Climate beta uncertainty in corporate bonds

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Abstract

Corporate bonds' exposure to climate risks is surrounded by substantial uncertainty. This climate beta uncertainty is both economically and statistically significantly priced in the cross-section of bond returns. Understanding this uncertainty is crucial, as it influences risk premia and the effectiveness of bonds as hedging instruments against climate risks. Since climate exposures exhibit distinct pricing patterns depending on return definitions, their impact on bond valuations varies. For total returns, bonds exposed to specific climate indices appear to offer potential hedges against future climate outcomes, but they trade at lower prices. For duration-adjusted returns, a higher climate beta is associated with higher future bond returns, indicating that greater exposure to climate risks commands a return premium once interest rate effects are controlled for. The results suggest that the hedging capacity of corporate bonds primarily stems from their linkage to duration-matched long-term government bonds, while credit returns—albeit small—compensate investors for bearing climate risk exposure.

Keywords: Climate change, news, duration, corporate bonds, parameter uncertainty

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1. Introduction

As climate change shocks become more frequent, companies face increased vulnerabilities to disruptions; in August 2024, Porsche reduced car production in Germany due to flooding at an aluminum supplier in Switzerland.[2] Such incidents highlight how climate risks can disrupt entire supply chains, potentially lowering operating income, increasing financial pressure and weakening creditworthiness (Acharya et al., 2022; Pankratz and Schiller, 2024). Moreover, rising awareness of climate change risks is driving capital reallocation in financial markets; in July 2022, the European Central Bank (ECB) prioritized purchasing corporate bonds from issuers with strong climate performance, using a scoring system based on emissions, decarbonization goals, and climate disclosures.[3] Therefore, integrating climate risks into investment decisions is becoming increasingly important (Moldovan et al., 2024), but accurately measuring their impact on corporate bond prices remains challenging (Krueger et al., 2020; Giglio et al., 2021; Campiglio et al., 2019). This challenge arises because a comprehensive climate risk assessment must account for multiple climate scenarios and conduct a location-specific analysis of the entire supply chain. As a result, precisely estimating the climate risk premium is difficult, with significant uncertainties regarding its sign and magnitude (Rebonato et al., 2023).

One approach is using market-based methods, such as estimating the covariance between asset returns and climate proxies—known as climate betas—to understand the asset pricing implications of climate risks (Hafez and Xie, 2016; Flammer, 2021; Jung et al., 2023; Dietz et al., 2018). Some studies have used meteorological or geographical climate measures, such as abnormal temperature (Barnett et al., 2020), precipitation (Hong and Kacperczyk, 2009), and sea level (Allman, 2022). However, recent research has expanded to incorporate climate-related news to model investor beliefs. Through textual analysis, researchers capture attention and sentiment in multiple dimensions related to regulatory changes and natural disasters (Engle et al., 2020; Faccini et al., 2021; Ardia et al., 2023; Alekseev et al., 2021; Bua et al., 2024; Apel et al., 2023). Some studies have adopted simpler approaches, such as analyzing Google search volume for climate-related terms (Brøgger and Kro-

[2] https://www.ft.com/content/8b988cfb-d2b0-47fd-841f-dcc0de437134

[3] https://www.ecb.europa.eu/press/pr/date/2022/html/ecb.pr220704~4f48a72462.en.html

nies, 2020) or measuring the frequency of uncertainty-related language in climate discourse (Gavriilidis, 2021). However, there is uncertainty on how to measure the risks of climate change (Painter, 2013; Barnett et al., 2020; Barnett, 2023).[4]

By design, some indices differ according to the construction method, the sources they use and the specific dimensions of climate risk they track. In this context, Maeso and O'Kane (2023) compare the volume-based against advanced natural language processing methods to construct climate news indices, finding that volume-based indices are more effective in capturing market reactions. In addition, the frequency of news aggregation involves a trade-off: daily news captures immediate market reactions while monthly aggregation smooths fluctuations, but risks overlooking short-term impacts. Likewise, the focus of climate news indices varies. For example, Bua et al. (2024); Apel et al. (2023) focus on transition and physical risks, while Ardia et al. (2023); Faccini et al. (2021) address climate policies, environmental impacts, and social issues.[5] However, the mechanisms linking these risks remain unclear, complicating climate risk assessments (Lemoine, 2021; Barnett et al., 2020).

This paper examines the implications for asset pricing of the uncertainty surrounding climate beta exposures for US and European corporate bonds. Climate beta uncertainty for each bond is defined as the cross-sectional divergence of different climate beta estimates. Significant differences between estimates from various approaches suggest high uncertainty, indicating considerable disagreement about climate risks. Conversely, similar estimates across approaches reflect a consensus on the asset's exposure to climate risk. The study investigates how this uncertainty affects bond pricing by analyzing the relationship between climate beta uncertainty and bond risk premia. Specifically, it tests whether investors demand a premium for bearing climate beta uncertainty and whether this premium varies across market conditions, industries, and firm characteristics. The findings offer insights into how market participants incorporate climate risk into bond valuations and the role

[4]The measurement of climate change risks is challenging, as they are unobservable until they materialize, and the underlying data-generating process is unknown. In addition, theoretical frameworks provide limited guidance on constructing risk proxies or estimating climate betas. In practice, estimates are based on historical data available.

[5]This distinction can be subtle and difficult to discern in textual data. For example, policy actions that mitigate physical risks often lead to the creation of new transition risks.

of heterogeneous beliefs about climate exposure in shaping asset prices. Furthermore, the study uses duration-adjusted returns to account for credit risk returns (van Binsbergen et al., 2025; Andreani et al., 2023; Bessembinder et al., 2008; Diep et al., 2021).[6] Failing to adjust for interest rate returns can lead to erroneous conclusions, especially when the relationship between interest rates and credit is negative, which can cause shifts in the direction of climate exposures.

From an asset pricing perspective, the hedging hypothesis suggests that investors seeking protection against climate-related risks are accepting lower returns on bonds that hedge against these risks (Merton, 1973). In contrast, the risk-return trade-off implies that climate-exposed bonds, seen as riskier due to the exposure to climate-related risks, should offer higher expected returns to compensate for these risks (Bannier et al., 2023; Duan et al., 2021). Several studies have identified the hedging hypothesis, showing that bonds with higher climate betas tend to have lower future returns (Huynh and Xia, 2020; Lalwani, 2024; Benkraiem et al., 2025). However, there is also evidence that investors demand higher returns on bonds vulnerable to physical or regulatory shocks, indicating a potential premium associated with this exposure (Bats et al., 2024). For example, companies with high carbon emissions face greater regulatory risks and thus provide higher yield spreads, particularly after the Paris Agreement (Seltzer et al., 2022).

Hedging climate risks has become a key focus in recent research, in order to enhance portfolio risk management (Andersson et al., 2016; Roston, 2021; Jurczenko, 2023; de Silva and Tenreyro, 2021). However, managing multiple climate risks presents challenges, as perfect hedges are rare and costly. When hedging is not possible, investors should be compensated for risk exposure. Climate uncertainty becomes crucial when assets have multiple climate exposures with different signs, preventing them from being effective hedges, and thus requiring a premium. Evaluating uncertainty and climate risks is crucial as it influences firms' climate change disclosures, especially post-Paris Agreement (Sautner et al., 2023; Danisman et al., 2025), or after climate-related shocks (Seltzer et al., 2020; Baker et al., 2016).

