Climate Attention and the Cross-Section of EUR Corporate Bond Returns

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Abstract

This paper examines whether attention to climate change is reflected in the pricing of Euro-denominated corporate bonds. To this end, we construct a climate media index using the volume of news articles published in European and North American newspapers from 2004 to 2022. Our model rise to a set of testable predictions for which we find strong support in the data: a higher climate exposure leads to a significant decline in future bond returns (around 5bps). This supports the notion that risk-averse investors tend to favor assets that provide a hedge against climate change, or exhibit a discount otherwise. Our study also reveals the existence of a "low-climate beta anomaly," where portfolios with low climate exposure are associated with higher returns. These relationships remain robust after controlling for conventional risk factors, bond characteristics, and different model specifications. The results indicate that climate regulatory shocks are priced, however, physical shocks are not. Further, a return decomposition analysis highlights that the discount rate climate beta is the dominant factor in the bond market.

Keywords: Climate change, investors attention, cross-sectional returns, corporate bond risk factors, bond characteristics.
JEL: G12, L82, M14, Q51, Q54

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1. Introduction

Understanding the effects of climate on asset prices has become of particular interest to sustainable investors. However, identifying, measuring, and disclosing climate-related information remains a challenge.[1] With regard to climate risks, there is a high degree of uncertainty as to how these risks are reflected in asset prices. Some studies have used news articles as a way to explore investors' attention, sentiment or concerns about climate change, risk perception, and environmental regulations (Engle et al., 2020; Ardia et al., 2020; Faccini et al., 2021; Campiglio et al., 2022; Seltzer et al., 2020). Yet, little is known about the implications of climate change on the corporate bond market, inasmuch as the body of literature on the cross-section of corporate bonds returns is still in its infancy (Bai et al., 2016, 2019; Bali et al., 2020), particularly in the European market (Pham and Huynh, 2020; Pieterse-Bloem and Mahieu, 2013; Castagnetti and Rossi, 2013).[2] However, evidence in this paper supports the view that individual corporate bond returns are influenced by unanticipated changes in climate attention, and that climate shocks have greater effects, particularly for longer duration and lower rated bonds. Contrary to general assumptions, there is heterogeneity in the market regarding the climate resilience of bonds within carbon-intensive industries (Battiston et al., 2021), and the environmental performance within issuer-level (Berg et al., 2019; Gibson Brandon et al., 2021) and bond-level characteristics.

To study the effects of climate media attention, we introduce the Climate Change Media Attention Index (CC^{ATT}) constructed using data from the Media and Climate Change Observatory, monitoring 126 sources (among newspapers, radio and TV) in 58 countries[3]. The data is assembled by accessing archives through the Nexis Uni, Proquest and Factiva databases. We consider the aggregated monthly volume of published newspapers articles ($MeCCO_t$) and the month-over-month changes ($\Delta MeCCO_t$). Two potential concerns are that the aggregate index (volume or changes) is not unexpected and has source aggregation. In order to help alleviate

1. The IFRS's International Sustainability Standards Board (ISSB) and the Task Force on Climate-related Financial Disclosures (TCFD) have joined forces in requiring companies to assess their climate resilience as a first step in quantifying the impact of environmental factors on financial reporting. Yet, there are no data providers measuring consistent exposures of climate change, at firm-level, let alone at the bond-level. MSCI's Climate-Value-at-Risk Scores, Trucost's Physical Risk Scores, and Refinitiv's Climate Opportunities have just a few firm-years observations and scarce historical data.

2. Researchers have shown particular interest on the pricing differential between green and traditional bonds (Zerbib, 2019; Flammer, 2021), on the growing demand and supply (Maltais and Nykvist, 2020), and the impacts (Tolliver et al., 2020). Nevertheless, the implications of the overall corporate bond market often remain unexplored from a sustainable standpoint.

3. The database is publicly available at: https://scholar.colorado.edu/concern/datasets/nz806067t

both of these problems, we construct CC^{ATT} as a measure of unexpectedness and impact (innovations) derived from the residuals of an AR(1) process controlling for each media source (Ardia et al., 2020; Engle et al., 2020).[4] We find that exposure to climate attention carry a statistically significant negative price of risk. Previous studies provide strong arguments as to why the exposure to climate change should reflect poor performance (Engle et al., 2020; Duan et al., 2020; Cornell and Damodaran, 2020), concluding that the higher demand for assets less exposed to climate increases their price and lowers their average return. However, incthis study, we show that there is a 'low-climate beta anomaly' since portfolios with lower climate betas (e.g. returns' sensitivity to climate news show higher positive returns. This can be implemented as a strategy for investors in order to quantify and minimize the risk associated in climate attention without forcing investors to give up on their returns.

Media attention towards climate change can affect bond prices as it measures investors' awareness and correlates with the materialization of physical and regulatory risks. When attention increases, sustainable investors may increase their demand for particular bonds driving up prices (Huynh and Xia, 2021). As well as, unexpected rises in media attention may lead investors to update their preferences on particular industries, issuers, ratings, and maturities (Pástor et al., 2022). Besides that attention is a necessary condition for generating investor sentiment (La Bruslerie, 2017; Ramos et al., 2020),[5] if investors are genuinely concerned about climate risks, higher attention may negatively affect bond returns, conversely, if investors are reluctant about such climate risks, the impact is expected to be marginal.

It is important to disentangle the physical risks associated with climate change (e.g. extreme weather events) from regulatory risks (e.g. changes in laws and policies to reduce carbon emissions) associated with climate change to fully comprehend the potential impacts on the bond market. We focus primarily on *realized* climate events, either physical or regulatory, because they provide tangible information to investors about the consequences to climate change. Furthermore, climate change can affect the pricing of bonds by influencing cash flows and discount rates (Ardia et al., 2020). Our analysis shows that regulatory climate risks primarily affects bonds via the discount rate channel.

4. In section B, we provide the construction methodology for CC^{ATT}. Alternative climate change news indices are found in the literature. Although climate betas can also be estimated from these alternative indices, in this study, we mainly focus on estimating climate beta relative to CC^{ATT}. The divergence between these indices constitutes an overall measure of climate change uncertainty.

5. Ramos et al. (2020) separate in more detail issues of attention, limits in attention, and salience of information.

Regarding climate news, Engle et al. (2020) and Bessec and Fouquau (2020) are two seminal studies focused on climate sentiment; both studies apply textual analysis to articles from the Wall Street Journal (WSJ). Our index differentiates from theirs in two ways. First, instead of one media source, we use 45 European and 11 North American newspapers. This allows for greater news coverage focused on the European landscape. Second, we focus exclusively in news discussing climate change, based on the criteria provided by the Media and Climate Change Observatory (MeCCO) database.[6] Our index is also related to Ardia et al. (2020). They create the Media Climate Change Concern index (MCCC) from 8 US media newspapers and identify 40 climate-related topics that explain positively (negatively) the cross-section of green (brown) stock returns. Pástor et al. (2022) make use of the MCCC index to estimate investors' memory of climate news over time. Other studies follow this line of research, for example Faccini et al. (2021) construct four climate news indices using topics related to international climate summits, global warming, natural disasters, and US climate policies, and Apel et al. (2021) focus solely on transition risks, using topics related to three drivers of transition risks: environmental and emission standards, decrease of production costs for renewable energy and shifts in consumer preferences. Our index is also closely associated with Brøgger and Kronies (2020) as they estimate investor's attention using the volume of Google searches on *Climate Change*. We further compare our results with climate and political uncertainty measures from Baker et al. (2016) and Gavriilidis (2021). These two uncertainty indices count the number of newspaper articles having *climate* and *uncertainty* terms.[7] Table 1 summarizes different climate change indices that are considered in this study.

The studies of Huynh and Xia (2020) and Duan et al. (2020) are among the first to take an interest in the effects of climate news on US corporate bond returns. Huynh and Xia (2020) apply Engle et al. (2020)'s WSJ index, and integrate ESG scores from MSCI/Sustainalytics; while Duan et al. (2020) use carbon emissions from S&P Trucost, and incidents from RepRisk. According to the authors' estimates of the climate change news beta, a higher level of exposure to climate change translates into poorer future bond returns. These findings are related to how the demand for bonds with climate change hedging properties has an impact on asset pricing. When investors are concerned about climate risks, they are willing to pay higher prices for bonds issued by companies with better environmental performance.

6. Barkemeyer et al. (2018) broaden the search criteria beyond climate to include social and environmental issues, such as poverty, HIV/AIDS, malaria discrimination, labor rights, and cleaner technologies. Exploring these topics constitutes an interesting avenue for further research.

7. Uncertainty indices are available online at: https://www.policyuncertainty.com

Table 1: **Climate Change News indices: Description.**

Indices	Authors	Sources	Frequency	Period
		Attention		
Climate salience	Brøgger and Kronies (2020)	Google Trends.	Monthly	2005/01 - 2017/12
		Sentiment		
WSJ Climate Change News Index	Engle et al. (2020)	Wall Street Journal.	Monthly	1984/01 - 2018/05
CH Negative Climate	Engle et al. (2020)	Crimson Hexagon: WSJ, NY Times, Washington Post, Reuters, BBC, CNN, and Yahoo News.	Monthly	2006/06 - 2018/05
Media Climate Change Concerns (MCCC)	Ardia et al. (2020)	DowJones Factiva, ProQuest, and LexisNexis.	Daily	2003/01 - 2018/06
Overall index	Faccini et al. (2021)	Reuters.	Monthly/Daily	2000/01 - 2019/11
Transition Risk Index (TRI)	Apel et al. (2021)	Dow Jones Newswires, Reuters, NY Times, The Washington Post, BBC, WSJ, MSN, and CNN.	Monthly/Weekly	2000/01 - 2020/12
		Uncertainty		
European Policy Economic Uncertainty Index (EPU)	Baker et al. (2016)	Le Monde, Le Figaro, Handelsblatt, Frankfurter Allgemeine Zeitung, Corriere Della Sera, La Stampa, El Mundo, El Pais, The Times of London, Financial Times.	Monthly	1987/01 - 2022/02
Climate Policy Uncertainty Index (CPU)	Gavriilidis (2021)	Boston Globe, Chicago Tribune, LA Times, Miami Herald, NY Times, Tampa Bay Times, USA Today and WSJ.	Monthly	2000/01 - 2021/12

Unlike carbon risks,[8] climate risks are harder to estimate because of their intricate nature and broader scope. For example, the materialization of climate risks can be either physical or regulatory. Physical risks include natural disasters, such as hurricanes, droughts, and extreme weather; and regulatory risks include laws and requirements that can arguably affect the future claims of a company (Sautner et al., 2021; Ilhan et al., 2021). Therefore, investors can also act against the uncertain impact of climate risks by minimizing the (relative or absolute) exposure to assets that do not perform well when physical and/or regulatory risks materialize and by requiring a risk premium from holding those assets. Our objective remains to identify climate risk exposures after the materialization of such events and explain the mispricing between carbon risks and climate risks. We explain this mispricing by testing if bonds with different sensitivities have different average returns and carbon intensities.

Over the sample period, the average monthly excess return on corporate bonds is 2.7%, with a standard deviation of 1.46. The representative corporate bond has a climate change news beta

8. Investors can manage carbon risks by using a fundamental or market-based approach (Görgen et al., 2020; Roncalli et al., 2021; Huij et al., 2021). The fundamental approach accounts for current emissions and sets targets to minimize risks. The market-based approach uses carbon data to assess impact at the asset-level, which can be aggregated at the portfolio-level. However, a portfolio that excludes carbon-intensive industries may be vulnerable to brown companies outperforming green companies without adjusting for industry exposure (Roncalli et al., 2021).

of -0.071 and a standard deviation of 1.14. The coefficients are also economically significant. For example, in column (4) of Table 12, the coefficient estimates on β^{CC} of -0.048 indicates that a 1-standard-deviation increase in the climate change news beta is associated with a drop of 5.47 bps (=-0.048 x 1.14) in the next month's bond excess return, which is equivalent to a decrease of 24.2% relative to the sample mean of excess returns. However, these estimates vary depending on the model specifications and especially after the Paris Agreement, also during periods of climate heightened attention, where these estimates increase. We can also interpret this estimate in terms of the dollar cost of debt financing by assuming the issuance of a new bond with the same characteristics as the average bond in our sample, but with a higher β^{CC}. Given that an average bond trades at € 105.48 for a notional amount of 778 (million, €), a decrease in excess bond returns by 5.47 bps means that the new bond is expected to be issued at a higher price with estimated saving of € 4.26 million in the cost of debt financing for a representative firm in the sample.

The paper is structured as follows. The introduction provides an overview of current climate change indices, and presents the motivations to construct a broader climate change attention index for the European corporate bond market. Section 2 and 3 present the data and the methodology. In section 4, we examine the empirical results relying on univariate sorts, bivariate sorts, and regression estimates. Section 5 concludes.

2. Data

Our study requires data from several sources. We start by describing bond-level and firm-level data. Then, we discuss the climate and media coverage data, and the construction of the Climate Media Attention Index (CC^{ATT}). Summary statistics are reported in Table 2, and definitions of the variables can be found in Table 5.

A. Corporate Bond Data

Bond-level data. We use data from the Markit IBOXX EURO Corporate Index from January 2004 to July 2022, which includes historically 4,548 bonds. The index selects investment grade bonds with a credit rating BBB or better, time to maturity of at least 1 year, and minimum amount outstanding of €500 millions.[9] After filtering out putable/sinking/callable/floating

9. Please refer to Markit (2021) for detailed rules and index calculations of EUR Corporate indices https://ihsmarkit.com/products/indices.html.

bonds and financials, we are left with 3,881 bonds, representing 179,271 month-bond observations. We use quoted month-end prices from Markit estimates from bid-ask quotes, as a reasonable approximation to transaction prices (Biais et al., 2006). Additionally, Markit provides information about the bond issue, including the underwriter, bond yield, offering price, offering date, maturity, and other bond characteristics. Markit credit ratings are the linearized average of the three rating agencies, from Fitch Ratings, S&P Global Ratings, and Moody's Investor Service. Markit maintains historical data prior to the inception of the index, which allows us to calibrate rolling windows estimations that require at least 36 months of data. Continuous variables are winsorized cross-sectionally at the 1st and 99th percentiles to control for outliers.[10] As shown in Table 2, bonds in our sample have an monthly return of 0.226% (or 2.7% annualized), average coupon of 2.83, average size of € 788 million, and an average modified duration of 5.21. Appendix C provides additional statistics over industries, credit ratings and duration.

Insert Table 2 about here.

Firm-level data. We merge environmental, social, and governance (ESG) scores from different providers using the issuer's international securities identification number (ISIN). The ESG scores are provided at different frequencies: ASSET4 and MSCI ESG Ratings are provided on a monthly basis, while Trucost ESG scores and emissions data are provided on a yearly basis. We merge these scores in the same way, either at a monthly or a yearly basis, depending on the data frequency. To calculate the carbon emission intensity (*CEI*), we use the method suggested by Duan et al. (2020) and divide the total emissions from Scope 1 and 2 (in metric tons) by the company's total revenue (in € million). This gives us the *CEI* in metric tons per € million revenue. To account for differences in carbon-intensities at the industry-level, we standardize using the 12 Fama-French industry sectors.

$$CEI = \frac{\text{Scope 1 (tCO2e) + Scope 2 (tCO2e)}}{\text{revenue (€ mil)}} \tag{1}$$

With no surprises, public issuers have larger coverage of ESG and carbon emissions data than private issuers. We identify those bonds that are issued by a private entity but we do not exclude them in the full sample analysis.[11] Additionally, we include firm fundamentals from S&P, such

10. To ensure the accuracy of our results, we also recalculate our findings while including potential outliers in our data. Although some slight variations may be observed, these do not alter the overall significance or direction of our results.

11. Identifying the parent issuer is not trivial because the relationship is not always straightforward. In the simplest case where the issuer is a public company, we retrieve the issuer's ISIN and use it to retrieve company

as the price-book value, debt-equity ratio, and total equity. Table 3 provides the cross-sectional correlations between these variables.

B. Climate Data

Climate disasters. First, to obtain natural disasters, we use the dataset provided by the Center for Research on the Epidemiology of Disasters (CRED).[12] This dataset contains over 15,000 extreme weather events such as, droughts, floods, extreme temperatures, avalanches, landslides, storms, fires, and hurricanes throughout our sample period. The dataset includes disaster categories by location, date and, the total number of people affected by the event, and the estimated economic cost of the event. Following S. Baker et al. (2020), we filter the sample and select those shocks that cause either 100 deaths or damages more than 0.1% of the GDP at the country-level. We aggregate by month the number of disasters that occur in the European Union.

Climate regulations. Second, we are able to get two sources that collect information about climate regulations. The first is provided by the Grantham Research Institute,[13] and the second is provided by the United Nations Principles for Responsible Investment (UNPRI).[14] UNPRI collects data from regulation databases worldwide. It provides the year of implementation, whether the measure is voluntary or mandatory, and the concerned parties. To have a timely assessment, we checked the provided sources to look for the month when the regulation was signed. For both databases, we select European regulations.

