general and could be applied to other forms of systemic risk — geopolitical, pandemic, technological — where media ambiguity may similarly attenuate agents' hedging responses.

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Appendix A. Variables definitions

Table 8: **Variables definitions**
This table describes the variables used in the study.

Variable	Definition
EBR	Excess corporate bond return, computed as corporate bond return (equation 1) minus one-month Treasury bill rate
Term_Spread	Difference between the monthly returns on the Ibbotson U.S. long-term government bond index and one-month Treasury bill rate.
Default_Spread	Difference between BAA and AAA-rated corporate bond yields
Market_Exc	Excess equity market return
TED_Spread	Difference between the 3-month London Interbank Offered Rate (LIBOR) and the three-month Treasury bill rate
Market_Illiquidity	Market illiquidity for all U.S.-listed corporate bonds by Dick-Nielsen et al. (2012)
B_transit_risk	Climate transition risk beta estimated from monthly rolling regressions over a 60-month window of corporate bond excess return on the innovation of transition risk after controlling for several variables (see equation 4)
B_sustain_risk	Sustainable investing risk beta estimated from monthly rolling regressions over a 60-month window of corporate bond excess return on the innovation of sustainable investing risk after controlling for several variables (see equation 4).
B_chro_phy_risk	Chronic climate physical risk beta estimated from monthly rolling regressions over a 60-month window of corporate bond excess return on the innovation of chronic climate physical risk after controlling for several variables (see equation 4)
B_acute_phy_risk	Acute climate physical risk beta estimated from monthly rolling regressions over a 60-month window of corporate bond excess return on the innovation of acute climate physical risk after controlling for several variables (see equation 4)
B_environ_risk	Environmental risk beta estimated from monthly rolling regressions over a 60-month window of corporate bond excess return on the innovation of environmental risk after controlling for several variables (see equation 4).
B_transit_ambg	Climate transition ambiguity beta estimated from monthly rolling regressions over a 60-month window of corporate bond excess return on the innovation of transition ambiguity after controlling for several variables (see equation 4)
B_sustain_ambg	Sustainable investing ambiguity beta estimated from monthly rolling regressions over a 60-month window of corporate bond excess return on the innovation of sustainable investing ambiguity after controlling for several variables (see equation 4)
B_chro_phy_ambg	Chronic climate physical ambiguity beta estimated from monthly rolling regressions over a 60-month window of corporate bond excess return on the innovation of chronic climate physical ambiguity after controlling for several variables (see equation 4)
B_acute_phy_ambg	Acute climate physical ambiguity beta estimated from monthly rolling regressions over a 60-month window of corporate bonds excess return on the innovation of acute climate physical ambiguity after controlling for several variables (see equation 4)
B_environ_ambg	Environmental ambiguity beta estimated from monthly rolling regressions over a 60-month window of corporate bond excess return on the innovation of environmental ambiguity after controlling for several variables (see equation 4)
B_Term	Term spread beta estimated from monthly rolling regressions over a 60-month window of corporate bond excess return on the term spread and several other variables (see equation 4)
B_Default	Default spread beta estimated from monthly rolling regressions over a 60-month window of corporate bond excess return on the default spread and several other variables (see equation 4)
B_Market	Market beta estimated from monthly rolling regressions over a 60-month window of corporate bond excess return on the market excess return and several other variables (see equation 4).
B_TED	TED spread beta estimated from monthly rolling regressions over a 60-month window of corporate bond excess return on the TED spread and several other variables (see equation 4)
B_Illiq	Market illiquidity beta estimated from monthly rolling regressions over a 60-month window of corporate bond excess return on market illiquidity and several other variables (see equation 4)
H_transit_risk	A dummy variable equal to 1 for months with innovation in climate transition risk above the 50th percentile of the sample period, and 0 otherwise
H_chro_phy_risk	A dummy variable equal to 1 for months with innovation in chronic climate physical risk above the 50th percentile of the sample period, and 0 otherwise
H_acute_phy_risk	A dummy variable equal to 1 for months with innovation in acute climate physical risk above the 50th percentile of the sample period, and 0 otherwise.
H_transit_ambg	A dummy variable equal to 1 for months with innovation in climate transition ambiguity above the 50th percentile of the sample period, and 0 otherwise
H_chro_phy_ambg	A dummy variable equal to 1 for months with innovation in chronic climate physical ambiguity above the 50th percentile of the sample period, and 0 otherwise
H_acute_phy_ambg	A dummy variable equal to 1 for months with innovation in acute climate physical ambiguity above the 50th percentile of the sample period, and 0 otherwise
Illiquidity	Covariance of the change in the natural logarithm of the bond price on a given day and the following day (Bao et al., 2011)
Reversal	Short-term reversal (Jegadeesh, 1990) is the previous month's bond returns
Profitability	Net income divided by the shareholder's equity
Size	Natural logarithm of the market capitalization (in thousands)
Solvency	Total debt divided by the shareholder's equity
No_Trasc	Natural logarithm of the average number of daily transactions over a month
Maturity	Natural logarithm of the number of years to bond maturity
Volume	Natural logarithm of the average daily amount of the bond traded over a month
DownSide_risk	Average of the four lowest bond returns below value-at-risk at the 10% threshold computed using rolling windows of 36 months
AmbiguityStock	Expected volatility of intraday stock returns (Izhakian, 2020)
Volatility	6-month rolling standard deviations of stock returns (Ang et al., 2006)
cc_expo	A firm's climate exposure estimated by Sautner et al. (2023)
Scope(1+2+3)	Total carbon intensity computed as scope 1, 2 and 3 total emissions divided by market capitalization
B_EGLKS	Climate change news risk beta estimated from monthly rolling regressions over a 60-month window of corporate bond excess return on the innovation of the Wall Street Journal climate change news index by Engle et al. (2020) after controlling for several variables (see equation 4).
B_MCCC	Media Climate Change Concern (MCCC) beta estimated from monthly rolling regressions over a 60-month window of corporate bond excess return on the innovation of the MCCC index by Ardia et al. (2023) after controlling for several variables (see equation 4).