[6] Studies on corporate bonds often use total returns in excess of the 1-month risk-free rate. This approach adds noise by including returns from long-term risk-free assets, making it difficult to isolate credit and illiquidity returns. This is especially problematic for investment grade bonds, where credit and illiquidity risks are marginal (Andreani et al., 2023)

The paper is structured as follows. The introduction provides an overview of current climate change indices, related literature, and hypothesis development. Section 2 presents the climate news and corporate bond data. Section 3 outlines the methodology and presents the empirical results. Section 4 offers a discussion and conclusion.

1.1. Related literature

The seminal studies by Engle et al. (2020) and Bessec and Fouquau (2020) focus on climate sentiment through the textual analysis of articles from the Wall Street Journal. Similarly, the Media Climate Change Concern Index (MCCC) developed by Ardia et al. (2023) analyze eight US newspapers and identifies 40 climate-related topics that influence green and brown stock returns. Pástor et al. (2022) utilize the MCCC index to assess temporal investor preferences with respect to climate news. Moreover, Andriollo et al. (2024) demonstrates that the MCCC is significant in explaining US corporate bond portfolios, even after accounting for *robust* estimations. Beyond the MCCC, several researchers have developed alternative climate indices. Faccini et al. (2021) build four climate news indices based on natural disasters, global warming, international summits, and climate policy. In related work, Apel et al. (2023) focus on transition risks linked to environmental standards and renewable energy costs, while Bua et al. (2024) examine European transition and physical risks. Our work also draws on alternative approaches to measuring climate risk attention. We align with Brøgger and Kronies (2020), who gauge investor attention through Google search volumes for *climate change*, and Gavriilidis (2021), who quantify articles containing *climate* and *uncertainty* terms. A summary of the various climate change indices considered in this study is presented in Table 10.

Huynh and Xia (2020); Duan et al. (2021) study climate news effects on US corporate bond returns. Huynh and Xia (2020) employs the WSJ index from Engle et al. (2020), while Duan et al. (2021) utilizes carbon emissions data from S&P Trucost and incidents from RepRisk. Their findings indicate that increased exposure to climate change correlates with diminished future bond returns, highlighting the influence of climate risk on asset pricing. Investors concerned about climate risks tend to favor bonds from companies with superior environmental performance, often willing to pay a premium for such securities. Huynh and Xia (2020); Duan et al. (2021); Lalwani (2024) find that climate risk sensitivity leads to lower returns, which aligns with the changes in investor preferences noted by Pástor et al. (2022).

Moreover, Lalwani (2024) finds that bonds that covariate highly only news related to global warming earn lower returns. Huynh and Xia (2020) focus on the hedging hypothesis and test the pricing implication of excess demand for assets that hedge against climate risk. They find that investors in US corporate bond markets accept lower future returns on bonds that are good hedges against climate risks. They suggest that while the negative sign is consistent with the asset pricing implications of demand for bonds with high potential to hedge against climate risk, the small coefficient may point to the fact that the market has not fully priced in climate risk. Additionally, Lalwani (2024) use Ardia et al. (2023) finding that bonds that covary highly with global warming news earn lower returns. Comparable results in magnitude to those of Huynh and Xia (2020), they show that the pricing effect is small. In contrast, Boermans et al. (2024) find a positive climate risk premium in bonds with higher betas related to the climate transition. In particular, Bats et al. (2024) use European climate news from Bua et al. (2024) that differentiate between transition news and regulatory news. They find that only regulatory news significantly impacts bond pricing. Moreover, Lin and Zhao (2023) builds on Gavriilidis (2021) by incorporating a climate uncertainty index (CPU) based on news, finding that climate uncertainty's effects are similar to those of other economic and political uncertainties; Kayani et al. (2024) examine the heterogeneous impacts of CPU on sectoral returns. The research presented in this study contributes to the debate on climate risk pricing in corporate bond markets by demonstrating that results vary when credit risk is isolated.

1.2. Hypothesis development

Previous research has assessed climate risk primarily through total bond returns, which capture both credit risk and long-term interest rate fluctuations. Duration-adjusted returns isolate climate risk impacts by accounting for bond price sensitivity to interest rate changes and removing interest rate movement effects (van Binsbergen et al., 2025). Climate risks influence investor sentiment and credit creditworthiness, suggesting that climate beta's impact on corporate bond returns may differ depending on whether total returns or duration-adjusted returns are used as the measure (Capasso et al., 2020). This leads to the following hypothesis:

Hypothesis 1 *The impact of climate beta on corporate bond returns varies significantly when measured using total returns versus duration-adjusted returns.*

Standard asset pricing theories suggest a positive correlation between risk and expected returns, as investors seek compensation for uncertainty (Merton, 1973). However, these models typically assume that parameters (in this case, climate beta) are known with certainty, even though they are unobservable and subject to estimation error (Hollstein et al., 2020; Chen and Demirer, 2022). This uncertainty, particularly regarding climate change risks, can influence capital allocation decisions (Barnett, 2023). The mixed evidence on the relationship between climate risks and bond performance complicates understanding whether climate beta or the uncertainties surrounding climate risks are properly priced into corporate bonds.

Moreover, the existence of multiple climate indices with varying effects on bond pricing highlights the market's difficulty in measuring and pricing climate risk. When investors are uncertain about climate risk exposure, they may demand higher compensation for bonds with higher dispersion exposures from different climate indices. This uncertainty may lead to higher credit risk premiums. Therefore, it is hypothesized that bonds with larger variations in climate betas will show higher future returns, reflecting an uncertainty premium beyond climate sensitivity.

Hypothesis 2 *A bond's climate risk uncertainty $Unc(\beta CC)$ is positively related to future returns.*

Investor perception and response to climate risks evolve as these risks materialize. Barnett et al. (2020) argue that materialization reduces uncertainty, enabling a more accurate assessment of the scope and impact of climate risk. This improved understanding leads to two opposing effects: while reduced uncertainty stabilizes market expectations, it may simultaneously diminish the influence of climate risk on bond returns as markets adjust to realized risks. Although investors generally demand higher returns to compensate for uncertainty, the predictability gained from the realized climate risks could decrease the market sensitivity to climate exposure. The following hypothesis proposes that as climate risks materialize and uncertainty decreases, the positive relationship between climate risk exposure and future returns weakens.

Hypothesis 3 *The positive relationship between a bond's climate risk exposure and future returns weakens when climate risks materialize.*

2. Data and summary statistics

This study draws on data from various sources. It begins with a description of selected climate indices from the literature, followed by the construction of the climate change uncertainty index. The next subsection presents bond-level data for the US and Europe from TRACE and Markit IBOXX. Firm-level data are sourced from Jensen et al. (2023). The bonds are matched using bond CUSIP to issuer COMPUSTAT GVKEY for the US, using the mapping provided by Fang (2024). For the EU, bond ISIN to issuer COMPUSTAT GVKEY using the Capital IQ mapping table. Descriptive statistics for the variables are provided in Table 2 and Table 3, respectively.

2.1. Climate news data

2.1.1. Climate change indices

The list of climate change news indices is: the WSJ and CHNEG from Engle et al. (2020); the Media Climate Change Concerns (MCCC) Aggregate, Business Impact (Bus.), Environmental impact (Env.), Societal Debate (Soc.), and Research (Res.) clusters from Ardia et al. (2023); the Climate Policy (Clim Pol.), International Summits (Int. Summ), Global Warming (Glob. Warm.), and Natural Disasters (Nat. Dis.) from Faccini et al. (2021), the Transition Regulatory (TRI) index from Apel et al. (2023); the Physical and Transition indices from Bua et al. (2024); the Natural Disasters (Nat. Dis.) index from Manela and Moreira (2017), and form Bybee et al. (2023); the Google Search Volume index on *climate change*; the Climate Policy Uncertainty (CPU) from Gavriilidis (2021); and the Climate Change Sentiment (CCsent) index from Brøgger and Kronies (2020).