Media Coverage. The newspaper coverage dataset is published by Media and Climate Change Observatory (MeCCO).[15] Data is assembled by accessing archives through the Lexis Nexis, Proquest and Factiva databases. They monitor 126 sources (across newspapers, radio and TV medias) from 58 countries across 7 different regions. MeCCO selects articles related

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financials and ESG scores. If the bond issuer is not a public company, we check if the ultimate parent is public. There are cases where the ultimate parent is not public. The ultimate parent may be a private company with a controlling interest in a public company. In this case, we get the ISIN from an immediate parent and traverse the ownership chain until we hit a public company. And then, there is a case where a public borrower may not have a parent/child relationship with private debt issuers, which is typical for debt issued through special purpose vehicles. In this case, we check if the borrower is a public company.

12. See http://www.emdat.be/database. CRED database provides a list of large-scale disasters with the aim of helping researchers, policymakers, and aid workers better respond to future events.

13. See https://climate-laws.org/methodology-legislation for the Grantham Research Institute database.

14. See https://www.unpri.org/policy/regulation-database for the UNPRI database.

15. The database is publicly available at: https://scholar.colorado.edu/concern/datasets/nz806067t

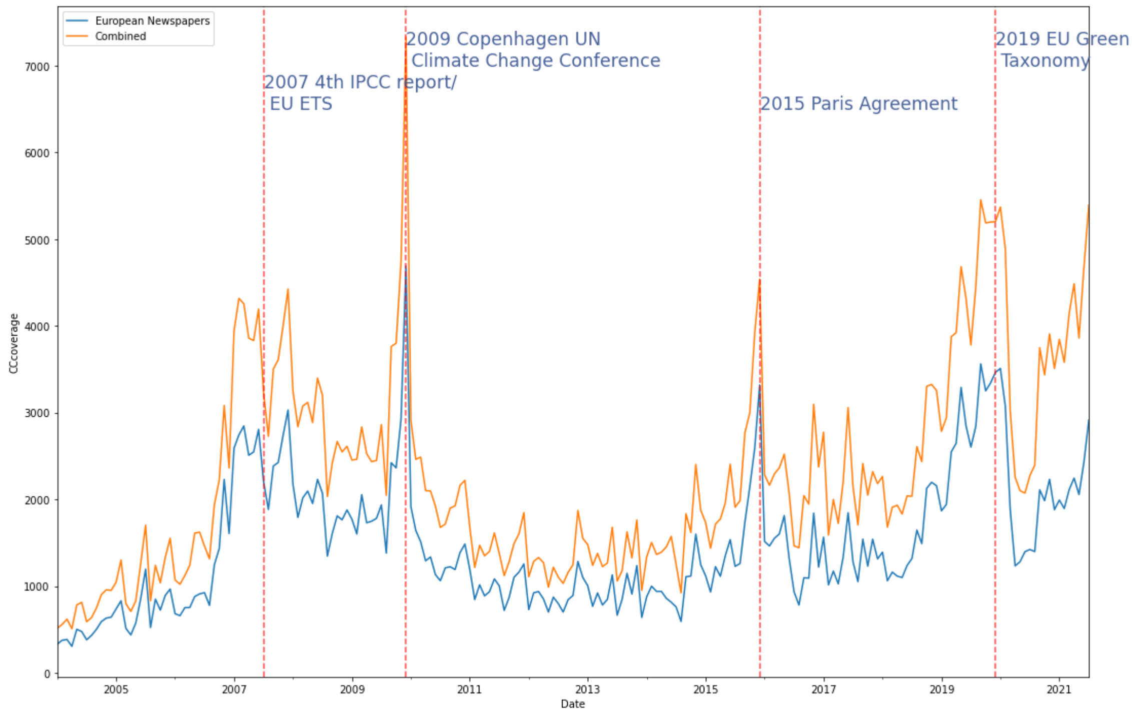

Figure 1: Aggregate media coverage of climate change or global warming articles in Europe, from January 2004 through June 2021.

to *Climate Change* OR *Global Warming*.[16] We focus mainly on European and North American regions. From 2004 to July 2022, we select the 45 European media sources to create the main index. Additionally, the combined index is complemented with 11 North American newspapers (Hawley et al., 2021). Figure 1 plots the coverage of the European and combined indices. During the sample period, the vertical red dotted line shows global meetings such as the Conference of the Parties (COP). Table 6 gives the list of the newspapers.

Climate Change Media Attention Index. The construction of the Climate Change media Attention index (CC^{ATT}) takes inspiration from previous methodologies, Gavriilidis (2021), Brøgger and Kronies (2020), Baker et al. (2016), Ardia et al. (2020), and Engle et al. (2020). Formally, the index is computed as follows.

Newspaper s publishes $n_{s,t}$ articles discussing topics about *climate change* & *global warming* in month $t = 1, \ldots, T$. We define $MeCCO_t$ as the aggregate sum of n across all the newspapers

16. Contributors check and eliminate duplicates manually. For German speaking sources, *Klimawandel* OR *Globale Erwärmung* is used. For Spanish speaking sources, *Calentamiento Global* OR *Cambio Climático* is used.

in the sample S in month t (volume)

(2) $$MeCCO_t = \sum_{s=1}^{S} n_{s,t}$$

and the month-over-month variation, $\Delta MeCCO_t$ (changes).

Barkemeyer et al. (2018) show that time-series media coverage presents a deterministic trend, low signal-to-noise ratio, and in some newspapers, seasonal patterns. Thus, to correct heterogeneity across sources, we standardize media coverage by newspaper source, following Baker and Wurgler (2012), Ardia et al. (2020), and Da et al. (2011). First, in month t, we demean $MeCCO_{t,s}$ by its 36-month (rolling-window) average and divide by its 36-month (rolling-window) standard deviation. Then, to construct CC_t, we aggregate the resulting source-specific data scaling by scaling the number of sources available, S_t,

(3) $$CC_t = h(\frac{1}{S_t}\sum_{s=1}^{S}\frac{n_{s,t} - \overline{n}_{s,t}}{\sigma_{s,t}})$$

where $\overline{n}_{s,t}$ and $\sigma_{s,t}$ are the mean and standard deviation computed from $t-36$ to t, and $h(\cdot)$ is an increasing concave function that simulates saturation and boredom effects caused by a decline in media attention (Barkemeyer et al., 2018; Ardia et al., 2020).[17]

This construction ensures the index in month t the data available is up to month t (and has no forward-looking bias) contrary to selecting the standard deviation and average of the source sample. Doing this gives more importance to within newspaper variation rather than variation between newspapers. Note that the length of the rolling-window makes the interpretation of the CC_t relative to its window values. This normalization accounts for a possible evolution in the media's news coverage. As previously discussed, we consider AR(1) innovations to extract the unexpected variation in newspapers.[18] Unexpected change in climate change media attention is defined as

(4) $$CC^{ATT} \equiv CC_t - \mathbb{E}[CC_t|I_{t-1}],$$

17. We replace $h(\cdot)$ for the square root function. The logarithmic transformation and 24 rolling window are tested for robustness, yielding similar results.

18. Ardia et al. (2020) argue that the relationship between climate concerns and returns for green and brown firms becomes clearer when there is a distinction between “expected” and ”unexpected” news. This, and most climate change indices in Table 1 estimate a first-order auto-regressive model and interpret the prediction error as the unexpected changes in climate change attention, sentiment, or concerns.

where I_{t-1} is the information set available at time $t-1$.

Validation of the index. Figure 1 displays the evolution of the aggregated $MECCO_t$ index (level, from Jan. 2004 to June 2021) with European newspapers and combined with American newspapers. The index spikes at major climate events. When looking over 18-year time horizon, four peaks are particularly large: the 2007 IPCC report, the 2009 Copenhagen UN Climate Change Conference, the 2015 Paris Agreement, and the 2019 EU Green taxonomy. Moreover, the index tends to be higher post-Paris Agreement. In comparison, American newspapers do not spike as much during the 2019 EU Green Taxonomy. This discrepancy could be attributed to differences in coverage from the newspapers used to build an aggregated index, raising questions about American coverage of European climate issues. A change in the media landscape justifies the need for a normalization approach.

3. Empirical Methodology

A. Bond Measures

We now outline the measures for the construction of the risk factors. Markit IBOXX EUR indices are market-value-weighted. The amount outstanding of a bond is only adjusted within the rebalancing process at the end-of-month. All calculations are based on the adjusted amount outstanding that reflects the outstanding bond notional at the last rebalancing. The bond prices relate to the nominal value of 100.

Returns. The calculation is based on market-value end-of-month prices. We use Bessembinder et al. (2008) methodology to calculate returns:

$$r_{i,t} = \frac{P_{i,t} + AI_{i,t} + C_{i,t}}{P_{i,t-1} + AI_{i,t-1}} - 1 \tag{5}$$

where $P_{i,t}$ is the price of bond i at the end-of-month t, $A_{i,t}$ is the accrued interest, and $C_{i,t}$ is the coupon payment, if any. The excess return is defined as the difference between the bond return and the risk-free rate, $r_{f,t}$, which is based on 1M Euribor.[19] Monthly excess returns are calculated as:

$$R_{i,t} = r_{i,t} - r_{f,t} \tag{6}$$

19. Euribor rates are downloaded from Datastream.

Credit Risk Measure. Credit ratings are utilized to create the risk factor components since they synthesize information on the issuer's financial condition, operating performance, risk-management strategies, and specific bond characteristics like coupon rate, seniority, and option features. As such, they are a standard choice for measuring the credit risk of corporate bonds. Historical ratings are assigned at the bond level. Investment grade is defined as BBB- or higher by Fitch Ratings and S&P Global Ratings and Baa3 or higher by Moody's Investor Service. Markit calculates *Markit IBOXX ratings* by taking the average of the three credit ratings.

Illiquidity Risk Measure. Illiquid bonds refer to bonds that cannot be sold or exchanged without substantial loss of value (for instance, high transaction costs or low trading volumes (below one million€/month), pushing prices away from the true midpoint. Studies focusing on illiquidity tend to look from different dimensions: width, depth, immediacy, or resiliency. (De Jong and Driessen, 2012; Amihud, 2002; Roll, 1984; Bao et al., 2011). We consider the bid-ask spread as our indicator (*ILLIQ*), which is a typical measure of the width component of liquidity (Zerbib, 2019).[20]

Downside Risk Measure. To minimize losses, investors are concerned with the protection against events that can be a source of default risk. Downside risk represent the potential decline in value if market conditions change, the Value-at-Risk at 5% (VaR, DOWNSIDE) has been commonly used to quantify risk. As a proxy, we take the second lowest monthly return observation over the past 36 months. The measure is multiplied by –1 so that a higher downside risk represents higher expected returns (Alessandrini et al., 2021; Bai et al., 2019; Huynh and Xia, 2020).

B. Risk Factors

This section describes the risk factor construction, designed to be representative in explaining the cross-section of bond returns.

Bond Market Factor. We compute bond market excess return (MKT^{Bond}) as the value-weighted average returns of all corporate bonds in our sample minus the one-month EURIBOR.

20. Usually, US studies that rely on TRACE use transaction data, and calculate illiquidity using the number and volume of monthly transactions (Bao et al., 2011; De Jong and Driessen, 2012; Amihud, 2002). Since transaction data is not available in Europe (Dick-Nielsen, 2009), we develop our analysis using quoted bid and ask prices. However, as the AMF (2019) warns, this measure should be taken with caution.

Fama and French (1993)'s Factors. The term factor (*TERM*) is the return spread between monthly long-term IBOXX Eurozone Government bond return (IBBEU007C) and the one-month EURIBOR. The default factor (*DEF*) is the return spread between the return on a market portfolio of long-term corporate bonds (IBBEU003E) and the long-term IBOXX Government bond return. [21]

Bai et al. (2019)'s Factors. Credit ratings play a key role in creating the components of the common corporate bond risk factors. Liquidity risk factor (*LRF*) is constructed by independently sorting corporate bonds into 2×3 portfolios based on illiquidity (ILLIQ) and credit rating (AAA/AA=1, A=2, and BBB=3). Downside risk factor (*DRF*) is constructed by independently sorting corporate bonds into 2×3 portfolios based on the 5% Value-at-Risk (VaR) and credit rating. *DRF* is the average return spread between the highest VaR portfolio minus the lowest VaR portfolio within each rating portfolio. Reversal (*REV*) is the average return spread between the short-term loser and short-term winner over credit rating. Credit risk factor *CRF* is the average obtained from forming *DRF*, *LRF*, and *REV*, where:

$$CRF = \frac{1}{3}(CRF_{VaR} + CRF_{ILLIQ} + CRF_{REV}) \tag{7}$$

Risk Factors and the Climate Change Beta.

It may be worthwhile to compare different factor models to measure the information gain related to the climate beta. Thus, when estimating the climate beta (β^{CC}), we use four different factor models. For each bond, we estimate the time series regressions of excess returns over a 36-month moving window, with a minimum of 12-month observations.

$$R_{i,t} = \alpha_i + \beta_i^{CC} \cdot CC_t + \sum_{k=1}^{m} \beta_i^k \cdot F_{k,t} + \epsilon_i \tag{8}$$

where α_i is the intercept, β_i^{CC} is the climate sensitivity of bond i which captures the covariance between returns and the climate change index, F is the value of factor k, β_i^k is the sensitivity to factor k, and the ϵ_i is the error term.[22] The four factor models are:

21. These risk premiums are, therefore, calculated based on excess returns. For alternatives calculations of risk premiums using excess yields, see Aussenegg et al. (2015), Castagnetti and Rossi (2013), Chen et al. (1986), and Cochrane and Piazzesi (2005).

22. We use heteroskedasticity and autocorrelation consistent (HAC) Newey and West (1987) standard errors with a lag equal to $4(T/100)^a$, where T is the number of periods in the sample and $a = \frac{2}{9}$ (i.e., the Bartlett kernel).

(i) *Market- model (CAPM):* Following Bekaert and De Santis (2021), we estimate the market model on the excess bond market return (*MKT*).

(ii) *2-bond-factor model (Macroeconomic):* Following Fama and French (1993), we estimate the returns with the default spread factor (*DEF*), and the term spread factor (*TERM*).

(iii) *5-bond-factor model (Corporate Bond):* Following the model introduced in Bai et al. (2019), we estimate a 5-factor model, including the excess bond market return (*MKT*), the downside risk factor (*DRF*), the credit risk factor (*CRF*), the bond liquidity risk factor (*LRF*), and the return reversal factor (*REV*).[23]

(iv) *7-bond-factor model.* We combine models (i), (ii) and (iii) to account for broader sources of risks emanating from the market, macroeconomic, and common corporate bond factors.

4. Empirical Results

In this section, we document the empirical analysis. Our implementation of climate media on corporate bonds follows closely the papers of Huynh and Xia (2020), Engle et al. (2020), Seltzer et al. (2020), and Duan et al. (2020). We first examine the relation between the climate betas, β^{CC} and bond returns through cross-sectional regressions. Specifically, each month, we sort bonds into quintiles based on their betas, estimated in the first pass of the Fama and MacBeth (1973) procedure (equation 8). We then examine the returns and other characteristics of these portfolios. We double sort on climate change betas and other bond-level characteristics to better understand the dynamics on climate sensitivity. To compare our results from Duan et al. (2020), we include portfolio sorts based on *CEI*.

A. Univariate Portfolio Analysis

This analysis consists in examining the relationship between β^{CC} and corporate bond returns through univariate portfolio sorts. For each portfolio sort, we perform a general analysis on excess returns, alphas from the factor models, and average portfolio characteristics. The analysis applies over the sample period from January 2004 to July. 2022. For each bond, with at least 12

23. As a direct application of Bai et al. (2019), Fama and French (1993), Castagnetti and Rossi (2013), and Alessandrini et al. (2021), the bond risk factors are constructed in a similar fashion. Please refer to Appendix B and 5 for more information on the construction methodology.

monthly return observations, we calculate climate betas through time-series regressions of excess returns on a constant, bond factors and β^{CC} as shown in equation 8. Then each month t, we sort all bonds with available month t returns and the corresponding climate beta into portfolio quintile. Quintile 1 contains bonds with the lowest β^{CC} values, while quintile 5 contains bonds with the highest β^{CC} values. In addition to providing the next-month average excess return for every quintile, we also include the risk-adjusted returns (alphas) produced from the four different factor models to understand if there is a monotonic relationship with returns, even after controlling for other factors. We regress portfolio excess returns on the bond market factors (i),(ii), (iii), and (iv). Alphas are named accordingly, the 1-factor alpha, 2-factor bond alpha, 4-factor bond alpha, and the 7-factor bond alpha.

Insert Table 7 about here.

Since we are interested in the pricing magnitude of climate attention, we start by forming portfolios based on absolute values of β^{CC}. Table 7 reports the results of quintiles formed on absolute climate betas $|\beta^{CC}|$. As the average $|\beta^{CC}|$ grows from 0.02 for the lowest quintile to 0.51 for highest quintile 5, the average $|\beta^{CC}|$ is 0.19. We observe that next-month average bond excess returns which grow from 0.07 to 0.14. The difference between high $|\beta^{CC}|$ and low $|\beta^{CC}|$ with an average next-month excess return difference of 0.07. Although, statistically insignificant.