Appendix B. Climate change risk and ambiguity

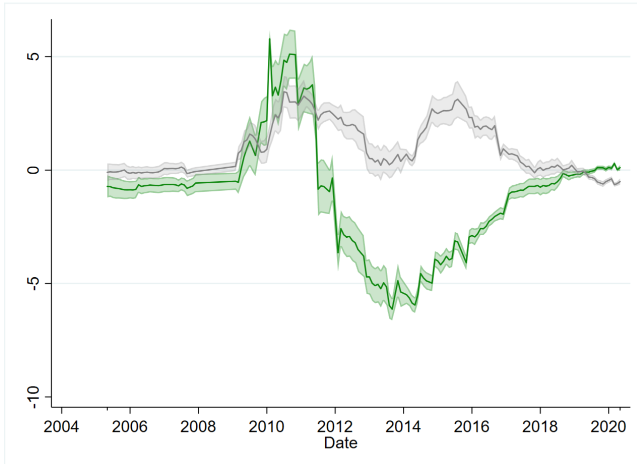
Table 9: **Terms-Topics in topic modelling classification of climate change risk related articles**
The table displays the results of applying the topic modeling method to news articles related to climate change risk. The table contains the top 15 sorted terms based on each term's probability (Prob) to identify a given topic k. We use lemmatization and stemming methods to transform words into their roots. We integrate two-gram words with three-gram words.

	Transit	Prob	Sustain_invs	Prob	Chro_phy	Prob	Acute_phy	Prob	Environment	Prob
1	climat_chang	0.0396	environ_social	0.0159	climat_chang	0.1057	climat_chang	0.0813	air_pollut	0.048
2	climat_risk	0.0176	climat_chang	0.013	increa_level	0.0361	natur_disast	0.0788	public_health	0.0199
3	fossil_fuel	0.0134	environ_impact	0.0087	sea_increa	0.0354	flood_risk	0.0779	health_risk	0.0155
4	chang_risk	0.0106	environ_risk	0.0085	sea_increa_level	0.0312	flood_insur	0.0482	water_suppli	0.0127
5	climat_chang_risk	0.0095	compani_risk	0.0081	sea_level	0.025	extrem_weather	0.0292	air_qualiti	0.0125
6	climat_financi	0.0065	impact_invest	0.0066	global_warm	0.0227	disast_risk_reduct	0.0287	drink_water	0.0112
7	emiss_scandal	0.0059	social_impact	0.0059	increa_sea	0.0213	environ_agenc	0.0248	resourc_water	0.0107
8	leighton_hold	0.0048	social_respons	0.0059	increa_sea_level	0.0136	weather_event	0.0245	environ_impact	0.0101
9	middl_east	0.0043	corpor_govern	0.0058	storm_surg	0.0112	damag_flood	0.02	natur_resourc	0.009
10	cold_chain	0.0042	natur_resourc	0.0054	climat_impact	0.0107	flood_defenc	0.0197	pollut_environ	0.0084
11	carbon_diox	0.004	develop_sustain	0.0051	greenhous_gas	0.0105	properti_insur	0.0172	water_qualiti	0.0078
12	financi_stabil	0.004	risk_opportun	0.0051	carbon_diox	0.0089	disast_risk	0.017	pollut_environ_impact	0.0077
13	pension_fund	0.0039	climat_risk	0.0048	greenhous_gase	0.0087	compani_insur	0.0166	food_secur	0.0075
14	vw_share	0.0038	sustain_invest	0.0048	gas_emiss	0.0085	sever_weather	0.0156	water_risk	0.0072
15	climat_impact	0.0037	respons_invest	0.0047	greenhous_gas_emiss	0.0083	extrem_weather_event	0.0144	environ_health	0.0066