Additionally, the MeCCO index incorporates climate news volume from US and European newspapers, ensuring coverage from both regions. Articles from the MeCCO database serve as the primary sources, with news collected through LexisNexis, ProQuest, and Factiva, spanning 126 media outlets across 58 countries.[7] MeCCO selects articles containing terms such as *climate change* or *global warming*.[8] The focus remains on Europe and

[7]Available at: https://scholar.colorado.edu/concern/datasets/nz806067t.

[8]In german: *klimawandel* or *globale erwärmung*; in spanish: *calentamiento global* or *cambio climático*.

North America.[9] From 2004 to December 2023, the aggregated index includes 45 European and 11 North American sources (Hawley et al., 2021).[10]

Climate indices measuring weather events complement this approach. These include land surface temperature anomalies (Temp), the quasiperiodic Pacific Ocean temperature anomaly (Nino) from the National Oceanic and Atmospheric Administration, and the Actuaries Climate Index (ACI).

Table 1: **Summary Statistics: Climate Change indices**

	N.	mean	SD.	5th	25th	median	75th	95th
MeCCO US + EU	246	0.68	0.34	0.19	0.45	0.69	0.90	1.21
MeCCO US	246	0.66	0.40	-0.03	0.40	0.69	0.97	1.22
MeCCO EU	246	0.68	0.34	0.21	0.48	0.69	0.90	1.21
WSJ: Engle et al. (2020)	402	0.54	0.19	0.34	0.40	0.50	0.63	0.89
CHNEG: Engle et al. (2020)	120	0.21	0.12	0.10	0.13	0.17	0.25	0.44
MCCC Agg: Ardia et al. (2023)	258	1.26	0.56	0.51	0.84	1.11	1.67	2.31
MCCC Bus.: Ardia et al. (2023)	258	1.07	0.43	0.47	0.74	1.01	1.31	1.86
MCCC Env.: Ardia et al. (2023)	258	1.26	0.59	0.50	0.84	1.13	1.61	2.37
MCCC Soc.: Ardia et al. (2023)	258	1.22	0.64	0.43	0.76	1.06	1.63	2.31
MCCC Res.: Ardia et al. (2023)	258	1.04	0.44	0.50	0.74	0.96	1.26	1.78
Clim. Pol: Faccini et al. (2021)	282	0.78	0.76	0.06	0.22	0.55	1.11	2.13
Int'l Summ.: Faccini et al. (2021)	282	0.51	0.79	0.03	0.10	0.20	0.65	1.74
Glob. Warm.: Faccini et al. (2021)	282	0.53	0.49	0.10	0.21	0.40	0.70	1.38
Nat. Dis.: Faccini et al. (2021)	282	0.85	0.64	0.19	0.40	0.65	1.16	2.06
TRI.: Apel et al. (2023)	252	0.00	0.00	-0.00	-0.00	0.00	0.00	0.00
Trans.: Bua et al. (2024)	228	0.08	0.01	0.06	0.07	0.08	0.09	0.11
Phys.: Bua et al. (2024)	228	0.08	0.01	0.06	0.07	0.08	0.09	0.10
Nat. Dis.: Manela and Moreira (2017)	1514	-0.01	0.02	-0.05	-0.02	-0.00	0.00	0.01
Nat. Dis: Bybee et al. (2023)	402	0.56	0.31	0.35	0.40	0.47	0.65	0.99
GSVI	244	-0.00	2.62	-3.66	-0.55	0.00	0.36	2.47
CPU: Gavriilidis (2021)	446	0.07	0.39	-0.43	-0.21	0.02	0.28	0.75
CCsent: Brøgger and Kronies (2020)	156	-0.08	7.29	-12.71	-2.65	-0.21	2.11	11.78
Nino	249	0.01	0.81	-1.16	-0.60	-0.07	0.47	1.57
ACI	755	0.27	0.33	-0.21	0.02	0.13	0.58	0.92
Temp (ab.)	247	0.01	0.15	-0.18	-0.08	0.01	0.09	0.23

Table 1 provides descriptive statistics for the climate indices. Specifically, the table reports the mean, standard deviation, median, and the 5th, 25th,

[9] According to the ECB (ECB, 2017), investors outside the euro area (rest of the world) held 29.6% of the total market. Given the global distribution of bondholders, a news index must reflect both US and European sources.

[10] Appendix B details the construction method. Table ?? lists the newspapers used.

75th, and 95th percentiles for each index.[11] Figure 4 in the appendix shows the correlation heatmap among the various climate risk indices. The indices are divided mainly into two groups: one with positive correlations, including the MeCCO, MCCC, and Faccini et al. (2021) indices (shown in red), and another with lower correlations, comprising natural physical indices along with transition and physical indices (shown in blue).This grouping suggests that the correlations are primarily influenced by methodological similarities among the

To capture sudden shifts in climate news, an AR(1) model is used to estimate unexpected changes in climate indices. Past studies (Pástor et al. (2022); Engle et al. (2020); Ardia et al. (2023)) analyze market responses to unexpected climate news, specifically comparing green and brown stock performance. According to Ardia et al. (2023), unexpected news influences market reactions, as expected news is typically already factored into prices. The AR(1) model, represented by the equation (1), defines the climate index at time t as a function of its prior value and an error term u_t, representing innovation.

$$\begin{aligned} ClimateIndex_t^j &= \rho_0 + \rho \times ClimateIndex_{t-1}^j + u_t^j \\ CC_t^j &= u_t^j \end{aligned} \tag{1}$$

2.2. Corporate bond data

2.2.1. TRACE

The US sample includes data from the Trade Reporting and Compliance Engine (TRACE) and constituent bonds from the Bank of America (BAML) Investment Grade indices. The dataset, sourced from Dickerson et al. (2023); van Binsbergen et al. (2025), provides total and duration-adjusted returns, and includes equity and accounting data from CRSP and COMPUSTAT. This data is publicly available for download at `openbondassetpricing.com/data`. Following Andreani et al. (2023); Dickerson et al. (2023), bonds with insufficient issue size (below \$ 150M pre-Nov 2004 or \$ 250M post-Nov 2004 for IG bonds per BAML index rules), zero-coupon and convertible bonds, defaulted bonds, and those with less than one year remaining to maturity are excluded.

[11] Table 10 provides additional details on the sources used to construct the indices, including their descriptions, frequency, and time period.