Factor bond alphas show the opposite pattern with decreasing alphas. The 1-factor alphas decrease from an average of 0.04 for the lowest $|\beta^{CC}|$ quintile to -0.04 for the highest $|\beta^{CC}|$ quintile, with a statistical significant difference of -0.04. The 7-factor alphas show similar results with a difference of -0.07 in terms of returns difference. We further examine average bond characteristics of $|\beta^{CC}|$-sorted portfolios. We compute averages for illiquidity, downside, rating, and duration for each $|\beta^{CC}|$ quintile and observe that some relations might also explain next-month excess bond returns and some of these variables. Illiquidity goes from an average of 0.47 to 0.68, and duration grows from an average of 5.7 years to 7.56 years. Downside also shows increasing risks from 0.16 o 0.22. Credit rating increases, with average credit ratings going from 2.4 for the lowest $|\beta^{CC}|$ quintile to 2.53 for highest $|\beta^{CC}|$ quintile.

Insert Table 8 about here.

In Table 8, we redo this exercise sorting on *CEI*. This table is comparable to Duan et al. (2020)'s results based on the US corporate bond returns. Since carbon emissions intrinsically vary across industries, we form portfolios within each of the 12 Fama-French industries to control for the industry effect and to calculate the average alphas across industries. As the average *CEI* grows from 33.1 for the lowest quintile to 693.3 for highest quintile 5, the average *CEI* is 360.66. However, contrary the US market, sorting on carbon emissions intensity does not show no statistical nor economical difference between next-month's average excess returns and alphas.

B. Bivariate Portfolio Analysis

Insert Table 9 about here.

This section continues the analysis by examining the relationship between β^{CC} and corporate bond returns through bivariate portfolio sorts. We sort bonds monthly according to $|\beta^{CC}|$ and *CEI*. Table 9 presents the value-weighted bivariate portfolio results between $|\beta^{CC}|$ and *CEI*. Quintile 1 contains bonds with the lowest $|\beta^{CC}|$, and quintile 5 consists of bonds with the highest $|\beta^{CC}|$ in columns. *CEI* quintiles are in rows. For each quintile, one month ahead average excess returns and average 7-factor bond alpha are computed. The last row displays the difference across *CEI* for a given $|\beta^{CC}|$ quintile. The last column displays the difference across $|\beta^{CC}|$ for a given *CEI* quintile. The results are intriguing. The difference for High-Low $|\beta^{CC}|$ is positve for average returns but negative for 7-factor alphas. Meaning that after adjusting returns for factors exposures has negative returns. For the *CEI* quintiles, contrary to previous results, there is no particular relationship between returns or alphas. Only low-$|\beta^{CC}|$ show consistent positive alphas.

C. Characteristic-sorted Portfolios

We continue by examining the role played by climate change attention in driving the cross-sectional differences in expected bond returns. Gebhardt et al. (2005) attempt to explain the cross-section of corporate bond returns sorting various bond characteristics. We adjust for bond characteristics to judge how significant is the relation between climate change beta and future bond returns while controlling for duration and credit ratings. Each month, we sort all bonds independently into 3 ratings portfolios (1 is high quality (AAA-AA), 3 is low quality (BBB)) and 3 duration portfolios (1 is low duration, 3 is high duration). Thus, 9 portfolios are created at the intersection of rating and duration portfolios. Each of these rating-duration portfolios are then divided into three portfolios based on either pre-ranking absolute climate betas. Doing this portfolio sorting is intended to examine variation in climate betas independent of return variation from ratings and duration. Table 10 provides the intercepts of the 7-factor alphas from the model (iv) by ex-ante $|\beta^{CC}|$, and 11 reports the ex-posts climate betas.

Insert Table 10 about here.

In Table 10 each row provides the average alpha of low (1), medium (2), and high (3) climate beta portfolios, and the average difference on a zero-investment portfolio that is long high climate beta portfolio and short low climate beta portfolio. There are nine zero-investment portfolios, one for each rating-duration portfolio. Nine out of nine zero-investment portfolios earn negative returns ranging from -0.32% a month to -0.04% a month. Overall, the evidence suggests that there is a significant negative relationship between average corporate bond returns and climate betas that is independent of characteristics. This sorting procedure generates sufficient variation in ex-post climate betas suggesting pre-ranking betas are good proxies of post-ranking betas. The goal of this exercise is to determine whether there is cross-sectional variation in average bond returns related to climate betas unrelated to the variation in characteristics.

Insert Table 11 about here.

In Table 11 results show that high pre-ranking climate beta portfolios have high post-ranking default betas. There is a monotonic increase in post-ranking betas the 9 portfolio groups as we move from low to high pre-ranking climate beta portfolio. This suggests that pre-formation climate betas are reasonably good predictors of post- formation climate betas. According to expectations, longer duration bonds and worse credit ratings show higher ex-post absolute climate risk exposures.

Of more interest to us are the intercepts of these portfolios. If the characteristics model involving ratings and duration is correct, i.e., average bond returns are determined by variation in characteristics rather than betas (in this case $|\beta^{CC}|$) then the expected bond returns should be constant across the various pre-ranking climate beta portfolios. However, since the ex-post climate betas increase from the low climate beta portfolio to the high climate beta portfolio, the intercept on the low climate beta portfolio should be positive and the intercept on the high climate beta portfolio should be negative. Consequently, the zero-investment portfolio that is long high climate beta and short low climate beta should also have a negative intercept. There is a monotonic decrease in all the intercepts as we move from low to high pre-ranking climate beta portfolios. The zero-investment portfolio is negative and statistically significant in 7 of the 9 groups). We use the Gibbons et al. (1989) (GRS) statistic to test the null hypothesis that the 7-model produces regression intercepts on the 9 characteristics-based portfolios that are all equal to zero.[24] The results in Table 10 show that the GRS-statistic is 45.6 with a p-value of 0.001 which suggests that the null of zero intercepts can be rejected for the 9 characteristics-based bond portfolios. This, in turn, suggests that the 7-factor model is not fairly well specified in explaining the returns of characteristics-based bond portfolios, as we have just shown that variation in returns due to climate betas still exists within these portfolios.

D. Estimated risk premia

This section estimates risk premia using the two-stage procedure. The first stage uses time-series regressions of excess firm-level bond returns on bond factors to estimate betas (estimates from equation 8). The second stage uses cross-sectional regressions of excess returns on the estimated betas to obtain the price of risk (the λs from equation 9). For each bond i in each month t, panel regressions of one-month ahead excess returns ($R_{i,t+i}$) are regressed on the monthly β^{CC}. $X_{i,t}$ represents a vector of bond-level control variables (i.e., credit ratings, *ILLIQ*, *DOWN*, credit ratings, size, and time to maturity), and firm-level control variables (i.e., price-book value, debt-equity ratio, and log(total equity)). $\hat{\beta}^k$ can be either from model (i), (ii), (iii), or (iv).

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}^{CC}\hat{\beta}_{i,t}^{CC} + \sum_{k=1}^{m} \lambda_{k,t}\hat{\beta}_{i,t}^{k} + \gamma_{i,t}' X_{i,t} + \epsilon_{i,t} \tag{9}$$

Insert Table 12 about here.

Table 12 reports results panel regressions using individual bonds as asset tests between January 2004 to July 2022.[25] The average slope coefficients (λs) are the estimated risks premiums.

24. The GRS-statistic is given by:

$$[(T-N-K)/N][1+\mu'\Omega^{-1}\mu]^{-1}\alpha'\Sigma^{-1}\alpha$$

where T is the number of time-series observations, N is the number of assets, portfolios, or intercepts included in the test, K is the number of factor portfolios in the regression, α is the (N×1) column vector of regression intercepts, Σ is the maximum likelihood estimator of the (N×N) variance-covariance matrix of the residuals from the N time- series factor regressions, μ is the (K×1) column vector of average factor portfolio excess returns, and Ω is the maximum likelihood estimator of the (K×K) variance-covariance matrix of the factor portfolio excess returns. The statistic has a F(N,T-N-K) distribution under the null hypothesis that the intercepts are zero assuming normality of all variables (Gibbons et al., 1989).

25. Portfolios have traditionally been used to test asset pricing models in order to mitigate inherent errors-in-variable (EIV) bias. However, in some cases portfolios can omit relevant characteristics related to the performance

The univariate regression in column (1) results reveal a negative and statistically significant relationship between β^{CC} and future bond returns (at the 5% level). This relationship remains significant after adding bonds betas and characteristics in regressions (2), (3) and (4). Regression specification (2) tests the cross-sectional predictive power of β^{CC}, while controlling for other systematic risk measures, and shows a significantly negative relation, the coefficient is -0.040 (t-stat. = -1.748). Regression specification (3) in Table 12 shows that after we control for bond characteristics, namely downside (VaR 5%), illiquidity (bid-ask spread), credit rating, and lag return, the average slope coefficient remains negative and significant, the coefficient is -0.032 (t-stat. = -1.548). In other words, controlling for bond characteristics does not affect the significance of climate exposure in the corporate bond market. When controlling for bond characteristics and bond systematic betas in regression (4), the coefficient is -0.048 (t-stat. = -2.129).

Important to note is that in this second stage, we use fixed-effect panel regressions to account for a better estimation of standard errors. Using panel regressions controls for bond and issuer characteristics, industry, and time fixed effects. These fixed effects account for unobserved firm and issuer heterogeneity, macroeconomic trends, and time-invariant factors (Ferson, 2019). We conduct alternative estimations using Fama and MacBeth (1973) regressions demeaning the variables by firm and bond, both approaches yield similar results C.

E. Expected Returns

Table 13 reports the results using the regressions using different factor models. The month-ahead corporate bond excess returns on λ^{CC} shows negative estimates across the three models. All λ^{CC} coefficients show statistical significance at least at the 10% level, indicating a negative relation between the climate change media beta and future bond returns. Columns 1 and 2 report the results of regressions using model (*i*). Columns 3 and 4 report the results of regressions using model (*ii*). Columns 5 and 6 present the results of the main model (*iii*). All the model have bond- and firm-level control variables. In columns 1 and 3, and 5, we add firm, industry, year, and month fixed effects. Columns 2, 4, and 6 include bond, industry, year, and month fixed effects.

Insert Table 13 about here.

of individual assets (Amihud et al., 1992). We report in the appendix, a sensitivity analysis for the EIV problem Shanken (1992) and Jegadeesh et al. (2019)

The coefficients of λ^{CC} show economic significance. For example, in column 1 of Table 13, the coefficient estimate on λ^{CC} of -0.047 indicates that a one-standard-deviation increase in the climate change media beta is associated with a drop of 5.35 bps (= -0.047 $\times$ 1.14) in the next month's bond excess return, which is equivalent to a decrease of 26.61% relative to the sample mean of excess returns.

As a comparison, the macroeconomic term risk factor (λ^{TERM}) coefficient of -0.168 shows four times stronger effect that λ^{CC}. Following on the significance of additional bond factors, the bond market factor (λ^{MKT}) is the strongest factor that captures common return variation in corporate bonds, and shows a clear trade-off of higher risks with returns.[26]

F. Credit, Duration and Industry Adjusted-Returns

Given the conditional effect that both duration and credit ratings play in determining bond returns. As well as that some industries are more susceptible to climate risks (regulatory and physical), we re-estimate model (4) from Table 12 adjusting the returns for duration, credit and industries. Bond returns are adjusted for credit ratings by subtracting the average returns by credit rating: AAA/AA, A, or BBB (Cred-adj, $R_{i,t}$). Bond returns are adjusted for duration by subtracting the average return of one of the 3 terciles portfolios formed on duration (Dur-adj, $R_{i,t}$). Bonds are adjusted by duration/credit (Dur-Cred-adj, $R_{i,t}$) by subtracting the average return from the 3x3 independently sorted portfolios on duration and credit rating. Bond returns are adjusted for industry by subtracting the average return of one of the 12 Fama-French Industries to which the bond belongs (Ind-adj $R_{i,t}$).

The results hold after adjustments showing a negative effect of β^{CC} on future bonds returns. Returns adjusted for credit produce similar exposures with a negative coefficient of -0.044, and -0.67 (*t*-statistic of -2.034 and -2.737). Adjusting returns for duration and credit show highly statistical negative results of -0.058 and -0.063 (*t*-statistic of -5.893 and -5.805).

G. Environmental Profile

Now looking at the environmental performance at the issuer-level, we are unable to identify significant differences in λ^{CC} for ESG scores. This can be explained by several factors. The most salient one is that average ESG scores are not good proxies for bond-level climate exposures,

26. In the Online Appendix, we conduct a series of robustness checks in which we specify different models for the conditional mean of CC^{ATT}, we use windows of different estimation periods to form the β_{CC} portfolios.

since they include other dimensions besides climate. We do not observe significant differences between firms that are above or below median ESG scores for each industry. Additionally, there is no pricing for top polluter (high-*CEI*) which go in hand with the previous results from the univariate and bivariate sorts on *CEI*.

According to Bolton and Kacperczyk (2020), Pástor et al. (2022), and Ilhan et al. (2021), most of the environmental performance of the firms can be attributed to industries. Investors implement exclusionary screening based on direct emissions intensity in a few industries as a result, the asymmetry should be apparent when comparing environmental performance across industries rather than within industries.

H. Climate Change Shocks

Seltzer et al. (2020) discuss the implications of the December 2015 Paris Agreement on bond returns, affecting negatively firms that are in top polluting industries or have poor environmental performance in general. To test for changes around the Paris Agreement, along with other climate change shocks, we adapt the estimations using a paired sample, following Seltzer et al. (2020) specifications. Whether the shocks are regulatory (Paris Agreement, Grantham Research Institute, UNPRI, and COP) or natural (CRED), we codify the variables as dummies representing the month when the shocks materialize.

$$R_{i,t+1} = \beta_1(TopCC_i \times Shock_t) + \beta_2 TopCC_i + X_i + \kappa_t + \varepsilon_{i,t} \tag{10}$$

On July 2015, we match bonds with similar characteristics (time to maturity, credit rating and industry) to identify and match for every treated bond, and a control bond with similar characteristics.[27][28] Table 16 reports the effects of the Paris Agreement.

Insert Table 16 about here.

We augment the model to test the effects of climate change shocks before and after the Paris Agreement on a triple-interaction specification. Table 17 reports the effects from the climate

27. Seltzer et al. (2020) use one-to-one Mahalanobis matching with replacement, adjusting for continuous covariates with a caliper 0.4. We obtain 424 pairs.

28. Other studies in the green bond literature usually use similar matching techniques to compare against counterfactual bonds. For instance, Zerbib (2019), M. Baker et al. (2018), and Flammer (2021) match the nearest neighbors within a given range of characteristics.

change shocks.

Insert Table 17 about here.

In times of a regulatory shock after the Paris Agreements, bonds exposed to the CC index (above the median) have even lower bond returns. For example, during UNPRI's regulation shocks, bonds with a above median climate beta have $-0.036 + -0.368$ lower returns. The COP, and natural shocks, do not provide significant results.

I. Uncertainty Shocks

Huynh and Xia (2020) and Engle et al. (2020) suggest that the effect of the climate change media beta on future bond returns changes over time and is more pronounced during times of high climate change attention. In the same fashion, we test β^{CC} towards uncertainty measures in Table 18. We test the effects of high uncertainty in interaction with high climate attention.

Insert Table 18 about here.

$High^{CC}$ is a dummy variable representing the month when the number of media is higher than the historical median (2004-2022). In the first column, the Climate Policy uncertainty index (CPU) by Gavriilidis (2021)[29] is coded as dummy variable, which is either one in case of high uncertainty and zero otherwise. The second column test against the European policy-related economic uncertainty index (EPU) by Baker et al. (2016),[30] coded in the same way. The third column test against the volatility index on the Euro Stoxx 50 (V2TX)[31], coded in the same way. While uncertainty shocks have an aggregated impact on bond returns, the triple interaction shows that only climate policy uncertainty, after the Paris Agreement, is priced negatively. Interestingly, periods of high economic uncertainty and volatility have a positive premium on more exposed bonds.