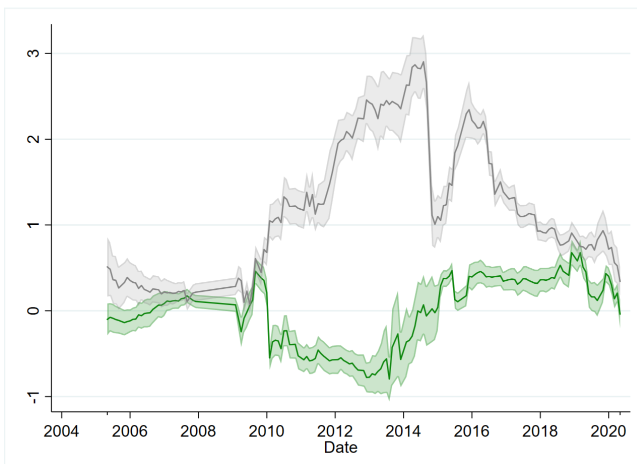
Table 10: **Topic validation with ClimateBERT**
This table presents the results of applying the ClimateBERT model (Bingler et al., 2024) to our sample of news articles related to climate risk. Results are reported separately for news articles on climate transition (*Transit*), sustainable investing (*Sustain_invs*), environment (*Environment*), chronic physical (*Chro_phy*), and acute physical (*Acute_phy*). Panel I displays the proportion of our news articles that are classified as related to climate change (Yes), and those that do not (No) according to the ClimateBERT model. Panel II presents the shares of news articles discussing risk, opportunity and neutral according to the sentiment analysis conducted with the ClimateBERT model.

	Panel I: News articles related to climate change					
	Transit	Sustain_invs	Environment	Chro_phy	Acute_phy	Total
Yes	92.31	86.12	88.59	99.32	93.91	92.19
No	7.69	13.88	11.41	0.68	6.09	7.81
Total	100.00	100.00	100.00	100.00	100.00	100.00
	Panel II: Sentiment associated with climate risk news articles					
	Transit	Sustain	Environment	Chro_phy	Acute_phy	Total
Risk	83.11	62.10	90.75	90.45	91.19	87.53
Neutral	10.26	23.8	4.37	6.24	2.54	5.95
Opportunity	6.64	16.50	4.88	3.31	6.27	6.52
Total	100.00	100.00	100.00	100.00	100.00	100.00

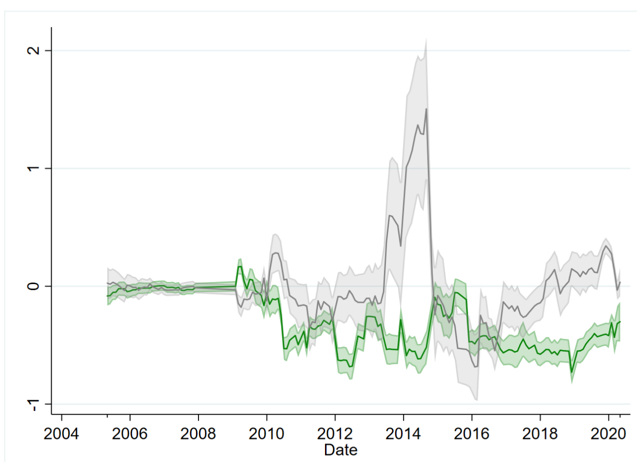
Fig. 1: **Time series plots of climate change risk and ambiguity betas**
These figures display the betas of climate change risk (green colour) and ambiguity (grey colour) over time for the average corporate bond. The shaded areas denote the 95% confidence intervals. Panel I shows the average climate transition risk and ambiguity betas, Panel II shows the average chronic climate physical risk and ambiguity betas, and Panel III shows the average climate acute physical risk and ambiguity betas. Variables are defined in Table 8.



Panel I: Average climate transition risk (green) and ambiguity (gray) betas



Panel II: Average climate chronic physical risk (green) and ambiguity (gray) betas



Panel III: Average climate acute physical risk (green) and ambiguity (gray) betas