Table 2: **Summary Statistics: US sample**

	N.	mean	SD.	5th	25th	median	75th	95th
Panel A: Bond								
Ret (r^{tot})	569750	0.19	2.77	-3.71	-0.61	0.17	1.13	3.91
Dur-Adj (r^{dur})	563247	0.11	2.44	-2.70	-0.46	0.09	0.74	3.04
Bond Price	569749	106.77	12.31	92.40	100.23	104.67	111.46	129.20
YTM	567744	3.50	1.80	0.95	2.28	3.37	4.57	6.17
CS	567954	1.53	1.30	0.36	0.78	1.28	1.92	3.39
Rating	569750	2.41	0.60	1.00	2.00	2.00	3.00	3.00
Duration	567954	7.17	4.87	1.45	3.29	5.77	11.05	16.38
Illiq	569620	0.53	7.43	-0.09	0.01	0.05	0.24	1.78
VaR95	366255	3.17	2.52	0.71	1.46	2.55	4.30	7.21
Amt Out ($)	569750	812973	684093	250000	400000	600000	1000000	2201664
Offering Amt ($)	569750	820763	709646	250000	400000	600000	1000000	2243830
Panel B: Issuer								
ME(log)	569750	10.63	1.24	8.55	9.79	10.61	11.55	12.52
Debt/BE	560903	0.66	2.49	0.23	0.38	0.50	0.64	1.29
ROE	557029	0.36	11.86	-0.01	0.07	0.12	0.20	0.56
IdioRisk	569692	1.23	0.91	0.51	0.76	1.02	1.42	2.56
Panel C: Estimaded betas								
β^{MKT}_{tot}	315435	0.09	0.44	-0.48	-0.10	0.05	0.24	0.79
β^{TERM}_{tot}	315435	-0.99	1.19	-3.19	-1.56	-0.75	-0.26	0.47
β^{DEF}_{tot}	315435	-1.07	3.44	-6.84	-2.55	-0.69	0.62	3.50
β^{TED}_{tot}	315435	-2.43	8.28	-13.89	-3.44	-0.86	0.66	4.75
β^{MKT}_{dur}	312262	0.07	0.49	-0.57	-0.14	0.02	0.24	0.87
β^{DEF}_{dur}	312262	0.53	2.58	-2.82	-0.39	0.36	1.34	4.23
β^{TED}_{dur}	312262	-1.68	5.25	-10.43	-2.96	-0.69	0.42	3.86
Panel D: Aggregated climate change betas								
$Med(\beta CC)_{tot}$	315435	-0.10	0.35	-0.71	-0.25	-0.08	0.07	0.43
$Med(\beta CC)_{dur}$	312262	0.01	0.30	-0.47	-0.12	0.02	0.15	0.49
$Mean(\beta CC)_{tot}$	315435	-0.07	0.81	-1.35	-0.46	-0.09	0.32	1.28
$Mean(\beta CC)_{dur}$	312262	-0.11	0.63	-1.19	-0.38	-0.06	0.20	0.81
Panel F: Uncertainty climate change betas								
$Unc(\beta CC)^{MAD}_{tot}$	315435	0.81	0.62	0.18	0.37	0.63	1.06	1.98
$Unc(\beta CC)^{MAD}_{dur}$	312262	0.64	0.55	0.12	0.26	0.48	0.83	1.72
$Unc(\beta CC)^{Std}_{tot}$	315435	2.23	2.13	0.35	0.82	1.53	2.94	6.36
$Unc(\beta CC)^{Std}_{dur}$	312262	1.75	1.79	0.24	0.59	1.14	2.23	5.33

Note: The table presents summary statistics for the US sample, including bond, issuer, and estimated betas. The statistics include the number of observations (N), the mean, standard deviation (SD), and percentiles (5th, 25th, median, 75th, and 95th) for each variable.

2.2.2. Markit IBOXX

The EU sample includes data from the Markit IBOXX EURO Corporate Index (January 2004 to December 2023) includes 4,548 investment-grade bonds with a BBB rating or higher, a maturity of at least one year, and a minimum outstanding amount of €500 million.[12] The filters applied to the European sample are similar to those used for the US sample. After excluding convertible, sinking, and floating bonds, 3,881 bonds remain, representing 114,047 month-bond observations. Markit also provides information on bond issuance, including the underwriter, yield, offer price, offer date, maturity, and other characteristics. Markit credit ratings represent the linearized average of ratings from Fitch Ratings, S&P Global Ratings, and Moody's.

2.2.3. Total and duration-adjusted returns

As mentioned earlier, distinguishing between total and duration-adjusted (credit) returns is crucial to estimate climate exposures. To achieve this, total returns are first calculated using the methodology from Bessembinder et al. (2008),

$$r_{i,t}^{tot} = \frac{P_{i,t} + AI_{i,t} + Cp_{i,t}}{P_{i,t-1} + AI_{i,t-1}} - 1 \tag{2}$$

where $P_{i,t}$ is the price of bond i at the end-of-month t, $AI_{i,t}$ is the accrued interest, and $Cp_{i,t}$ is the coupon payment, if any.[13] Then, the construction of duration-adjusted returns follows van Binsbergen et al. (2025). Given the fixed nature of corporate bond coupons, the duration decomposition can be computed using Macaulay duration, which represents the time-weighted present value of bond cash flows, expressed as:

$$D_t = \sum_{t=1}^{\infty} w_{t,k} t_k \tag{3}$$

[12]Please refer to for detailed rules and index calculations of the EUR Corporate indices https://ihsmarkit.com/products/indices.html.

[13]For the EU, prices are sourced from end-of-month quotes, while for the US, transaction prices are used. While quoted data typically provide advantages in cross-sectional comparability and reduced noise, transaction prices more accurately reflect realized market values (Biais et al., 2006). The choice of methodology is mainly influenced by data availability constraints, since transaction-level data for the EU corporate bond market is currently unavailable.

Table 3: **Summary Statistics: EU sample**

	N.	mean	SD.	5th	25th	median	75th	95th
Panel A: Bond								
Ret (r^{tot})	114019	0.18	2.77	-3.72	-0.55	0.18	1.10	3.86
Dur-Adj (r^{dur})	113848	0.05	1.52	-1.74	-0.27	0.07	0.45	1.78
Bond Price	114019	104.88	9.40	92.25	100.63	104.17	108.64	118.51
YTM	114019	2.25	2.43	-0.06	0.49	1.38	3.43	7.00
CS	113848	0.87	1.17	-0.14	0.39	0.65	1.08	2.51
Rating	114019	2.50	0.60	1.00	2.00	3.00	3.00	3.00
Duration	114019	5.23	2.92	1.46	3.02	4.75	6.84	10.44
Illiq	114019	0.63	0.54	0.18	0.33	0.50	0.73	1.50
VaR95	68481	2.15	1.95	0.52	1.01	1.59	2.57	5.44
Amt Out (€)	114019	929070	472191	546974	609765	797048	1086977	1796649
Offering Amt (€)	114019	773561	356454	500000	500000	700000	925800	1500000
Panel B: Issuer								
ME(log)	114019	10.00	1.08	8.09	9.34	10.14	10.79	11.52
Debt/BE	113400	0.57	0.72	0.22	0.38	0.49	0.63	0.98
ROE	112417	0.11	0.49	-0.04	0.06	0.10	0.15	0.27
IdioRisk	113488	1.19	0.69	0.54	0.79	1.03	1.39	2.31
Panel C: Estimated betas								
β_{tot}^{MKT}	66590	0.14	0.36	-0.30	-0.04	0.10	0.28	0.69
β_{tot}^{TERM}	66590	-0.73	1.12	-2.70	-1.13	-0.50	-0.11	0.53
β_{tot}^{DEF}	66590	-0.82	3.30	-6.30	-2.23	-0.63	0.67	3.94
β_{tot}^{TED}	66590	-2.53	8.42	-14.12	-4.59	-1.70	-0.02	9.19
β_{dur}^{MKT}	65190	0.06	0.31	-0.37	-0.10	0.03	0.19	0.56
β_{dur}^{DEF}	65190	0.01	1.63	-2.28	-0.83	-0.06	0.67	2.65
β_{dur}^{TED}	65190	-0.87	3.54	-5.69	-1.70	-0.45	0.34	3.01
Panel D: Aggregate climate change betas								
$Med(\beta CC)_{tot}$	66590	-0.16	0.37	-0.83	-0.34	-0.12	0.07	0.32
$Med(\beta CC)_{dur}$	65190	-0.03	0.17	-0.30	-0.11	-0.02	0.06	0.20
$Mean(\beta CC)_{tot}$	66590	-0.03	0.81	-1.32	-0.40	0.01	0.38	1.15
$Mean(\beta CC)_{dur}$	65190	0.03	0.33	-0.50	-0.09	0.05	0.19	0.47
Panel F: Uncertainty climate change betas								
$Unc(\beta CC)_{tot}^{MAD}$	66590	0.78	0.60	0.18	0.38	0.63	1.00	1.86
$Unc(\beta CC)_{dur}^{MAD}$	65190	0.34	0.27	0.09	0.17	0.27	0.43	0.82
$Unc(\beta CC)_{tot}^{Std}$	66590	2.22	2.03	0.35	0.88	1.67	2.89	5.87
$Unc(\beta CC)_{dur}^{Std}$	65190	0.93	0.88	0.17	0.38	0.67	1.18	2.48