29. See: https://www.policyuncertainty.com/climate_uncertainty.html
30. See: https//www.policyuncertainty.com/europe_monthly.html
31. See: https://qontigo.com/index/v2tx/

J. Bond Return Decomposition: Cash-flows and Discount rate news

To refine the connection between bond returns and climate sensitivity, we use the return decomposition framework of Campbell (1991) and Vuolteenaho (2002), more recently applied to ESG news reactions in (Derrien et al., 2021). We decompose bond returns into cash-flows news and expected-returns news in order to identify and compare the sources of climate sensitivity that contribute to the risk premium in the bond market. This is because the climate risk could manifest in financial assets through uncertainty in cash flows or discount rates. More precisely, we apply the return decomposition to individual bond returns in accordance with the methodology of Bali et al. (2021), which extracts the residual cash flow news as the difference between unexpected returns and discount rate news. Specifically, we use return on assets (EBIT/Assets) as a proxy for firm-level cash flows and Tobin's Q as a proxy for firm's overall growth opportunities. Expected-returns news indicate changes in expectations about the firm's discount rate. Cash-flow news indicates changes in expectations about future cash-flows. Following the procedure proposed in Callen and Segal (2010) and Bali et al. (2019), bond returns are decomposed to extract these two elements. Specifically, we calculate unexpected returns and discount rate news, and then back out residual cash flow news as the difference between unexpected returns and discount rate news. The results show that discount rate climate beta is the main driver of the premium in the bond market. Our results are consistent with Bali et al. (2019) and Ardia et al. (2020), we find that the discount rate channels is predominantly significant, and cash-flows channel is insignificant. These results confirm the main finding that the investor channel anticipate increased constraints on bonds with higher climate exposures by adjusting discount rates.

Insert Table 19 about here.

Table 19 reports univariate portfolios of corporate sorted by discount rate climate beta (β_{DR}^{CC}) and cash flows climate beta (β_{CF}^{CC}). These are calculated using (i), as follows:

$$e_{DR,t} = \alpha_{i,t} + \beta_{CF}^{CC} CC_t^{ATT} + \beta_t^{MKT} MKT_t + \varepsilon_t \tag{11}$$

$$e_{CF,t} = \alpha_{i,t} + \beta_{DR}^{CC} CC_t^{ATT} + \beta_t^{MKT} MKT_t + \varepsilon_t \tag{12}$$

Table 19 shows that the discount rate beta (β_{DR}^{CC}) is has a significant premium in the bond market, whereas the cash flow uncertainty beta (β_{CF}^{CC}) has weak predictive power for future bond returns.

Specifically, the value-weighted average return and alpha spreads between high-β_{DR}^{CC} and low-β_{DR}^{CC} quintiles are economically and statistically significant, ranging from -0.25% to -0.37% per month.

K. Concurrent Climate Change indices

In this study, we do not argue about the optimal construction of a climate change index, but simply assess the ability replicate investors' attention to climate change using media coverage. We verify our assumptions by comparing our findings with alternative climate change media indices, that rely often, on more complex estimation techniques. To do so, we redo the exercise proposed in Alekseev et al. (2021), and examine a wide range of measures, previously described in table 1. Given that the period of observation differs from index to index, we estimate the results in period subsamples, which depend on the availability of the indices. Figure 2 plots the estimated β^{CC} by industry.

Insert Table 2 about here.

5. Discussion & Conclusion

Carbon risks are different from climate risks. It is likely that some carbon emissions and intensity are connected with climate risks, however, climate beta include information that is not priced in by the market or that is not specifically related to carbon risk. The climate beta offers a market-related measure of climate risk that builds on carbon emissions and the E pillar of ESG, while being more influenced by investors' expectations other than by their carbon emissions. We also notice that the climate beta of the Energy sector depends on carbon intensity, the lower *CEI* tercile has a considerably lower climate beta than the top two terciles. Climate beta increases with an increase in *CEI*, which illustrates again the intricated relationship between environmental, carbon and climate risks. While employing the absolute value of $|\beta^{CC}|$, for which portfolios with low $|\beta^{CC}|$ minimize climate exposure, we have shown that being exposed to climate change does might dampen returns Fabozzi et al. (2019), Zerbib (2020), Pástor et al. (2020), and Cornell and Damodaran (2020).

Despite being statistically significant, the estimates of the price of climate change are small in magnitude (0.048% per month, or approximately 0.57% per annum, Table 12). Given that climate change is 'inherently unpredictable' by definition, even if the materialization of such risk becomes recurrent, a Peso problem offers a potential explanation for the low returns on high

$|\beta^{CC}|$. The cross-sectional estimates of the negative price of risk of $|\beta^{CC}|$ oppose a risk-based story. Increased attention to climate change has a significant negative effect on the risk premia (λ^{CC}), steeper after the Paris Agreement, and other climate regulations. When regressing on climate change shocks (physical and regulatory), we find that the latter affects mainly bond returns.

Our results have some implications for how environmental profiles relate to market participants' assessments of their corporate bonds. The results suggest that credit rating analysts and bond investors are concerned with issuers' environmental scores due to the anticipation regulatory costs De Angelis et al. (2022). Thus, if bond investors expect issuers to be penalized for poor environmental performance, they are more likely to price those costs. When assessing climate risks for the fixed income, ESG scores include other dimensions besides climate risks, diluting the estimations on two levels, at the issuer level (one ESG score for multiple bonds) and sustainability level (e.g .divergence between the ESG providers, (Berg et al., 2019)). Besides ESG, carbon intensity and absolute emissions are not enough in accounting climate risks. While the inclusion of Scope 3 can enhance the estimation of carbon risks, alternative market metrics regarding climate change are still needed. This study presented a potential option.

Natural disasters, according to Manela and Moreira (2017), do not account for variation in risk premiums, and Hong (2019) find that increasing risks of droughts caused by global warming are not efficiently discounted by prices. Krueger et al. (2020) find similar conjectures while surveying institutional investors about these risks, in which physical risk tends to be left behind (or in other words, not all bonds and issuers are affected by physical risks, which depend mainly on location.) Furthermore, Gostlow (2021) finds that investors struggle to price a material risks. Our findings are consistent with previous ones in that bond prices only reflect the effects of regulatory shock, not the direct effects of climate change.

Since bondholders are located globally, we reemphasize the importance of a news index to consider both US and European newspapers. According to the European Central Bank (ECB, 2017), investors located outside the euro area (rest of the world) were the second largest group of owners, owning 29.6% of the total market. European insurance companies and pension funds held 14.1% and non-Money Market Funds held 12.0%, still investors, while investing in Europe, abide by European regulations.

We propose a simple index construction to proxy climate change attention (CC^{ATT}). This climate change news attention index is able to capture unexpected changes in investors' attention about the climate. To test this index on their implications on future bonds returns, we propose regressing individual bond returns on CC^{ATT} after controlling for Fama and French (1993) and Bai et al. (2019) bond factors, firm-level and bond-level controls to get the exposures. We regard the coefficients of β_{CC} as our bond-level exposure to climate change news risk. Given the fact that corporate bonds are a complex asset class, we execute different specifications based on these bond characteristics. Overall, the results highlight the importance of differentiated analyses to assess the pricing of climate aspects in corporate bonds. Models should differentiate between bond characteristics that describe bonds' duration, credit rating, and sector, besides additional systematic bond risk factors. Due to the inherent nature of our measure, any climate risk deemed relevant for publication in newspapers is reflected. We show in related analyses that returns between low and high climate beta bonds differ significantly in the months when climate shocks materialize, depending on the type of climate risk, physical or regulatory. However, we find that while regulatory climate risks are explained, natural climate shocks are not. Our results indicate that during months of high climate uncertainty, bonds with high exposure to climate change underperform.

Investors can use our framework to identify covariances between assets and climate change attention, in order to hedge future climate risks. New climate regulations create winners and losers from regulatory risks. Since β^{CC} refers mainly to regulatory risks, less exposed bonds might increase the probabilities of success in the case of stricter regulations. As it is straightforward, and easily replicated, academics can use our approach to replicate and construct investors' climate change attention proxies. Last but not the least, regulators and policymakers have the burden of care to identify firms that are highly exposed to climate risks and to reward those that present opportunities for a sustainable economy. Results show that exposure to regulatory climate risks, especially in high emission-intensive sectors, is reflected in climate change betas, but not all industries are correctly identified. Regulators should review and improve climate laws and policies to better target overlooked industries.

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A. Appendix

Table 2: **Descriptive statistics.**
Table 2 reports the number of bond-month observations, the cross-sectional mean, standard deviation, and percentiles of the bond-level variables. The table summarizes monthly excess returns, annual yield, and bond characteristics including credit rating (AAA-AA=1, A=2, and BBB=3), coupon, years to maturity (log, years), notional (size, € million), illiquidity (bid ask spread), and downside risk (5% VaR). Downside risk is the 5% VaR of corporate bond return, defined as the second lowest monthly return observation over the past 36 months. Downside is multiplied by –1 so that a higher number indicates higher downside risk. The sample period is from January 2004 to July 2022. Table 5 provides the variable definitions.

Cross-sectional statistics over the sample period of January 2004 – June 2022								
				Percentiles				
Variable	N	Mean	SD	5th	25th	50th	75th	95th
Monthly Return	178271	0.226	1.460	-2.029	-0.254	.187	0.803	2.510
Annual Yield	178271	1.531	1.714	-0.081	0.320	0.979	2.195	4.964
ILLIQ (bid ask spread)	178271	0.513	0.398	0.151	0.281	0.422	0.618	1.178
DOWNSIDE (5%, VaR)	178271	0.011	0.010	0.001	0.005	0.009	0.014	0.028
Rating	178271	2.46	1	1	2	3	3	3
Coupon	178271	2.83	1.85	0.50	1.37	2.37	4.37	6.125
Notional Amount (million, €)	178271	788	340	500	500	750	1000	1500
Modified Duration	165890	5.214	3.080	1.412	2.908	4.670	6.812	10.832
Years to Maturity (log, years)	178271	1.566	0.652	0.380	1.136	1.626	2.020	2.567

Table 3: **Average cross-sectional correlations.**
This table reports the time-series average of the cross-sectional correlations.The sample period is from January 2004 to July 2022. Table 5 provides the variable definitions.

	Monthly Return	Annual yield	ILLIQ	DOWNSIDE	Rating	Coupon	Not.Amount	Mod.Duration
Monthly Return	1							
Annual yield	-0.053	1						
ILLIQ	0.062	0.555	1					
DOWNSIDE	0.017	0.406	0.417	1				
Rating	-0.005	0.055	-0.024	0.058	1			
Coupon	0.057	0.524	0.244	0.344	0.021	1		
Notional Amount	0.012	0.070	-0.054	0.043	-0.149	0.157	1	
Modified Duration	-0.004	0.246	0.618	0.308	-0.116	-0.148	-0.024	1

Table 4: **Descriptive statistics: Extra-financial data.**
Table 4 reports the summary statistics of extra-financial data, the cross-sectional mean, standard deviation, and percentiles of the issuer-level variables. The table summarizes Carbon Intensity (*CEI*) and absolute emissions from Trucost. ESG and Environmental Scores from S&P, MSCI and ASSET 4. The sample period is from January 2004 to July 2022. Table 5 provides the variable definitions.

Cross-sectional statistics over the sample period of January 2004 – June 2022: Extra-financial data

				Percentiles				
Variable	N	Mean	SD	5th	25th	50th	75th	95th
CEI (Scope 1, tons C02/€mill)	127821	306.2	810.1	0	3.7	14.6	248.2	1497.4
CEI (Scope 2, tons C02/€mill)	127821	53.2	126.9	0	7.9	19.7	42.9	230.0
CEI (Scope 3, tons C02/€mill)	127821	587.8	1428.6	0	66.8	215.9	442.9	2598.1
Carbon Emissions (Scope 1, tons C02)	154620	10200	28200	0	6	292	2459	65400
Carbon Emissions (Scope 2, tons C02)	154620	1366	2558	0	14	343	1539	6000
Carbon Emissions (Scope 3, tons C02)	154620	30900	106000	0	80	3365	14400	125000
ESG Score (S&P)	134732	56.9	25.8	0.0	37.0	66.0	79.0	88.0
Environmental Score (S&P)	136170	60.9	27.9	0.0	47.0	68.0	83.0	94.0
ESG Score (MSCI)	84675	66.2	19.3	36.0	54.7	64.0	78.0	100.0
Environmental Score (MSCI)	84675	64.8	22.7	22.6	53.0	68.0	82.0	100.0
ESG Score (ASSET4)	127485	72.8	14.7	42.6	65.4	75.6	83.7	90.8
Environmental Score (ASSET4)	127485	74.2	18.2	36.1	66.1	79.0	86.4	95.4

Table 5: **Variable Definitions**

Bond-level variables	**Definition**
Return ($R_{i,t}$,%)	Monthly bond return from Markit in excess of the monthly risk-free rate, measured as a percentage. A bond's monthly return is calculated as in equation (1). The risk-free rate is proxied by the one-month Euribor.
Cred-adj $R_{i,t}$	Bond return are adjusted by subtracting from each bond return the average bond return by rating to which the bond belongs (AAA/AA, A, BBB).
Dur-adj $R_{i,t}$	Returns are adjusted by subtracting from each return the average return by duration tercile to which the bond belongs.
Dur-Cred-adj $R_{i,t}$	Bond return adjusted, through a 3 × 3 sort for rating and duration, by subtracting from each return the average return of the rating- duration portfolio to which the bond belongs.
Ind-adj $R_{i,t}$	Bond return net of the current month mean returns of the industry to which the stock belongs, using Fama-French 12 industries.
Price	Month-end bond bid prices from Markit.
Annual yield	The annualized yield as a percentage of the price.
Coupon	The interest rate assigned to a bond when it is issued.
Time to maturity (log)	The natural logarithm of a bond's time to maturity, measured in years
ILLIQ (bid ask spread)	The difference between the bid and ask quoted prices.
DOWNSIDE (VaR, 5%)	The average of the second lowest monthly return observation over the past 36 months (beyond the 5% VaR threshold), multiplied by –1 and measured as a percentage.
Markit Credit Rating	Markit credit ratings are the average from three credit rating agencies (Fitch, Moody's and S&P Global). Investment grade is defined as BBB- or higher from Fitch and S&P Global and Baa3 or higher from Moody's. (AAA/AA=1, A=2, BBB=3).

Firm-level variables	Definition
Fundamentals	
Price-Book Value	Price-to-book value (P/B) is the ratio of the market value of a company's shares (share price) over its book value of equity. The book value of equity, in turn, is the value of a company's assets expressed on the balance sheet..
Debt-Equity Ratio	All debt, senior and subordinated, as a multiple of equity
Log Total Equity	Logarithm of total equity which is the value left in the company after subtracting total liabilities from total assets.
ROA	Return on Assets is the net profit as a percent of total assets.
Tobin's Q	The ratio of the market value of assets (market cap of equity plus book value of debt) divided by the book value of assets.
Extra-financials	
ESG	ESG is the standardized average of MSCI, ASSET4 and S&P Overall ESG scores.
ESG (Industry-adj.)	ESG scores are the average scores standardized using the Fama-French 12 industries.
Log CEI	The Carbon Emissions Intensity is the natural logarithm of Greenhouse gas (GHG) emissions from Scope 1 and 2 scaled by total revenues (in €millions)
Log CEI (Industry-adj.)	CEI is standardized at the industry-level using the Fama-French 12 sector classification.
Is ESG	A dummy variable indicating that the bond is labeled as green bond, sustainability-linked, transition-linked, social bonds. Includes self-labeled and might not be certified by Climate Bond Initiative.

Factors	**Definition**
MKT	The bond market factor (*MKT*) is constructed as the average monthly excess bond market return.
TERM	TERM Spread is the return spread between monthly long-term Euro-zone Sovereign bond returns and the 1 month Euribor rate of the previous month.
DEF	DEFAULT Spread is the return spread between a composite index of Markit IG (ex-financials) index (with an average tenor of 8.5 years) and maturity-matched composite Euro-zone Sovereign bond returns.
DRF	Downside Risk Factor (*DRF*) is the average return spread between the highest-VaR portfolio minus the lowest-VaR portfolio within each rating portfolio.
LRF	Liquidity Risk Factor (*LRF*) is the average return spread between the highest-illiquidity portfolio minus the lowest-illiquidity portfolio within each rating portfolio.
REV	Reversal (REV) is the average return spread between the short-term loser and short-term winner portfolios within each rating portfolio.
CRF	Credit Risk Factor (*CRF*) is the average return spread between *DRF*, *LRF*, and *REV*. $CRF = \frac{1}{3}(CRF_{VaR} + CRF_{ILLIQ} + CRF_{REV})$

Table 6: **Newspapers from MeCCO database.**
This table 6 reports the European Newspaper and North American coverage of news articles about *Climate Change* and *Global Warming.* The dataset is provided by the Media and Climate Change Observatory (MeCCO) database. The sample period is from January 2004 to August 2022.