Note: The table presents summary statistics for the EU sample, including bond, issuer, and estimated betas. The statistics include the number of observations (N), the mean, standard deviation (SD), and percentiles (5th, 25th, median, 75th, and 95th) for each variable.

where $w_{t,k}$ represents the present value weight of the kth cash flow, and t_k denotes the time until that cash flow occurs. To calculate duration-matched risk-free rates, we use ECB benchmark interest rates derived from AAA-rated euro sovereign bonds. These rates cover maturities of $k = \{1, 2, 3, 4, 5, 7, 10, 15, 20, 30\}$ years. Following Swinkels (2019), monthly returns are derived for the k-period zero-coupon bonds using the ECB yield curve. The modified duration $D_{k,t}$ of a risk-free bond at par value is then approximated using yield-to-maturity $Y_{k,t}$ and remaining maturity $M_{k,t}$, as shown in the following equation:

$$D_{k,t}(Y_{k,t}, M_{k,t}) = \frac{1}{Y_{k,t}} \left[1 - \frac{1}{(1 + 0.5 \cdot Y_{k,t})^2} \cdot M_{k,t} \right] \tag{4}$$

The bond's convexity, denoted as $C_{k,t}$, captures the non-linear relationship between price and yield, and is defined as follows:

$$C_{k,t}(Y_{k,t}, M_{k,t}) = \frac{2}{Y_{k,t}^2} \left[1 - \frac{1}{(1 + 0.5 \cdot Y_{k,t})^2} \cdot M_{k,t} \right] - \frac{2 \cdot M_{k,t}}{Y_{k,t} \cdot (1 + 0.5 \cdot Y_{k,t})^2} \cdot M_{k,t} + 1 \tag{5}$$

Then the kth-period return $r_{k,t}^{ecb}$ is calculated using:

$$r_{k,t}^{ecb}(Y_{t-1}, Y_{k,t}, M_{k,t}) = Y_{t-1} - D_{k,t} \cdot (Y_{k,t} - Y_{t-1}) + \frac{1}{2} \cdot C_{k,t} \cdot (Y_{k,t} - Y_{k,t-1})^2 \tag{6}$$

Note that for monthly returns, $Y_{k,t-1}$ in the first term must be expressed as $(1 + Y_{k,t})^{1/12} - 1$ of the annual yield, while duration and yields in other terms maintain annual units. When interest rates remain constant, the second and third terms become zero, equalizing realized and expected returns (Swinkels, 2019). The duration adjustment measures excess returns relative to the duration-matched risk-free rate. It is calculated as the bond's total return minus the interpolated risk-free rate for the same duration:

$$r_{i,t}^{dur} = r_{i,t}^{tot} - r_{i,t}^{ecb} \tag{7}$$

Tables 2 and 3 present summary statistics for bond-month observations from September 2004 to September 2022. While EU total and duration-adjusted returns are converted to USD using Compustat exchange rates, EU bond prices remain in euros to preserve the standard face value of 100. European bonds yield an average monthly return of 0.18% (2.16% annualized), slightly lower than the US average of 0.19%. Both markets exhibit the same volatility. Duration-adjusted returns are significantly lower at 0.11% and 0.05%, respectively, reflecting compensation for credit risk.The gap between total and duration-adjusted returns is driven by Treasury returns rather than credit risk.

The EU sample has an average yield to maturity (YTM) of 2.25% and an average credit spread (CS) of 0.87%, with bond durations ranging from 1.46 years (5th percentile) to 10.44 years (95th percentile). In the US, the yield to maturity (YTM) is 3.50%, and the credit spread (CS) is 1.53%. Bond durations vary more widely, from 1.45 years (5th percentile) to 16.38 years (95th percentile). Illiquidity ($Illiq$) is lower in the US (0.53) than in the EU (0.63). Due to the higher number of issuances, the total outstanding amount in the US corporate bond market is larger.

2.2.4. Climate betas

For each bond i in each month t, the climate beta $\beta^{(j)}$ is estimated from the monthly rolling regression of the bond's total (duration-adjusted) excess returns on innovations in the monthly climate change index j, using a 36-month window with a minimum of 24 monthly return observations.[14] The model is specified in equations (8), and controls for market excess returns (Mkt), illiquidity ($ILLIQ$), term spread ($TERM$), default spread (DEF) and Treasury-EuroDollar rate spread (TED). Note that the term spread is excluded for duration-adjusted return estimation, as its effect is already incorporated by using corporate bond excess returns over the matched treasuries.

Total Returns	**Duration-Adjusted Return**
$\begin{aligned} r^{tot}_{i,t} - r_{f,t} &= \alpha_{i,t} + \beta^{(j)}_{i,t} CC^j_t \\ &+ \beta^{Mkt}_{i,t} Mkt_t + \beta^{ILLIQ}_{i,t} ILLIQ_t \\ &+ \beta^{DEF}_{i,t} DEF_t + \beta^{TED}_{i,t} TED_t \\ &+ \beta^{TERM}_{i,t} TERM_t \\ &+ \varepsilon_{i,t} \end{aligned}$	$\begin{aligned} r^{dur}_{i,t} &= \alpha_{i,t} + \beta^{(j)}_{i,t} CC^j_t \\ &+ \beta^{Mkt}_{i,t} Mkt_t + \beta^{ILLIQ}_{i,t} ILLIQ_t \\ &+ \beta^{DEF}_{i,t} DEF_t + \beta^{TED}_{i,t} TED_t \\ &+ \varepsilon_{i,t} \end{aligned}$

(8)

[14] To simplify notation, a climate beta is estimated separately for each climate index using total (tot) or duration-adjusted returns (dur). When necessary, the subscripts $\beta^{(j)}_{ret(i,t)}$ or $\beta^{(j)}_{tot(i,t)}$ will specify the return used for the estimation. If no subscript is provided, the statement applies in both cases.