Newspaper	Country	Total	Yearly Avg.	Monthly			
				Avg.	Std.	Min	Max
Berlingske Tidende	Denmark	5859	334.8	27.8	20.3	4	202
Jyllandsposten	Denmark	6712	383.5	31.8	19.0	6	165
Politiken	Denmark	8342	476.7	39.5	21.1	6	184
Daily Mail and Mail on Sunday	England	8585	490.6	40.7	29.6	7	167
Guardian and Observer	England	45244	2585.4	214.4	149.9	40	981
Sun and News of the World or Sunday Sun	England	9349	534.2	44.3	35.2	1	205
Telegraph and Telegraph on Sunday	England	17933	1024.7	85.0	40.8	14	224
The Daily Mirror and Sunday Mirror	England	8483	484.7	40.2	34.6	4	252
Times and The Sunday Times	England	36540	2088.0	173.2	112.4	20	580
Helsingin Sanomat	Finland	9349	534.2	44.3	29.3	4	202
Ilta-Sanomat	Finland	2374	135.7	11.3	11.4	0	72
Agence France Presse	France	30936	1767.8	146.6	111.2	15	735
Le Figaro	France	5251	300.1	24.9	17.2	3	101
Le Monde	France	7977	455.8	37.8	19.5	2	123
Die Tageszeitung	Germany	7326	418.6	34.7	24.5	2	156
Süddeutsche Zeitung	Germany	16680	953.1	79.1	48.5	1	278
Irish Times	Ireland	12016	686.6	56.9	34.5	12	207
Corriere della Sera	Italy	3546	202.6	16.8	14.7	0	80
La Repubblica	Italy	3349	191.4	15.9	15.7	0	110
Associated Press	North America	24256	1386.1	115.0	75.2	12	406
Globe & Mail	North America	15489	885.1	73.4	41.6	18	236
Los Angeles Times	North America	10772	615.5	51.1	23.7	8	119
National Post	North America	17025	972.9	80.7	139.9	0	880
New York Times	North America	30538	1745.0	144.7	120.8	21	537
The Canadian Press	North America	32496	1856.9	154.0	128.0	15	1202
Toronto Star	North America	14766	843.8	70.0	41.7	14	301
USA Today	North America	3182	181.8	15.1	7.9	0	45
United Press International	North America	8182	467.5	38.8	19.3	9	144
Wall Street Journal	North America	3568	203.9	16.9	11.7	1	93
Washington Post	North America	13095	748.3	62.1	34.0	8	164
Aftenposten	Norway	5503	314.5	26.1	15.5	5	86
Dagbladet	Norway	2873	164.2	13.6	9.9	2	70
VG	Norway	2838	162.2	13.5	9.1	1	64
Correio da Manhã	Portugal	1886	107.8	8.9	13.5	0	79
Izvestiya	Russia	688	39.3	3.3	3.2	0	21
Komsomolskaya Pravda	Russia	514	29.4	2.4	2.4	0	16
Nezavisimaya Gazeta	Russia	1328	75.9	6.3	4.3	0	25
Rossiskaya Gazeta	Russia	1683	96.2	8.0	5.5	0	32
El Mundo	Spain	13076	747.2	62.0	44.5	7	218
El País	Spain	13589	776.5	64.4	45.8	7	281
Expansión	Spain	4561	260.6	21.6	18.8	1	137
La Vanguardia	Spain	8269	472.5	39.2	25.7	5	144
Aftonbladet	Sweden	2331	133.2	11.0	10.4	0	60
Dagens Nyheter	Sweden	4888	279.3	23.2	16.2	2	91
Expressen	Sweden	2251	128.6	10.7	12.1	0	76
	Total European Newspapers	312129	17835.9	1479.2	763.2	306	4690
	Total North American Newspapers	173369	9906.8	821.2	473.2	182	2639
	Total Combined Newspapers	485498	27742.7	2300.9	1202.9	509	7329

Table 7: **Univariate on $|\beta^{CC}|$.**
This table presents the portfolios formed using the absolute value of β^{CC}. We form quintile portfolios of corporate bonds based on $|\beta^{CC}|$ which is defined as the bond-level exposure from time-series regressions of excess bond returns on the climate attention index (CC^{ATT}) controlling for the market factor (i):

$$R_{i,t} = \alpha_i + \beta_i^{CC} \cdot CC_t^{ATT} + \beta_{i,t}^{MKT} \cdot MKT_t + \epsilon_{i,t}$$

We form portfolios within each of the 12 Fama-French industries to control for the industry effects. Quintile 1 (Low) is the portfolio with the lowest $|\beta^{CC}|$ and Quintile 5 (High) is the portfolio with the highest $|\beta^{CC}|$. For each quintile, the table reports the average β^{CC}, the next-month average excess return, the 1-factor alpha from the market factor (i), the 2-factor from macroeconomic factors (ii), the 4-factor alpha from common bond factors (iii) , and the 7-factor alpha (iv) from the combined factors. The last row shows the monthly average returns of the differences between High and Low. The 7-factor model with bond market factors includes the excess bond market return (*MKT*), the default risk factor (*DEF*), the term risk factor (*TERM*), the downside risk factor (*DRF*), the liquidity risk factor (*LRF*), the credit risk factor (*CRF*), and the reversal risk factor (*REV*). Average returns and alphas are defined in monthly percentage terms. Newey and West (1987) adjusted t-statistics are reported in parentheses. Numbers in bold denote statistical significance at the 5% level or below. The sample period is from January 2006 to July 2022.

	Average	1- Factor	2- Factor	3- Factor	7- Factor	Average Portfolio Characteristics					
	Return	Alpha	Alpha	Alpha	Alpha	$\lvert\beta^{CC}\rvert$	Average CEI	Bid-Ask Spread	Downside (VaR 5%)	Rating	Duration
Low-$\lvert\beta^{CC}\rvert$	0.07	**0.04**	0.03	**0.06**	**0.03**	0.02	168.7	0.47	0.16	2.4	5.7
1	(0.91)	(8.82)	(1.43)	(3.25)	(5.05)						
2	0.07	**0.03**	0.02	**0.05**	**0.02**	0.06	154.6	0.49	0.17	2.4	5.69
	(1)	(8.1)	(1.12)	(2.88)	(5.33)						
3	0.07	**0.03**	0.02	**0.05**	**0.02**	0.12	154.4	0.53	0.18	2.4	6.05
	(0.85)	(6.49)	(1.01)	(2.62)	(2.24)						
4	0.07	**0.02**	0.01	**0.05**	-0.00	0.21	163.8	0.6	0.20	2.42	6.74
	(0.77)	(3.83)	(0.55)	(2.51)	(-0.04)						
High-$\lvert\beta^{CC}\rvert$	0.14	-0.01	-0.01	0.04	-0.04	0.51	162.7	0.68	0.22	2.53	7.56
	(1.21)	(-0.59)	(-0.31)	(1.45)	(-1.54)						
High-Low	0.07	**-0.04**	**-0.04**	-0.02	**-0.07**						
	(1.32)	(-3.57)	(-2.39)	(-1.48)	(-2.51)						

Table 8: **Univariate on Carbon Emission Intensity (*CEI*)**. We form quintile portfolios of corporate bonds based on the firm-level carbon emissions intensity (*CEI*). *CEI* is defined as the firm-level greenhouse gas emission in CO2 equivalents (Scope 1 + 2) divided by the total revenue of the firm in millions of euros. We form portfolios within each of the 12 Fama-French industries to control for the industry effects. Quintile 1 (Low) is the portfolio with the lowest *CEI* and Quintile 5 (High) is the portfolio with the highest *CEI*. The table reports the average *CEI*, the next-month average excess return, the 2-factor alpha (ii), the 5-factor alpha (iii), and the 7-factor alpha (iv) for each quintile. The last row shows the monthly average returns of the differences between high and low. The 7-factor model includes includes the excess bond market return (*MKT*), the default risk factor (*DEF*), the term risk factor (*TERM*), the downside risk factor (*DRF*), the liquidity risk factor (*LRF*), the credit risk factor (*CRF*), and the reversal risk factor (*REV*). Average returns and alphas are defined in monthly percentage terms. Newey and West (1987) adjusted t-statistics are reported in parentheses. Numbers in bold denote statistical significance at the 5% level or below. The sample period is from January 2006 to July 2022.

	Average	1 - Factor	2 - Factor	3 - Factor	7 - Factor	Average Portfolio Characteristics					
	Return	Alpha	Alpha	Alpha	Alpha	$\lvert\beta^{CC}\rvert$	Average CEI	Bid-Ask Spread	Downside (VaR 5%)	Rating	Duration
Low-CEI	0.12	**0.02**	0.02	**0.05**	0.01	0.21	33.1	0.55	0.02	2.42	6.3
	(1.64)	(6.74)	(0.72)	(2.44)	(0.25)						
2	0.15	0.01	-0.01	**0.05**	-0.02	0.19	95.6	0.54	0.02	2.4	6.32
	(1.9)	(1.03)	(-0.51)	(2.4)	(-1.33)						
3	**0.18**	-0.00	-0.01	**0.04**	0.02	0.2	253.5	0.58	0.02	2.45	6.03
	(2.06)	(-0.04)	(-0.25)	(2.45)	(1.85)						
4	**0.16**	**0.03**	0.02	**0.07**	**0.03**	0.19	437.4	0.58	0.02	2.42	6.82
	(1.96)	(4.64)	(0.85)	(2.97)	(3.45)						
High-CEI	0.13	**0.03**	-0.01	**0.06**	**0.03**	0.20	693.3	0.63	0.02	2.45	6.38
	(1.63)	(3.69)	(-0.18)	(2.86)	(2.33)						
High-Low	-0.01	**0.01**	-0.01	0.01	0.02						
	(-0.37)	(0.58)	(-1.37)	(-0.73)	(1.93)						

Table 9: **Bivariate on climate beta and carbon emission intensity** ($|\beta^{CC}|$ **and CEI.)**
We form double sort portfolios of corporate bonds based on the bond-level absolute value of climate beta ($|\beta^{CC}|$) and carbon emissions intensity (*CEI*) on a monthly basis. β^{CC} is defined as the bond-level exposure from time-series regressions of excess bond returns on using the the climate attention index (CC^{ATT}) controlling for the market factor (i):

$$R_{i,t} = \alpha_i + \beta_i^{CC} \cdot CC_t^{ATT} + \beta_{i,t}^{MKT} \cdot MKT_t +$$

Carbon Emissions Intensity (*CEI*) is defined as the firm-level greenhouse gas emissions (Scope 1 + 2, in tCO2) divided by the total revenue of the firm in millions of euros. We form portfolios within each of the 12 Fama-French industries to control for industry effects. Quintile 1 (Low-$|\beta^{CC}|$) is the portfolio with the lowest $|\beta^{CC}|$ and Quintile 5 (High-$|\beta^{CC}|$) is the portfolio with the highest $|\beta^{CC}|$. Quintile 1 (Low-*CEI*) is the portfolio with the lowest carbon emission intensity and Quintile 5 (High-*CEI*) is the portfolio with the highest carbon emission intensity. Average returns and alphas are defined in monthly percentage terms. Newey and West (1987) adjusted t-statistics are reported in parentheses. Numbers in bold denote statistical significance at the 5% level or below. The sample period is from January 2006 to July 2022.

	Low-$\|\beta^{CC}\|$	2	3	4	High-$\|\beta^{CC}\|$	High-Low $\|\beta^{CC}\|$
Panel A : Average Return						
Low-CEI	0.11	0.11	0.1	0.11	0.19	**0.08**
	(1.69)	(1.72)	(1.38)	(1.42)	(1.81)	(4.02)
2	0.14	**0.18**	0.11	0.14	0.2	**0.06**
	(1.78)	(2.56)	(1.49)	(1.73)	(1.84)	(2.05)
3	0.12	0.16	**0.17**	0.16	**0.3**	**0.18**
	(1.59)	(1.92)	(2.17)	(1.61)	(2.57)	(5.55)
4	0.14	**0.14**	0.11	0.15	**0.26**	**0.12**
	(1.84)	(1.99)	(1.24)	(1.7)	(2.33)	(4.03)
High-CEI	0.09	0.13	0.11	0.12	0.20	**0.11**
	(1.28)	(1.82)	(1.38)	(1.31)	(1.83)	(3.21)
High-Low CEI	**-0.02**	0.02	-0.01	-0.02	-0.01	
	(-1.96)	(1.36)	(-0.47)	(-1.13)	(-0.47)	
Panel B : 7- Factor Alpha						
Low-CEI	**0.03**	0.01	0.01	-0.01	-0.04	**-0.07**
	(3.97)	(1.67)	(1.48)	(-1.22)	(-1.61)	(-5)
2	**0.04**	0.02	-0.01	-0.01	**-0.18**	**-0.22**
	(2.81)	(1.16)	(-0.84)	(-0.45)	(-2.14)	(-5.42)
3	**0.05**	0.05	0.03	0.00	-0.04	**-0.09**
	(3.78)	(1.84)	(1.01)	(0.23)	(-1.65)	(-8.16)
4	**0.04**	**0.05**	0.04	**0.04**	-0.04	**-0.08**
	(3.6)	(4.96)	(1.69)	(2.04)	(-1.55)	(-6.71)
High-CEI	**0.06**	-0.02	**0.04**	0.01	-0.04	**-0.10**
	(5.3)	(-0.32)	(3.09)	(0.99)	(-0.67)	(-3.4)
High-Low CEI	**0.03**	-0.04	**0.02**	**0.02**	-0.02	
	(6.21)	(-1.25)	(3.68)	(3.32)	(-0.88)	

Table 10: **Factors vs Characteristics. Monthly Excess Returns of Portfolios Sorted by Rating, Duration, and Climate Beta.** Each month bonds are independently sorted into 3 ratings portfolios (AAA/AA=1, A=2, and BBB=3) and 3 duration portfolios. 9 portfolios are created at the intersection of the rating and duration portfolios. Within each of these portfolios, 3 portfolios are created based on either pre-ranking climate beta (Panel A). The pre-ranking β^{CC} are estimated on a time-series regression of excess bond return on the the climate attention index (CC^{ATT}) controlling for the market factor (i):

$$R_{i,t} = \alpha_i + \beta_i^{CC} \cdot CC_t^{ATT} + \beta_{i,t}^{MKT} \cdot MKT_t +$$

The time-series average monthly excess return (in percent) of each portfolio is reported along with the difference in average return between the high beta and the low beta portfolio. The t-statistic is a simple t-test of differences. There are 199 monthly observations.

Panel: 7-factor alphas					
Characteristics		Pre-ranking climate beta portfolio			
		Low-$\lvert\beta^{CC}\rvert$	2	High-$\lvert\beta^{CC}\rvert$	H-L
Rating	Duration				
1	1	**0.03**	0.01	-0.02	**-0.05**
		(2.69)	(0.82)	(0.71)	(-1.98)
1	2	**0.13**	**0.05**	0.09	-0.04
		(3.21)	(5.17)	(1.69)	(0.71)
1	3	0.00	**0.02**	-0.1	**-0.1**
		(0.09)	(2.22)	(-3.47)	(4.49)
2	1	**0.05**	**0.09**	-0.03	**-0.07**
		(2.69)	(2.55)	(-1.11)	(3.74)
2	2	-0.01	**0.04**	-0.10	**-0.09**
		(-0.22)	(3.01)	(-1.85)	(2.36)
2	3	**0.02**	0.02	-0.03	**-0.05**
		(2.18)	(1.17)	(-1.34)	(3.11)
3	1	0.00	-0.02	**-0.05**	**-0.05**
		(0.2)	(-1.37)	(-1.93)	(2.58)
3	2	0.01	0.01	-0.04	-0.06
		(0.46)	(0.46)	(-0.85)	(1.43)
3	3	0.02	-0.03	-0.30	**-0.32**
		(0.76)	(-1.27)	(-1.11)	(2.17)
GRS Test	F-stat:	45.6	p-value:	0.001	

Table 11: **Factors vs Characteristics. Monthly Excess Returns of Portfolios Sorted by Rating, Duration, and Climate Beta.** Each month bonds are independently sorted into 3 ratings portfolios (AAA/AA=1, A=2, and BBB=3) and 3 duration portfolios. 9 portfolios are created at the intersection of the rating and duration portfolios. Within each of these portfolios, 3 portfolios are created based on either pre-ranking climate beta (Panel A). The pre-ranking β^{CC} are estimated on a time-series regression of excess bond return on the the climate attention index (CC^{ATT}) controlling for the market factor (i):

$$R_{i,t} = \alpha_i + \beta_i^{CC} \cdot CC_t^{ATT} + \beta_{i,t}^{MKT} \cdot MKT_t +$$

The time-series average monthly excess return (in percent) of each portfolio is reported along with the difference in average return between the high beta and the low beta portfolio. The t-statistic is a simple t-test of differences. There are 199 monthly observations.

Panel: Ex-post climate beta					
Characteristics		Pre-ranking climate beta portfolio			
		Low-$\|\beta^{CC}\|$	2	High-$\|\beta^{CC}\|$	H-L
Rating	Duration				
1	1	0.04	0.12	0.26	0.22
1	2	0.04	0.12	0.35	0.31
1	3	0.04	0.14	0.37	0.33
2	1	0.04	0.12	0.3	0.26
2	2	0.04	0.13	0.37	0.33
2	3	0.04	0.14	0.42	0.38
3	1	0.04	0.14	0.36	0.32
3	2	0.04	0.14	0.44	0.41
3	3	0.04	0.14	0.49	0.45

Table 12: **Panel Regressions: Expected Returns on Corporate Bonds**.

Table 12 reports the results from the panel regressions of 1-month-ahead bond excess returns ($R_{i,t+1}$) on β^{CC} over the sample period from Jan. 2004 to July. 2022. The first stage uses time-series regressions of excess bond returns on bond factors to estimate betas:

$$R_{i,t} = \alpha_i + \beta_i^{CCN} \cdot CCN_t + \sum_{k=1}^{m} \beta_i^k \cdot F_{k,t} + \epsilon_i$$

The second stage uses panel regressions of excess returns on the estimated betas to obtain factor premia:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}^{CCN} \hat{\beta}_{i,t}^{CCN} + \sum_{k=1}^{m} \lambda_{k,t} \hat{\beta}_{i,t}^{k} + \gamma_{i,t}' X_{i,t} + \epsilon_{i,t}$$

Column 1 reports the univariate regression with β^{CC} estimated from the model (i). Column 2 reports the multivariate regression including β^{CC} and controlling for the factor loadings estimated from the model (iv). Column 3 reports the regression results with β^{CC} controlling for bond characteristics. Column 4 reports the regression results on β^{CC} controlling for bond betas and characteristics. T-statistics computed using clustered standard error at the bond-level are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Table 5 provides the variable definitions.

	Dependent Variable: Future Excess Return ($R_{i,t+1}$)			
	Univariate	**Bond Betas**	**Bond Characteristics**	**All Ctrls.**
	(1)	(2)	(3)	(4)
λ^{CC}	-0.041**	-0.040*	-0.032*	-0.048**
	(-2.316)	(-1.745)	(-1.748)	(-2.129)
λ^{MKT}		0.185***		0.227***
		(10.505)		(11.885)
λ^{DEF}		-0.027*		-0.028**
		(-1.934)		(-2.006)
λ^{TERM}		-0.163***		-0.155***
		(-5.412)		(-5.203)
λ^{DRF}		-0.001		0.002
		(-0.211)		(0.378)
λ^{LRF}		0.004		0.007
		(0.498)		(0.819)
λ^{CRF}		0.056***		0.056***
		(10.356)		(9.896)
λ^{REV}		-0.032***		-0.035***
		(-3.116)		(-3.472)
DOWN			1.095*	0.865
			(1.944)	(1.546)
ILLIQ			0.416***	0.453***
			(4.051)	(5.545)
Rating			0.058***	0.035**
			(3.420)	(2.152)
lag(Return)			0.003	-0.000
			(0.784)	(-0.046)
log(years to maturity)			-0.067*	-0.127***
			(-1.815)	(-4.060)
Size			-1.035***	-1.073***
			(-9.719)	(-10.101)
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No. of obs.	174217	166791	170574	166763
Adj.R^2	0.042	0.117	0.149	0.154

Table 13: **Panel Regressions: Bond Factors.**
Table 13 reports the results from the fixed effects panel regressions of 1-month-ahead bond excess returns ($R_{i,t+1}$) on β^{CC} over the sample period from Jan. 2004 to July. 2022. The first stage uses time-series regressions of excess bond returns on bond factors to estimate betas:

$$R_{i,t} = \alpha_i + \beta_i^{CC} \cdot CC_t + \sum_{k=1}^{m} \beta_i^k \cdot F_{k,t} + \epsilon_i$$

The second stage uses cross-sectional regressions of excess returns on the estimated betas to obtain factor premia:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}^{CC} \hat{\beta}_{i,t}^{CC} + \sum_{k=1}^{m} \lambda_{k,t} \hat{\beta}_{i,t}^{k} + \gamma_{i,t}' X_{i,t} + \epsilon_{i,t}$$

Columns 1 and 2 report the regression results with β^{CC} estimated from the model (i) using the bond market factor (MKT). Columns 3 and 4 report the regressions from model (ii) using Fama and French (1993) risk factors. Columns 5 and 6 report the regression results estimated from the model (iii) using Bai et al. (2019) risk factors. Columns 7 and 8 report the regression results estimated from the combined model (iv). T-statistics (in parenthesis) are computed using clustered standard errors at the bond and issuer level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Table 5 provides the variable definitions.

	Dependent Variable: Future Excess Return ($R_{i,t+1}$)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
λ^{CC}	-0.047***	-0.066***	-0.041**	-0.066***	-0.036	-0.072***	-0.040*	-0.069***
	(-2.701)	(-3.436)	(-2.281)	(-3.378)	(-1.544)	(-3.093)	(-1.745)	(-3.012)
λ^{MKT}	0.109***	0.075***					0.185***	0.122***
	(8.159)	(8.976)					(10.505)	(7.990)
λ^{DEF}			0.010	0.023***			-0.027*	0.009
			(0.985)	(2.684)			(-1.934)	(0.755)
λ^{TERM}			-0.090***	0.011			-0.163***	-0.120***
			(-4.101)	(0.613)			(-5.412)	(-4.746)
λ^{DRF}					-0.010**	-0.027***	-0.001	-0.007
					(-2.073)	(-6.847)	(-0.211)	(-1.451)
λ^{LRF}					-0.013	-0.037***	0.004	0.004
					(-1.499)	(-6.078)	(0.498)	(0.481)
λ^{CRF}					0.051***	0.036***	0.056***	0.040***
					(9.400)	(6.719)	(10.356)	(7.581)
λ^{REV}					-0.019*	0.012	-0.032***	-0.002
					(-1.898)	(1.145)	(-3.116)	(-0.215)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Bond	Yes	No	Yes	No	Yes	No	Yes	No
Cluster Issuer	No	Yes	No	Yes	No	Yes	No	Yes
No. of Obs.	174217	174217	174217	174217	166791	166791	166791	166791
Adj. R^2	0.141	0.140	0.140	0.139	0.137	0.136	0.138	0.137

Table 14: **Regressions with Return Adjustments: Credit-adj, Industry-adj. and Duration-adj.** Table 14 reports the results from the fixed effect panel regressions of 1-month-ahead bond adjusted-excess returns (Adj-$R_{i,t+1}$) on β^{CC} over the sample period from Jan. 2004 to July. 2022. Adjusted-returns are calculated as the return differential between the bond and its matching portfolio average return, using 3 credit portfolios (AAA/AA, A, and BBB), 12 industry portfolio returns, 3 duration portfolio returns, and 3x3 credit, and duration portfolios returns. Reported results are estimated from the model (iv) including CC^{ATT} using Fama and French (1993) and Bai et al. (2019) risk factors, controlling for bond variables. Columns 1 and 2 report the regression using credit-adjusted returns. Credit-adjusted returns are calculated by subtracting from each bond return the average bond return mean returns by credit rating. Columns 3 and 4 report the regression using industry-adjusted returns. Industry-adjusted return are calculated by subtracting from each bond return the average bond return mean returns by industry to which the issuer belongs, using the 12 Fama-French industries. Columns 5 and 6 report the regression using duration-adjusted returns. Duration-adjusted return are calculated by subtracting from each bond return the average bond return mean returns by duration tercile. Columns 7 and 8 report credit-duration-adjusted returns, through a 3×3 sort, for rating and duration, by subtracting from each bond return the average bond return of the rating and duration portfolio to which the bond belongs. t-statistics computed using clustered standard error at the bond and issuer level are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Table 5 provides the variable definitions.

	Cred-adj. $R_{i,t+1}$		Ind-adj. $R_{i,t+1}$		Dur-adj. $R_{i,t+1}$		Dur-Cred-adj. $R_{i,t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
λ^{CC}	-0.044**	-0.067***	-0.057***	-0.075***	0.025	0.015	-0.058***	-0.063***
	(-2.034)	(-2.737)	(-2.612)	(-3.042)	(1.303)	(0.696)	(-5.893)	(-5.805)
λ^{MKT}	0.203***	0.138***	0.209***	0.146***	0.155***	0.094***	-0.095***	-0.069***
	(10.890)	(7.896)	(11.234)	(8.294)	(9.569)	(6.020)	(-10.130)	(-8.810)
λ^{DEF}	-0.024*	0.005	-0.024*	0.005	-0.019	-0.008	0.041***	0.008
	(-1.761)	(0.431)	(-1.796)	(0.374)	(-1.482)	(-0.642)	(4.868)	(1.038)
λ^{TERM}	-0.157***	-0.141***	-0.160***	-0.148***	-0.011	-0.019	0.096***	0.074***
	(-5.550)	(-5.572)	(-5.512)	(-5.619)	(-0.402)	(-0.743)	(5.699)	(5.397)
λ^{DRF}	0.002	-0.008	-0.000	-0.010*	0.006	0.001	0.003	0.008***
	(0.378)	(-1.628)	(-0.010)	(-1.894)	(1.445)	(0.201)	(1.246)	(3.473)
λ^{LRF}	0.006	0.004	0.003	0.001	0.018**	0.016*	0.006	0.004
	(0.723)	(0.459)	(0.361)	(0.134)	(2.269)	(1.923)	(1.356)	(0.869)
λ^{CRF}	0.057***	0.045***	0.053***	0.041***	0.043***	0.033***	-0.010***	-0.009***
	(10.241)	(7.391)	(9.755)	(6.997)	(9.487)	(6.697)	(-3.546)	(-3.195)
λ^{REV}	-0.032***	0.002	-0.032***	0.003	-0.039***	-0.012	-0.002	-0.016***
	(-3.214)	(0.226)	(-3.218)	(0.289)	(-4.433)	(-1.173)	(-0.376)	(-3.231)
Bond Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster Bond	Yes	No	Yes	No	Yes	No	Yes	No
Cluster Issuer	No	Yes	No	Yes	No	Yes	No	Yes
No. of Obs.	166763	161839	166763	161839	166763	161839	168732	163739
Adj-R^2	0.124	0.142	0.218	0.239	0.110	0.211	0.175	0.182

Table 15: **Subsample Analysis:** ESG, Environmental and Emissions Profile
Table 15 reports the results from the fixed effect panel regressions of 1-month-ahead bond excess returns ($R_{i,t+1}$) on β^{CC} over the sample period from Jan. 2006 to July. 2022. Columns 1 and 2present the results of the sub-sample analysis based on whether the company has an average ESG score (S&P, MSCI, ASSET4) above the cross-sectional median. Columns 3 and 4 present the results of the sub-sample analysis according to whether the company has an environmental score (S&P, MSCI, ASSET4) above the cross-sectional median. Columns 5 and 6 present the results of the sub-sample analysis according to whether the company's carbon emissions intensity (CEI, SP) is above the above the cross-sectional median. *t*-statistics computed using clustered standard error at the issuer level are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Table 5 provides the variable definitions.

	Dependent Variable: Future Excess Return ($R_{i,t+1}$)					
	Low ESG	High ESG	Low ENV	High ENV	Top Polutter	Non-Top Polluter
	(1)	(2)	(3)	(4)	(5)	(6)
λ^{CC}	0.006	-0.042	0.039	-0.056**	0.054	-0.100***
	(0.141)	(-1.290)	(0.823)	(-2.213)	(1.297)	(-3.385)
λ^{MKT}	0.141***	0.084***	0.106***	0.116***	0.161***	0.069**
	(4.186)	(2.773)	(3.071)	(4.988)	(4.560)	(2.525)
λ^{DEF}	-0.017	-0.031	-0.010	-0.038**	-0.036	-0.014
	(-0.703)	(-1.403)	(-0.345)	(-2.170)	(-1.299)	(-0.635)
λ^{TERM}	-0.108***	-0.041	-0.081*	-0.073*	-0.074*	-0.093*
	(-2.839)	(-0.794)	(-1.809)	(-1.720)	(-1.933)	(-1.947)
λ^{DRF}	-0.004	-0.013	-0.006	-0.011	0.004	-0.023***
	(-0.538)	(-1.226)	(-0.708)	(-1.150)	(0.371)	(-2.906)
λ^{LRF}	-0.008	-0.006	-0.010	-0.010	0.011	-0.031**
	(-0.658)	(-0.339)	(-0.621)	(-0.580)	(0.686)	(-2.009)
λ^{CRF}	0.035***	0.028**	0.021**	0.042***	0.025**	0.036***
	(3.983)	(2.098)	(2.365)	(3.969)	(2.260)	(3.684)
λ^{REV}	-0.022	0.020	-0.022	0.020	-0.025	0.036**
	(-1.086)	(1.209)	(-1.104)	(1.245)	(-1.325)	(2.414)
Bond Controls	Yes	Yes	Yes	Yes	Yes	Yes
Issuer Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	49654	54765	46266	58153	54784	49635
Adj. R^2	0.136	0.144	0.141	0.139	0.168	0.128

Table 16: **Effects of the Paris Agreement.**
The table displays results from the following regression:

$$R_{t+1,i} = \beta_1(TopCC_i \times Paris) + \beta_2 TopCC_i + X_{i,t} + \kappa_t + \varepsilon_{i,t}$$

where $R_{t+1,i}$ is the one-month ahead excess return. Paris is a dummy equal to one if the observation occurs in December 2015 or later and $TopCC$ is either a dummy equal to one if bond i has an above-median climate beta (β^{CC}) estimated on model (i). Odd columns compute $TopCC$ on the full sample. Even columns compute $TopCC$ for each of the 12 Fama-French Industries. Standard errors, clustered at the bond level, are shown in parentheses. ***, ** and * indicate that the parameter estimate is significantly different from zero at the 1%, 5% and 10% level, respectively.

	Dependent Variable: Future Excess Returns ($R_{t+1,i}$)					
	Full Sample		At-Paris		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)
$TopCC$	-0.004	-0.005	-0.064***	-0.060***	-0.146***	-0.115**
	(-0.276)	(-0.354)	(-4.531)	(-4.268)	(-3.677)	(-2.593)
$TopCC \times Paris$	-0.050***	-0.047***	-0.071***	-0.062***	-0.222***	-0.167***
	(-3.032)	(-2.834)	(-4.148)	(-3.607)	(-4.082)	(-3.113)
Industry FE	No	Yes	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	175549	175549	71372	71372	7348	7447
Adj. R^2	0.098	0.097	0.077	0.077	0.073	0.076

Table 17: **Climate Change Shocks**
The table displays results from the following regression:

$$R_{t+1,i} = \beta_1(TopCC_i \times Paris \times Shock_t) + \beta_2 TopCC_i + X_{i,t} + \kappa_t + \varepsilon_{i,t}$$

where $R_{t+1,i}$ is the one-month ahead excess return. Paris is a dummy equal to one if the observation occurs in December 2015 or later. $TopCC$ is either a dummy equal to one if bond i has an above-median climate beta (β^{CC}) for each of the 12 Fama-French Industries estimated on model (i). $Shock$ is either a dummy equal to one if there is a climate shock (regulatory or physical) on month t. Standard errors, clustered at the bond level, are shown in parentheses. ***, ** and * indicate that the parameter estimate is significantly different from zero at the 1%, 5% and 10% level, respectively

	Dependent Variable: Future Excess Returns ($R_{I,t+1}$)			
	(1)	(2)	(3)	(4)
$TopCC \times Paris \times UNPRI$	-0.369***			
	(-2.891)			
$TopCC \times Paris \times EUReg$		-0.097**		
		(-2.468)		
$TopCC \times Paris \times COP$			0.071	
			(0.774)	
$TopCC \times Paris \times CRED$				-0.040
				(-1.066)
$TopCC \times Paris$	-0.036**	-0.048***	-0.056***	-0.038**
	(-2.427)	(-3.178)	(-3.812)	(-2.436)
$TopCC$	0.020*	0.022*	0.015	0.008
	(1.716)	(1.794)	(1.209)	(0.652)
Ctrls/Betas	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No. of Obs.	174217	174217	174217	174217
Adj. R^2	0.135	0.144	0.142	0.104

Table 18: **Controlling for European economic policy uncertainty, climate uncertainty, and volatility** This Table 18 displays results from the following triple-interactions on $R_{i,t+1}$where $High^{CC}$ is a dummy variable equals to 1 if CC^{ATT} is above than the median. EPU is a dummy equal to one if Baker et al. (2016)'s the European Uncertainty Index (EPU). is higher than the median. CPU is a dummy equal to one if Gavriilidis (2021)'s Climate Uncertainty Index (CPU) is higher than the median. V2TX is a dummy equal to one if the index is above the historical median. The table displays results from the following triple interaction :

$$ClimateBeta_{i,t} \times UNC_t \times High_t^{CC}$$

t-statistics computed using clustered standard error at the issuer level are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Table 5 provides the variable definitions.