2.2.5. Climate beta uncertainty

The uncertainty of the climate beta is calculated using the mean absolute deviation over the median (MAD) between the estimates of the Climate betas, following the methodology outlined by Hollstein et al. (2020); Chen and Demirer (2022).[15] The the climate beta uncertainty, $Unc^{\text{MAD}}_{r(i,t)}$, is computed as follows:

$$Unc(\beta CC)^{\text{MAD}}_{r(i,t)} = \frac{1}{N_t - 1} \sum_{j=1}^{N_t} \left| \beta^{(j)}_{r(i,t)} - Med(\beta CC)_{r(i,t)} \right| \tag{9}$$

where N_t represents the number of available climate indices at time t,[16] and $Med(\beta CC)_{r(i,t)}$ denote the median of the climate beta across all climate indices for the bond i at time t. These estimates of climate beta uncertainty are calculated for both excess total and duration-adjusted returns, where r represents either tot or dur, respectively.

For robustness, the uncertainty of the climate beta is estimated using the standard deviation (Std), calculated as follows:

$$Unc(\beta CC)^{\text{Std}}_{r(i,t)} = \sqrt{\frac{1}{N_t - 1} \sum_{j=1}^{N_t} \left(\beta^{(j)}_{r(i,t)} - Mean(\beta CC)_{r(i,t)} \right)^2} \tag{10}$$

Here, N_t again represents the number of climate indices, and $Mean(\beta CC)_{r(i,t)}$ denotes the average climate beta estimates for bond i at time t, and r represents tot or dur, respectively. Table 4 presents the correlations between the returns and the uncertainty (aggregated) climate betas. The negative correlations between median climate betas and uncertainty indicate that higher median values associate with lower dispersion measured by MAD, and vice versa. This relation appears in both the US and EU samples. Figure 1 shows the time series of the aggregate climate beta uncertainty (and median) along the other climate beta estimates.

[15] As noted by Hollstein et al. (2020), CAPM market betas are not directly observable and are influenced by estimation uncertainties that depend on the sample period and methods used. Recent research indicates that market beta uncertainty is priced in stock returns in the US, and uncertainty from oil beta estimations is priced in international markets Chen and Demirer (2022).

[16] Figure 3 in the appendix shows the number of available climate indices over time.

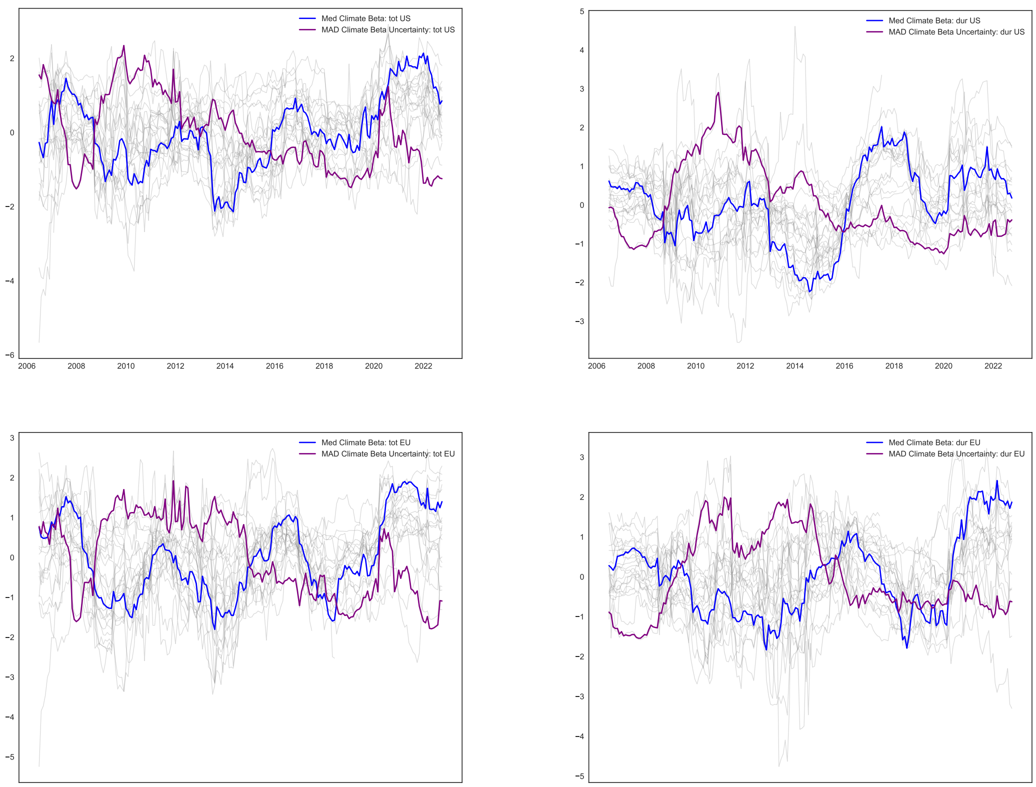

Figure 1: **Time Series of Climate beta aggregates**
These figures plots the (standardized) time series of the cross-sectional value-weighted average of the beta uncertainty measure (in purple), the median climate beta (in blue) along with the other climate indices (in grey). US total returns (top left), US duration-adjusted returns (top right), EU total returns (bottom left), and EU duration-adjusted returns (bottom right).

Table 4: **Correlations: returns and climate betas**

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Panel A: US											
1	Ret (r^{tot})	1.00									
2	Dur-Adj (r^{dur})	0.73	1.00								
3	$Mean(\beta CC)_{dur}$	0.03	0.05	1.00							
4	$Unc(\beta CC)^{Std}_{dur}$	0.03	0.04	-0.42	1.00						
5	$Med(\beta CC)_{dur}$	-0.03	0.03	0.59	-0.02	1.00					
6	$Unc(\beta CC)^{MAD}_{dur}$	0.04	0.04	-0.37	0.94	-0.06	1.00				
7	$Mean(\beta CC)_{tot}$	-0.01	0.04	0.58	-0.15	0.43	-0.18	1.00			
8	$Unc(\beta CC)^{Std}_{tot}$	0.09	0.07	-0.04	0.54	0.01	0.57	0.14	1.00		
9	$Med(\beta CC)_{tot}$	-0.08	0.01	0.40	-0.07	0.72	-0.17	0.60	-0.04	1.00	
10	$Unc(\beta CC)^{MAD}_{tot}$	0.05	0.04	-0.15	0.61	-0.11	0.82	-0.02	0.93	-0.20	1.00
Panel B: EU											
1	Ret (r^{tot})	1.00									
2	Dur-Adj (r^{dur})	0.82	1.00								
3	$Mean(\beta CC)_{dur}$	-0.05	-0.01	1.00							
4	$Unc(\beta CC)^{Std}_{dur}$	0.11	0.07	-0.09	1.00						
5	$Med(\beta CC)_{dur}$	-0.13	-0.03	0.62	-0.14	1.00					
6	$Unc(\beta CC)^{MAD}_{dur}$	0.07	0.04	-0.17	0.94	-0.23	1.00				
7	$Mean(\beta CC)_{tot}$	-0.03	0.00	0.72	-0.11	0.49	-0.16	1.00			
8	$Unc(\beta CC)^{Std}_{tot}$	0.15	0.10	-0.08	0.67	-0.11	0.66	0.03	1.00		
9	$Med(\beta CC)_{tot}$	-0.16	-0.04	0.50	-0.21	0.80	-0.32	0.65	-0.09	1.00	
10	$Unc(\beta CC)^{MAD}_{tot}$	0.08	0.05	-0.19	0.70	-0.26	0.86	-0.19	0.92	-0.33	1.00

Note: This table displays the correlations between the returns and the aggregated and uncertainty climate betas for the US and EU samples.

3. Methodology & empirical findings

This section presents the model and results, beginning with an examination of the impact of using duration-adjusted returns versus total returns on selected climate indices.