	Dependent Variable: Future Excess Return ($R_{i,t+1}$)		
	(1)	(2)	(3)
$\beta^{CC} \times EPU$	-0.010		
	(-1.150)		
$\beta^{CC} \times EPU \times High^{CC}$	0.016*		
	(1.668)		
$\beta^{CC} \times CPU$		-0.128***	
		(-14.739)	
$\beta^{CC} \times CPU \times High^{CC}$		-0.086***	
		(-8.136)	
$\beta^{CC} \times V2TX$			0.026***
			(2.903)
$\beta^{CC} \times V2TX \times High^{CC}$			0.034***
			(3.113)
Ctrls/Betas			
Ctrls/Betas	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
No. of Obs.	174303	174303	174303
Adj. R^2	0.096	0.102	0.096

Table 19: **Return Decomposition: Cash-flow and Discount rate.**
This table reports univariate portfolios of corporate bonds sorted by discount rates and cash-flows climate beta. We calculate unexpected returns, cashflow news (ϵ_{CF} and discount rates news ($\epsilon_{DR,}$) using the decomposition framework. We estimate climate betas associated to cash flows (β^{CC}_{CF}) and discount rates (β^{CC}_{DR}), over 36 month windows while controlling for the market ((i)), as follows:

$$e_{DR,t} = \alpha_{i,t} + \beta^{CC}_{CF} CC^{ATT}_t + \beta^{MKT}_t MKT_t + \epsilon_t$$

$$e_{CF,t} = \alpha_{i,t} + \beta^{CC}_{DR} CC^{ATT}_t + \beta^{MKT}_t MKT_t + \epsilon_t$$

We calculate VAR using the return on assets (ROA) as a proxy for issuer-level cash flows, and Tobin's Q as a proxy for overall growth opportunity. We follow Callen and Segal (2010) and run a VAR for each of the 12-Fama-French industries. This approach estimates VAR parameters at the industry level, but the residuals at the firm-year level. The portfolios reports the next-month average excess returns, the alphas from the models (i), (ii), (iii) , and (iv). The last row shows the differences in monthly average returns and the differences in alphas with respect to the factor models. Newey-West adjusted t-statistics are given in parentheses. Bold numbers indicate significance at least at the 5% level. The sample period is from January 2004 to July 2022.

	Sorted by β^{CC}_{DR}						Sorted by β^{CC}_{CF}				
	Average Return	1 - Factor Alpha	2 - Factor Alpha	3 - Factor Alpha	7 - Factor Alpha		Average Return	1 - Factor Alpha	2 - Factor Alpha	3 - Factor Alpha	7 - Factor Alpha
Low-β^{CC}_{DR}	0.83	**0.26**	0.27	**0.61**	0.14	Low-β^{CC}_{CF}	0.13	0	0	0.03	-0.02
	(0.91)	(3.86)	(1.18)	(2.93)	(1.83)		(1.32)	(-0.03)	(0.11)	(1.07)	(-1.15)
2	1.15	0.07	**0.41**	**0.72**	0.05	2	0.07	**0.03**	0.03	**0.05**	0.03
	(1.19)	(0.9)	(2.58)	(4.17)	(0.57)		(1.01)	(7.29)	(1.49)	(2.7)	(5.82)
3	1.38	**0.26**	**0.69**	**1.04**	0.04	3	0.06	0.04	0.03	**0.06**	**0.04**
	(1.24)	(3.16)	(2.72)	(3.6)	(0.24)		(0.91)	(9.04)	(1.54)	(3.42)	(5.04)
4	1.21	**0.16**	0.39	**0.66**	0.24	4	0.07	**0.03**	0.01	**0.05**	0.01
	(1.17)	(1.99)	(1.35)	(2.18)	(1.17)		(0.83)	(5.29)	(0.64)	(2.69)	(1.15)
High-β^{CC}_{DR}	1.35	**0.01**	-0.04	**0.33**	**-0.23**	High-β^{CC}_{CF}	0.07	0.01	0	**0.06**	-0.01
	(1.39)	(0.2)	(-0.21)	(1.69)	**(-1.65)**		(0.68)	(1.23)	(-0.06)	(2.65)	(-0.84)
High-Low	0.52	**-0.25**	**-0.31**	**-0.28**	**-0.37**	High-Low	-0.06	0.01	-0.01	**0.04**	0.01
	(1.82)	(-4.75)	(-3.85)	(-3.56)	(-2.45)		(-1.45)	(0.65)	(-0.25)	(2.32)	(0.28)

Table 20: **Predictability of future bond returns.**

This table presents the results from the panel regressions of future excess bond returns in month $t+1$ to month $t+12$ on β_{CCN} and control variables measured in month t. The first group of estimations use bond's excess returns ($R_{i,t+i}$) in month t+2 to month t+12, respectively. The second group of estimations use the duration-adjusted bond's excess returns (Duration-adj. $R_{i,t+i}$) in month t+2 to month t+12, respectively. Table 5 provides the variable definitions.

Variable	Dependent Variable: Future Excess Returns ($R_{i,t+i}$)											
	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$	$t+6$	$t+7$	$t+8$	$t+9$	$t+10$	$t+11$	$t+12$
β_{CCN}	-0.031**	-0.006	-0.004	-0.021	-0.040***	-0.028***	-0.005	-0.001	-0.001	0.001	-0.003	0.012
	(-2.368)	(-0.333)	(-0.243)	(-1.289)	(-2.719)	(-2.851)	(-0.674)	(-0.158)	(-0.075)	(0.157)	(-0.413)	(1.018)
Bond controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Issuer controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Issuer fixed effects	No	No	No	No	No	No	No	No	No	No	No	No
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.142	0.131	0.126	0.104	0.097	0.092	0.094	0.099	0.099	0.113	0.112	0.103
No. of obs.	86616	85255	83897	82535	81174	79813	77997	76201	74412	72634	70869	69123

Table 21: Correlation Table: Climate Indices

	CC^{ATT}	MECCO (lvl)	MECCO (ch)	$CC^{Brogger}$	$CC^{Faccini}$	$CC^{Overall}$	$CC^{Int'lSummits}$	CC^{Apel}	$CC^{Engle-WSJ}$	$CC^{Engle-CH}$	$CC^{Gravriilidis}$
CC^{ATT}	1.00										
MECCO (level)	0.43	1.00									
MECCO (changes)	0.93	0.36	1.00								
$CC^{Brogger}$	-0.07	-0.01	-0.10	1.00							
$CC^{Faccini}$	0.08	0.64	0.14	-0.03	1.00						
$CC^{Overall}$	0.54	0.63	0.42	0.10	0.10	1.00					
$CC^{Int'lSummits}$	0.57	0.75	0.47	0.04	0.25	0.82	1.00				
CC^{Apel}	-0.18	-0.29	-0.19	0.26	-0.05	-0.25	-0.31	1.00			
$CC^{Engle-WSJ}$	0.43	0.39	0.33	-0.05	0.17	0.43	0.39	-0.21	1.00		
$CC^{Engle-CH}$	0.68	0.45	0.65	-0.10	0.30	0.37	0.41	-0.15	0.49	1.00	
$CC^{Gravriilidis}$	0.11	0.18	0.12	-0.06	0.05	0.22	0.17	-0.26	-0.12	0.05	1.00

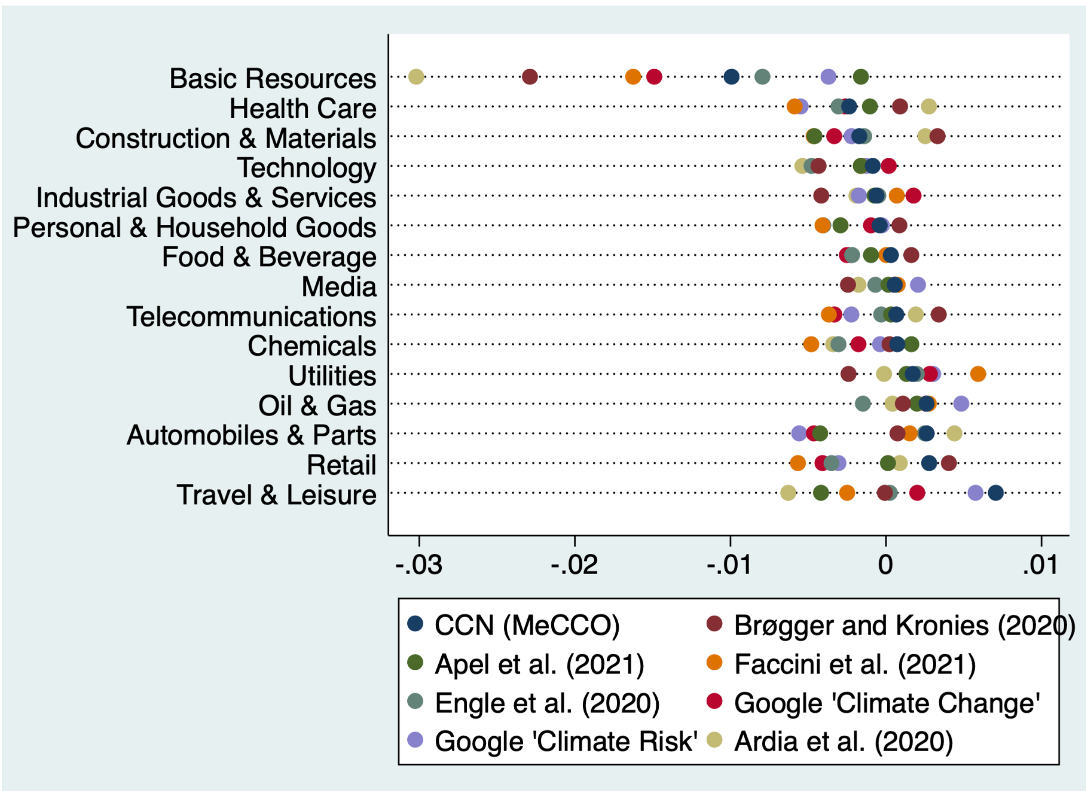

Figure 2: Relative β^{CC} over industry sectors

Table 22: **Summary Statistics: Climate Betas β^{CC}.**
This table 22 reports the summary statistics for the climate betas from the indices described in 1. The number of observations, mean, standard deviation, and percentiles (5, 25, 50, 75 and 95) are shown in columns. The sample period for each climate news index is from January 2004 to June 2021. Other CC indices with shorter periods are excluded.

β^{CC}	N	Mean	SD	5th	25th	50th	75th	95th
CC^{ATT}	126318	-0.071	1.139	-1.665	-0.345	-0.046	0.506	1.901
Brøgger and Kronies	75865	-0.073	2.708	-3.455	-0.741	-0.004	0.790	3.166
Apel (TRI)	117876	-0.037	2.623	-3.123	-0.559	-0.010	0.558	2.996
Faccini Global Summt	101486	-0.020	2.831	-3.450	-0.862	-0.042	0.748	3.457
Engle (WSJ)	70172	-0.054	2.540	-2.564	-0.631	-0.051	0.522	2.603
SVI Climate Change	126318	-0.074	2.548	-3.011	-0.773	0.018	0.663	2.686
SVI Climate Risk	126318	-0.061	2.509	-3.101	-0.663	0.008	0.691	2.707
Ardia Overall	83106	-0.071	2.984	-3.389	-0.632	0.003	0.715	3.135

B. Robustness Checks

Errors-in-Variables Adjustment

The estimation of climate betas as explanatory variables leads to an errors-in-variables (EIV) problem, in which the explanatory variables are subject to measurement errors, biasing regression coefficients towards zero. This *attenuation bias* overestimates the *true* coefficient when it is negative and underestimates it when it is positive. Standard OLS regressions (as performed in Fama and MacBeth (1973)) would underestimate the effect of the factor loadings, and the other coefficients in the model can be biased to the extent that they are correlated with the poorly measured variable. Typically to attenuate potential EIV bias, portfolios are widely employed as test assets. However, since β^{CC} is estimated at the bond-level, some estimation errors might arise. Thus, an EIV-correction is needed when one or more of the independent variables are measured with additive noise (Jegadeesh et al., 2019). We can analyze the sensitivity of the estimates by assuming a certain degree reliability (i.e. confidence level) by assuming the ratio of noise to total variance, as follows:

$$\text{reliability} = 1 - \frac{\text{noise variance}}{\text{total variance}} \tag{13}$$

That is, given the linear model $y = X + u$, for some variable x_i in X, x_i is observed with error, $x_i = x_i^* + \mathbf{e}$, and the noise variance is the variance of $\mathbf{e}$. The total variance is the variance of x_i. For an in-depth review of the different methods to correct for the errors-in-variable bias in the empirical asset pricing literature, please refer to Collot and Hemauer (2021).

C. Online Appendix

This section provides additional details on the composition of the sample index. Table 24 provides the description of returns by rating. Table 26 provides the description of returns by maturity bucket.

While in Europe the bond market is dominated by the financial intermediaries, the bond market in the United States is dominated by the non-financial corporate sector. The finance literature in general excludes the financial sector (banks, insurance companies, among others), ADRs, REITs, and also as suggested by Fama and French (1993) *"units of beneficial interest are excluded"*. For example, banks have a much complex debt structure and financial assets than corporations. Financials account for (40.81%) of the Overall Markit IBOXX EUR Corporates index benchmark. Due to their special characteristics, we exclude them from our analysis. We address the analysis without Financials, including Real Estate companies.

For non-financials, using the Global Industry Classification Standard (GISCS) to classify issuers has its limitations. There is a high concentration among the Consumer Discretionary sector representing 80% of the total sample, followed by Consumer Services (9%), Industrials (3%). Other classifications have more granular industry sectors, for instance, the Fama-French Industries link the existing 4-digit Standard Industrial Classification (SIC) to 12, 17, 30 or 49 industries. The Markit Market Sectors has either 7, 14, or 22 categories. With more categories, each classification divides the sample into groups that are too small, and sometimes some industries may not have a bonds. To go along with similar academic studies, we use the Fama-French classification system.

Table 23: **Top-10 issuer country.**
Number of bond-month observations by issuer country domicile over the sample period from Jan. 2006 to July. 2022.

Issuer Country	Freq.	Percent(%)	Cum(%)
France	38,061	21.35	21.35
Netherlands	34,443	19.32	40.67
USA	23,254	13.04	53.71
UK	15,075	8.46	62.17
Germany	13,741	7.71	69.88
Italy	9,117	5.11	74.99
Luxembourg	7,723	4.33	79.33
Spain	7,093	3.98	83.3
Sweden	4,316	2.42	85.73
Australia	4,081	2.29	88.01
Top 10	156,904	88.01	
Total	178,271		

Table 24: **Return statistics: Markit IBOXX ratings.**
This table reports the number of bond-month observations, the cross-sectional mean, median, standard deviation, and monthly return percentiles of corporate bonds. Tabulation on corporate bonds into 4 credit categories based on Markit IBOXX ratings. Markit IBOXX ratings are the average of the three rating agencies, from Fitch Ratings, S&P Global Ratings, and Moody's Investor Service Ratings are in conventional numerical scores, where 1 refers to an AAA rating, 2 refers to an AA, 3 refers to A, and 4 refers to a BBB rating. Higher numerical score means higher credit risk. BBB (or better) are considered investment grade, worse than BBB are labeled high yield, and hence not included in the index.

Bond return statistics over the sample period of January 2004 – June 2021									
					Percentiles				
Markit IBOXX Rating	N	Perc.(%)	Mean	SD	5th	25th	50th	75th	95th
AAA	246	0.20	0.16	1.17	-1.71	-0.25	0.04	0.46	2.46
AA	10027	8.30	0.25	1.24	-1.61	-0.24	0.18	0.75	2.32
A	51446	42.60	0.28	1.24	-1.56	-0.17	0.20	0.77	2.34
BBB	58784	48.67	0.30	1.38	-1.75	-0.17	0.20	0.80	2.63

Table 25: **Return statistics: Maturity.**
This table reports the number of bond-month observations, the cross-sectional mean, median, standard deviation, and monthly return percentiles of corporate bonds. Tabulation on corporate bonds into 5 different maturities (Corporates 1–3, 3–5, 5–7, 7–10, 10+). The sample period is from January 2004 to June 2021.

Bond return statistics over the sample period of January 2004 – June 2021									
					Percentiles				
Maturities	N	Perc.(%)	Mean	SD	5th	25th	50th	75th	95th
Corporates 1-3 Y	32301	26.74	0.15	0.56	-0.43	-0.02	0.10	0.29	0.89
Corporates 3-5 Y	32472	26.89	0.28	1.02	-1.02	-0.16	0.25	0.68	1.82
Corporates 5-7 Y	24765	20.50	0.33	1.37	-1.65	-0.39	0.36	1.01	2.49
Corporates 7-10 Y	19650	16.27	0.41	1.70	-2.28	-0.59	0.48	1.36	3.26
Corporates 10+ Y	11299	9.36	0.42	2.26	-3.55	-1.07	0.46	1.84	4.65

Table 26: **Return statistics: Maturity-Credit.**
This table reports the number of bond-month observations, the cross-sectional mean, median, standard deviation, and monthly return percentiles of corporate bonds. Tabulation on corporate bonds into 5 different maturities (Corporates 1–3, 3–5, 5–7, 7–10, 10+) and three credit ratings (Corporates AAA-AA, A, and BBB). The categories represent different maturities in each of the credit rating categories. Overall The sample period is from January 2004 to June 2021.

Bond return statistics over the sample period of January 2004 – June 2021									
					Percentiles				
Maturities	N	Perc.(%)	Mean	SD	5th	25th	50th	75th	95th
Corporates AAA-AA 1-3Y	2261	1.87	0.10	0.41	-0.44	-0.04	0.07	0.24	0.71
Corporates A 1-3Y	13352	11.05	0.13	0.46	-0.38	-0.02	0.10	0.27	0.80
Corporates BBB 1-3 Y	16688	13.82	0.16	0.65	-0.46	-0.02	0.11	0.31	1.00
Corporates AAA-AA 3-5 Y	2343	1.94	0.20	0.78	-0.85	-0.17	0.19	0.57	1.37
Corporates A 3-5 Y	13381	11.08	0.25	0.88	-0.94	-0.16	0.23	0.62	1.60
Corporates BBB 3-5 Y	16748	13.87	0.31	1.14	-1.15	-0.16	0.27	0.74	2.07
Corporates AAA-AA 5-7 Y	2140	1.77	0.25	1.09	-1.39	-0.39	0.30	0.88	1.87
Corporates A 5-7 Y	10205	8.45	0.33	1.24	-1.44	-0.37	0.37	0.96	2.30
Corporates BBB 5-7 Y	12420	10.28	0.35	1.51	-1.97	-0.40	0.37	1.09	2.79
Corporates AAA-AA 7-10 Y	1978	1.64	0.34	1.49	-1.94	-0.56	0.38	1.22	2.78
Corporates A 7-10 Y	8963	7.42	0.41	1.60	-2.05	-0.58	0.51	1.32	3.07
Corporates BBB 7-10 Y	8709	7.21	0.42	1.84	-2.66	-0.61	0.48	1.46	3.58
Corporates AAA-AA 10+	1547	1.28	0.38	2.10	-3.26	-1.12	0.48	1.68	4.08
Corporates A 10+	5541	4.59	0.41	2.22	-3.41	-1.08	0.50	1.81	4.51
Corporates 10+	4211	3.49	0.44	2.37	-3.89	-1.04	0.40	1.98	4.90

Table 27: **Univariate on β^{CC}.**

This table presents the portfolios formed using β^{CC}. We form quintile portfolios of corporate bonds based on β^{CC} which is defined as the bond-level exposure from time-series regressions of excess bond returns on the climate attention index (CC^{ATT}) controlling for the market factor (i):

$$R_{i,t} = \alpha_i + \beta_i^{CC} \cdot CC_t^{ATT} + \beta_{i,t}^{MKT} \cdot MKT_t + \epsilon_{i,t}$$

We form portfolios within each of the 12 Fama-French industries to control for the industry effects. Quintile 1 (Low) is the portfolio with the lowest β^{CC} and Quintile 5 (High) is the portfolio with the highest β^{CC}. For each quintile, the table reports the average β^{CC}, the next-month average excess return, the 1-factor alpha from the market factor (i), the 2-factor from macroeconomic factors (ii), the 4-factor alpha from common bond factors (iii) , and the 7-factor alpha (iv) from the combined factors. The last row shows the monthly average returns of the differences between High and Low. The 7-factor model with bond market factors includes the excess bond market return (*MKT*), the default risk factor (*DEF*), the term risk factor (*TERM*), the downside risk factor (*DRF*), the liquidity risk factor (*LRF*), the credit risk factor (*CRF*), and the reversal risk factor (*REV*). Average returns and alphas are defined in monthly percentage terms. Newey and West (1987) adjusted t-statistics are reported in parentheses. Numbers in bold denote statistical significance at the 5% level or below. The sample period is from January 2006 to July 2022.

	Average	1 - Factor	2 - Factor	3 - Factor	7 - Factor	Average Portfolio Characteristics					
	Return	Alpha	Alpha	Alpha	Alpha	Average CEI	β^{CC}	Bid-Ask Spread	Downside (VaR 5%)	Rating	Duration
Low-β^{CC}	0.13	**0.01**	-0.02	**-0.01**	-0.09	184.93	-0.42	0.7	0.02	2.41	7.84
	(1.12)	(0.49)	(-0.9)	(-0.34)	(-3.03)						
2	0.09	**0.03**	0.04	**0.05**	0.01	153.08	-0.11	0.51	0.02	2.41	6.06
	(1.12)	(6.8)	(1.88)	(2.84)	(1.4)						
3	**0.06**	**0.03**	**0.05**	**0.07**	**0.03**	135.06	0.01	0.47	0.02	2.38	5.39
	(0.85)	(7.06)	(2.82)	(3.81)	(5.42)						
4	**0.07**	**0.03**	**0.03**	**0.07**	**0.04**	159.45	0.13	0.49	0.02	2.41	5.43
	(1.02)	(5.5)	(1.98)	(3.61)	(5.03)						
High-β^{CC}	0.13	**0.02**	0.02	**0.09**	**0.08**	165.8	0.42	0.61	0.02	2.55	6.2
	(1.44)	(1.96)	(0.73)	(3.34)	**(4.48)**						
High-Low	0	**0.01**	**0.04**	**0.1**	**0.17**						
	(0.01)	(0.51)	(2.5)	(5.03)	(3.8)						

Table 28: **Bivariate on climate beta and carbon emission intensity. (β^{CC} and CEI.)**
We form double sort portfolios of corporate bonds based on the bond-level absolute value of climate beta (β^{CC}) and carbon emissions intensity (*CEI*) on a monthly basis. β^{CC} is defined as the bond-level exposure from time-series regressions of excess bond returns on using the the climate attention index (CC^{ATT}) controlling for the market factor:

$$R_{i,t} = \alpha_i + \beta_i^{CC} \cdot CC_t^{ATT} + \beta_{i,t}^{MKT} \cdot MKT_t + \epsilon_{i,t}$$

The Carbon Emissions Intensity (*CEI*) is defined as the firm-level greenhouse gas emissions (Scope 1 + 2, in tCO2) divided by the total revenue of the firm in millions of euros. We form portfolios within each of the 12 Fama-French industries to control for industry effects. Quintile 1 (Low-β^{CC}) is the portfolio with the lowest β^{CC} and Quintile 5 (High-β^{CC}) is the portfolio with the highest β^{CC}. Quintile 1 (Low-*CEI*) is the portfolio with the lowest carbon emission intensity and Quintile 5 (High-*CEI*) is the portfolio with the highest carbon emission intensity. Average returns and alphas are defined in monthly percentage terms. Newey and West (1987) adjusted t-statistics are reported in parentheses. Numbers in bold denote statistical significance at the 5% level or below. The sample period is from January 2006 to July 2022.

Quintiles	Low-β^{CCN}	2	3	4	High-β^{CCN}	Total
Low-CEI	0.01	**0.05**	**0.06**	0.04	**0.07**	**0.06**
	(0.32)	(2.15)	(3.02)	(1.75)	(2.64)	(6.7)
2	0.08	**0.1**	**0.12**	**0.13**	**0.17**	**0.08**
	(1.32)	(2.41)	(2.61)	(2.37)	(2.25)	(5.42)
3	0.05	0.04	**0.06**	0.05	0.01	-0.03
	(1.57)	(1.46)	(2.24)	(1.8)	(0.5)	(-4.19)
4	0.02	**0.07**	**0.09**	**0.06**	0.02	0
	(0.67)	(2.69)	(3.98)	(2.95)	(0.92)	(-0.14)
High-CEI	0.04	0.04	**0.05**	**0.08**	**0.07**	**0.03**
	(1.36)	(1.89)	(2.58)	(3.2)	(3.35)	(3.16)
Total	**0.03**	-0.01	-0.02	**0.02**	0	
	(4.72)	(-3.46)	(-6.1)	(5.27)	(-0.52)	

This section provides more details on the composition of the sample index. To be included in the index benchmark, only corporate debt denominated in EUR is eligible, regardless of risk or origin country. Because of the Eurozone's economic integration, investors may be tempted to view corporate debt issued by European companies as undifferentiated. Within the same currency, treating European and Global corporations as interchangeable is reasonable. Table 23 shows the top-10 countries with more issuers.

Table 29: **Fama-MacBeth Cross-Sectional Regressions.** This table reports the coefficients from the Fama and MacBeth (1973) cross-sectional regressions of future corporate bond excess returns on β^{CC} with and without controls. The dependent variable is the corporate bond excess return over the sample period from Jan.2004 to July 2022. The first stage uses time-series regressions of excess bond returns on risk factors from model (iv) to estimate betas:

$$R_{i,t} = \alpha_i + \beta_i^{CC} \cdot CC_t^{ATT} + \sum_{k=1}^{m} \beta_i^k \cdot F_{k,t} + \epsilon_i$$

The second stage uses cross-sectional regressions of excess returns on the estimated betas to obtain the factor premia:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}^{CC} \hat{\beta}_{i,t}^{CC} + \sum_{k=1}^{m} \lambda_{k,t} \hat{\beta}_{i,t}^{k} + \gamma_{i,t}' X_{i,t} + \epsilon_{i,t+1}$$

Systematic risk betas include the default beta (β^{DEF}), term beta (β^{TERM}), credit beta (β^{CRF}), credit beta (β^{DRF}), liquidity beta (β^{LRF}), and reversal beta (β^{REV}) from model (iv). Control variables include bond characteristics: ILLIQ, years to maturity, credit rating, DOWNSIDE, and one-month lagged returns). Credit ratings are numerical Markit IBOXX ratings (from 1 to 3), a higher numerical score implies higher credit risk. Time-to-maturity is defined in terms of years. ILLIQ is the monthly average bid-ask spread of the daily ask and bid prices within each month. The last row reports the average adjusted R^2 values and control for the Fama-French 12 industry fixed effects in all specifications. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively Newey and West (1987) adjusted t-statistics are reported in parentheses. Table 5 provides the variable definitions.

	Univariate	Ctrl. Bond Characteristics	Ctrl. Bond Betas	All Ctrls.
	(1)	(2)	(3)	(4)
λ^{CC}	-0.038*	-0.011*	-0.023*	-0.021**
	(-1.82)	(-1.817)	(-2.624)	(-2.463)
ILLIQ		0.165***		0.139***
		(-3.599)		-3.482
Maturity		0.063		0.076
		(-1.202)		-1.552
Rating		0.027		0.013
		(-1.309)		-0.872
DOWN		0.366***		0.283**
		(-2.73)		(-2.608)
Lag Return		-1.824		-1.472
		(-0.913)		(-0.807)
λ^{MKT}			0.024***	0.008**
			(-3.977)	(-2.154)
λ^{DEF}			0.017*	0.006
			(-1.724)	(-0.91)
λ^{TERM}			0.001	0.004
			(-0.011)	(-0.578)
λ^{DRF}			0.021***	0.009***
			(-4.007)	(-2.94)
λ^{LRF}			0.022***	0.006*
			(-3.277)	(-1.795)
λ^{REV}			0.001	-0.005
			(-0.058)	(-1.154)
λ^{CRF}			-0.001	-0.002
			(-1.023)	(-1.545)
Industry. FE	Yes	Yes	Yes	Yes
Adj. R^2	0.081	0.368	0.357	0.442
N	174333	127983	127990	127983

Table 30: **Climate Change News attention index using European, North American and Combined newspapers.**

This Table 30 presents the results from the panel regressions of one-month-ahead bond excess returns ($R_{i,t+1}$) using European, North American and combined newspapers to construct the Climate Change News attention betas. Columns 1 and 2 report the regression results from 45 European newspapers. Columns 3 and 4 report the regression results from 11 North American newspapers. Columns 5 and 6 report the regression results using the combined database. Standard errors are clustered at the issuer level in all regressions. t-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Table 5 provides the variable definitions.

Variable	Dependent Variable: Future Excess Returns ($R_{i,t+1}$)					
	EU		US		EU+US	
	1	2	3	4	5	6
β_{CCN}	-0.031*	-0.027*	-0.036***	-0.033***	-0.031**	-0.026**
	(-1.656)	(-1.831)	(-2.611)	(-3.060)	(-2.368)	(-2.555)
β_{MKT}	-0.113***	-0.115***	-0.091**	-0.096***	-0.112***	-0.112***
	(-2.613)	(-3.480)	(-2.242)	(-3.005)	(-2.690)	(-3.469)
β_{TERM}	-0.029	-0.031	-0.047	-0.043	-0.037	-0.037
	(-0.867)	(-1.272)	(-1.254)	(-1.515)	(-1.090)	(-1.459)
β_{DEF}	0.047	0.022	0.069**	0.038	0.058**	0.032
	(1.486)	(0.804)	(2.162)	(1.482)	(2.051)	(1.298)
β_{DRF}	-0.096***	-0.107***	-0.069**	-0.083***	-0.090***	-0.100***
	(-2.803)	(-4.087)	(-2.001)	(-3.152)	(-2.710)	(-3.892)
β_{LRF}	-0.103***	-0.128***	-0.081**	-0.108***	-0.098***	-0.123***
	(-2.675)	(-4.359)	(-2.020)	(-3.553)	(-2.602)	(-4.254)
β_{REV}	-0.065	-0.057	-0.112**	-0.105**	-0.086	-0.077
	(-0.868)	(-0.870)	(-1.969)	(-2.026)	(-1.250)	(-1.248)
β_{CRF}	0.058*	0.067**	0.051*	0.061**	0.055*	0.064**
	(1.666)	(2.557)	(1.750)	(2.377)	(1.686)	(2.583)
Bond controls	Yes	Yes	Yes	Yes	Yes	Yes
Issuer controls	Yes	Yes	Yes	Yes	Yes	Yes
Bond fixed effects	No	Yes	No	Yes	No	Yes
Issuer fixed effects	Yes	No	Yes	No	Yes	No
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.142	0.136	0.142	0.136	0.142	0.136
No. of obs.	86616	86616	86616	86616	86616	86616

Table 31: **Return statistics: 12 Fama-French industries.**
This table reports the number of bond-month observations, the cross-sectional mean, median, standard deviation, and monthly return percentiles of corporate bonds. Tabulation on corporate bonds into the 12 Fama-French industries. The sample period is from January 2004 to June 2021.

Bond return statistics over the sample period of January 2004 – June 2021									
					Percentiles				
Industry Classification	N	Perc.(%)	Mean	SD	5th	25th	50th	75th	95th
Business Equipment	6131	3.65	0.25	1.62	-1.40	-0.19	0.15	0.69	2.32
Chemicals	5326	3.17	0.27	1.42	-1.33	-0.18	0.19	0.74	2.16
Consumer Durables	3299	1.96	0.22	1.85	-1.25	-0.17	0.13	0.62	2.18
Consumer NonDurables	8149	4.85	0.27	1.49	-1.50	-0.19	0.17	0.76	2.39
Energy	4076	2.42	0.30	1.76	-1.97	-0.17	0.23	0.91	2.82
Finance	65711	39.08	0.29	1.82	-1.61	-0.17	0.20	0.79	2.56
Healthcare	6829	4.06	0.27	1.59	-1.50	-0.19	0.14	0.72	2.47
Manufacturing	6182	3.68	0.29	1.95	-1.86	-0.21	0.22	0.88	2.74
Other	18002	10.71	0.29	1.94	-1.71	-0.21	0.21	0.91	2.70
Shops	6952	4.13	0.30	1.61	-1.57	-0.18	0.22	0.82	2.40
Telecommunication	16960	10.09	0.35	1.69	-1.76	-0.20	0.22	0.90	2.80
Utilities	20531	12.21	0.32	1.53	-1.61	-0.19	0.22	0.87	2.62

Table 32: **Rolling windows β_{CCNews} estimation.**
This table 32 shows the results from the panel regressions of one-month-ahead bond excess returns ($R_{i,t+1}$) on using 24 and 36 months to estimate the climate change news betas. Columns 1 and 2 report the regression results using $\beta_{CCNews,24}$, is estimated over a 24-month window requiring at least 12 month-return observations. Columns 3 and 4 report the regression results using $\beta_{CCNews,24}$, which is estimated over a 36-month window requiring at least 12 valid observations. Standard errors are clustered at the issuer level in all regressions. t-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Table 5 provides the variable definitions.

Variable	Dependent Variable: Future Excess Returns ($R_{i,t+1}$)			
	24 month		*36 month*	
	1	2	3	4
λ^{CCN}	-0.023*	-0.023**	-0.031**	-0.026**
	(-1.851)	(-2.194)	(-2.368)	(-2.555)
λ^{MKT}	-0.107***	-0.104***	-0.112***	-0.112***
	(-2.778)	(-3.125)	(-2.690)	(-3.469)
λ^{TERM}	-0.002	-0.003	-0.037	-0.037
	(-0.059)	(-0.101)	(-1.090)	(-1.459)
λ^{DEF}	0.081***	0.057***	0.058**	0.032
	(3.912)	(2.725)	(2.051)	(1.298)
λ^{DRF}	-0.069**	-0.081***	-0.090***	-0.100***
	(-2.129)	(-2.894)	(-2.710)	(-3.892)
λ^{LRF}	-0.077**	-0.105***	-0.098***	-0.123***
	(-2.184)	(-3.486)	(-2.602)	(-4.254)
λ^{REV}	-0.057	-0.059	-0.086	-0.077
	(-0.911)	(-0.929)	(-1.250)	(-1.248)
λ^{CRF}	0.052*	0.056**	0.055*	0.064**
	(1.824)	(2.193)	(1.686)	(2.583)
Bond controls	Yes	Yes	Yes	Yes
Issuer controls	Yes	Yes	Yes	Yes
Bond fixed effects	Yes	No	Yes	No
Issuer fixed effects	No	Yes	No	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.143	0.136	0.142	0.136
No. of obs.	86558	86558	86616	86616