3.1. The impact of climate betas on total and duration-adjusted returns

This part analyzes the relationship between a bond's climate-change beta and its one-month ahead total and duration-adjusted returns. Based on Huynh and Xia (2020), we estimate the following model specification:

$$r_{i,t+1} = \alpha + \gamma_j \beta_{i,t}^{(j)} + \delta' X_{i,t} + \theta_i + \tau + \varepsilon_{i,t} \tag{11}$$

for climate change index j, for bond i month t, the model includes bond-level control variables such as downside risks, maturity, rating, amount outstanding, liquidity, bond market beta, term spread beta (for total returns only), default spread beta, and TED spread beta. In addition, issuer-level variables such as idiosyncratic risk, leverage ratio, market capitalization, and return on equity are considered. Fixed effects for issuer (θ_i), time (τ), and Fama-French 17 industries (υ) are incorporated to account for the unobserved heterogeneity between different time periods, issuers, and industries.[17] Control variables are winsorized cross-sectionally at the 1st and 99th percentiles, and standardized cross-sectionally by region to control for outliers. The model is estimated for total and duration-adjusted returns, separately.

Table 5 reports the regression coefficients for one-month-ahead total and duration-adjusted returns, regressed on three climate betas: WSJ, MCCC, and MeCCO. These indices aggregate various climate topics and are used in previous studies, enabling comparisons. Columns 1 and 2 present results for the US, while columns 3 and 4 display results for the EU. All estimates account for fixed effects at the issuer, time, and industry levels. The analysis explores the impact of aggregate climate attention and sentiment on returns in both regions.

[17]Fixed effects are used to account for biases from unobserved heterogeneity, macroeconomic trends, seasonality, and industry-specific factors. It captures both cross-sectional differences and time-varying betas. More importantly, it produces robust standard errors clustered at the firm level, which mitigates serial correlation issues within firms (Petersen, 2008). This is relevant for corporate bonds, which experience high attrition due to bond maturities or defaults. Although there have been only 33 instances of IG defaults since 2004, 1,400 out of 4,352 bonds have exited the sample, representing 30% of it.

Table 5: **Panel Regressions Bond Returns on selected Climate Change Betas**

	US		**EU**	
	Tot	**Dur**	**Tot**	**Dur**
	1	**2**	**3**	**4**
Panel A: WSJ from Engle et al. (2020) [2005-2016]				
$\beta_{tot}^{(wsj)}$	-0.02*		0.01	
	(-1.92)		(0.13))	
$\beta_{dur}^{(wsj)}$		0.03***		0.05*
		(3.50)		(1.66)
Obs.	145466	145132	29803	28434
Adj. R^2	0.268	0.255	0.358	0.324
Panel B : MeCCO from Benham et al. (2020) [2004-2022]				
$\beta_{tot}^{(MeCCO)}$	-0.04****		-0.17***	
	(-3.50)		(-8.33)	
$\beta_{dur}^{(MeCCO)}$		0.04***		0.00
		(3.60)		(0.41)
Obs.	283714	282765	63314	62176
Adj. R^2	0.399	0.343	0.504	0.482
Panel C : MCCC from Ardia et al. (2023) [2004-2022]				
$\beta_{tot}^{(MCCC)}$	-0.04***		-0.15***	
	(-3.99)		(-7.38)	
$\beta_{dur}^{(MCCC)}$		0.03***		-0.01
		(4.56)		(-0.40)
Obs.	285216	284263	63546	62176
Adj. R^2	0.398	0.342	0.503	0.482
Controls	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Note: This table presents the results from the panel regressions of one-month-ahead bond (Total and Duration-Adjusted) returns on βCC. Panel A reports the estimates using the WSJ index from Engle et al. (2020). Panel B reports the estimates using the MeCCO index from Benham et al. (2020). Panel C reports the estimates using the MCCC index from Ardia et al. (2023). Columns 1 and 2 report the regression results for the US sample. Columns 3 and 4 report the regression results for the EU sample. t-statistics are presented in parentheses using issuer-level clustered standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A presents the results using the WSJ index from 2005 to 2016, revealing regional differences in the impact of climate exposure on bond returns. A one-unit increase in the WSJ beta is associated with a 0.02 percentage point decrease in future total bond returns, statistically significant at the 10% level. This indicates that higher climate exposure is related to lower future returns. This result supports the hedging hypothesis and is in agreement with previous findings in Huynh and Xia (2020); Lalwani (2024). For duration-adjusted returns, the WSJ beta is associated with a 0.03 percentage point increase in future returns, statistically significant at the 5% level. This finding contrasts with the total return results and supports the risk-return trade-off hypothesis, implying that exposure to climate risks is priced with higher future credit returns. These findings suggest that in the US, climate risk captured by the WSJ index negatively affects total returns but is priced positively in duration-adjusted returns. In the EU, although no clear relationship emerges for total returns, the WSJ index has a significant positive effect on duration-adjusted returns, with a coefficient of 0.05, statistically significant at the level 5%.

Panel B, using the MeCCO index from 2004 to 2022, reveals a negative and significant relationship between climate betas $\beta_{tot}^{(MeCCO)}$ and total returns in the US (-0.04), in contrast to the positive coefficient between $\beta_{dur}^{(MeCCO)}$ and duration-adjusted returns (0.04), both statistically significant at the 1% level. This further supports the distinction between a climate discount for total returns and a climate premium for duration-adjusted returns. In the EU, the coefficient for total returns is negative (-0.17), indicating higher costs for hedging climate risks, likely due to stronger climate policies, stricter sustainability regulations, and greater sensitivity to climate risks. These factors suggest that investors may accept even lower returns. However, the duration-adjusted return coefficient remains statistically insignificant, reinforcing the absence of a credit climate premium in the EU (Bats et al., 2024).

Panel C, based on the MCCC index from 2004 to 2022, reveals the same negative coefficient between climate beta $\beta_{tot}^{(MCCC)}$ and total returns in the US (-0.04), and a similar positive coefficient for duration adjusted returns (0.03). Not surprinsingly, the estimates from the MeCCO and MCCC betas align closely, as both indices use similar sources.[18] Overall, the results suggest a

[18]Figures 7 and 8 in the appendix compares the evolution of these indices over time, showing similar variations.The time-series show a correlation of 0.61 with all MeCCO

generally negative effect of climate betas on total returns, while the effect on duration-adjusted returns varies by region and climate index.

3.2. Distribution of climate betas loadings

Figure 2 presents the coefficients (loadings) of the remaining climate indices, including aggregated indices, topic-specific indices, and climate indicators, estimated using the model (11). A significant challenge in analyzing these indices is their varying observation periods. Since not all indices are available consistently over time, mainly due to infrequent updates from the authors, data gaps may exist. These limitations must be considered when interpreting the results and comparing trends across indices. To address this, two sets of sub-samples are presented. The subplots in the left column show results from a reduced sample period (2010-2016), during which all climate indices have available data. This removes temporal disparities and allows for direct comparisons of the coefficients; however, this reduces the sample size considerably. In contrast, the right-column subplots use the full available data for each climate index, highlighting how variations in the sample period can substantially influence the estimated coefficients.

The indices are sorted in ascending order on estimations based on total returns; at the bottom are those indices with negative coefficients (e.g., those that provide climate hedges) and at the top those indices that provide positive coefficients (those that give a premium). For example, the first subplot on the top left shows the coefficients for US returns, where indices from Ardia et al. (2023) on topics such as business, environmental research, and the aggregate index are among those that offer better climate hedges for total returns. However, for duration-adjusted returns the coefficients become less negative (or even positive). In contrast, climate indices with positive coefficients are somewhat related to physical risks, such as NatDis of Bybee et al. (2023), climate policies of Faccini et al. (2021), and temperature, which are correlated with higher future returns (Balvers et al., 2017). Their coefficient on duration-adjusted returns are even higher. Interestingly, the WSJ index shows a negative but insignificant coefficient during this period. However, it becomes positive and significant when considering the entire available period. Similarly, for other indices, when the full sample with available observations

newspapers and 0.89 with MCCC's newspapers (New York Times, Washington Post, Los Angeles Times, Wall Street Journal, USA Today, and Associated Press).

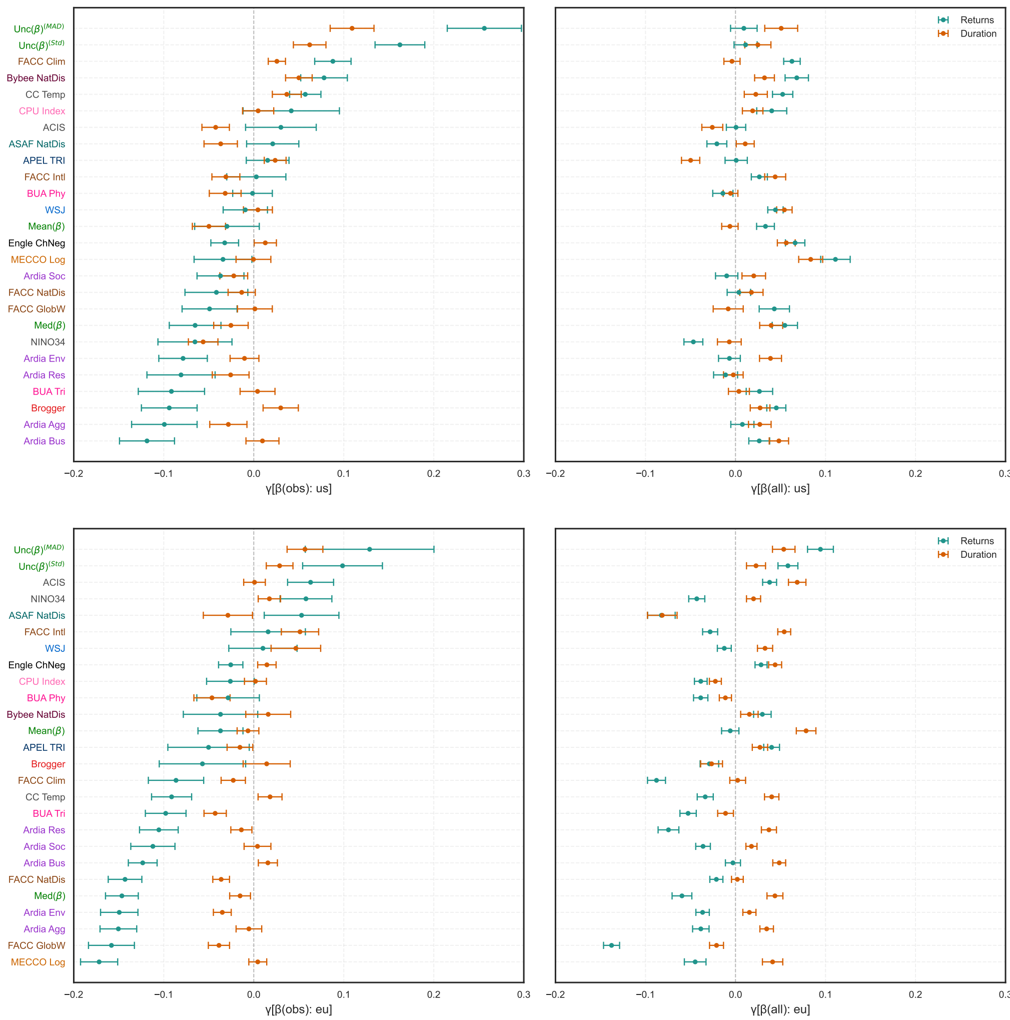

Figure 2: **Coefficients for total and duration adjusted returns for US (top) and EU (bottom)** The left subplots show obvservations where all climate indices are avaialble (2010-05 to 2016-03); the right subplots display the coefficients across all available months for each index.

is considered, some indices that were negative and significant become positive or insignificant, for example the climate index from Brøgger and Kronies (2020). The order of the coefficients of the indices varies by region, in the EU the indices that offer better hedges are MeCCO and Global Warming from Faccini et al. (2021). Considering all indices, the evidence suggests that climate risks are priced in corporate bonds.[19]

These findings support Hypothesis 1, showing that climate beta affects corporate bond returns differently for total versus duration-adjusted returns. Bonds with higher climate beta show on average lower total returns (climate discount) but higher duration-adjusted returns (climate premium).

3.3. Climate beta aggregation or dispersion?

This part considers different approaches to aggregated climate betas using the median and dispersion with the climate beta uncertainty measured by MAD. Table 4 presents the pairwise correlation coefficients between the returns and the aggregated and uncertainty climate betas.[20]

The results show that the climate beta $Med(\beta CC)$ shows a significant negative relationship with the total returns in the two regions. In the US, the coefficient is -0.06, while in the EU, it reaches -0.15, suggesting a stronger inverse relationship between climate beta and returns in the European market. For duration-adjusted returns, $Med(\beta CC)$ has a positive and significant effect in the US, with a coefficient of 0.04, while in the EU, the coefficient is insignificant. This reveals that higher climate betas are associated with lower total returns in both regions. However, the significance of duration-adjusted returns is positive and significant only in the US.

Looking at the beta uncertainty of the climate, as captured by $Unc(\beta CC)^{MAD}$, the results reveal a clear positive relationship on future bond returns for all samples and return measures. This suggests that investors demand a risk premium for bonds with a higher uncertainty about climate risk exposures.

[19] Figure 5 in the appendix shows the p-value distribution for significance of the different climate indices. The p-values are adjusted using Benjamini and Hochberg (1995) to account for multiple testing at the 5% threshold. Despite this, many climate indices remain significant in predicting returns, both positively or negatively.

[20] Figure 4 shows the correlations between the climate indices (in some cases exceeding 0.7). To address potential multicollinearity, climate betas are aggregated using mean/median values and uncertainty measures (MAD/standard deviation). Subsequent analyzes employ median and MAD for their robustness to outliers.

Table 6: **Panel Regressions of Bond Returns on Climate Change: Interaction Between Median Climate Beta and Uncertainty**

	US			**EU**		
	1	2	3	4	5	6
Panel A: Total Returns						
$Med(\beta CC)$	-0.06***		-0.12***	-0.15***		-0.16***
	(-5.12)		(-8.69)	(-8.05)		(-3.53)
$Unc(\beta CC)^{MAD}$		0.09***	0.09***		0.13*	0.13**
		(6.38)	(5.96)		(1.80)	(2.22)
$Med(\beta CC) \times Unc(\beta CC)^{MAD}$			0.04***			0.01
			(3.93)			(0.26)
Obs	285216	285216	285216	63546	63546	63546
Adj. R^2	0.398	0.398	0.399	0.503	0.501	0.503
Panel B: Duration-Adjusted Returns						
$Med(\beta CC)$	0.04***		0.03***	-0.01		-0.05*
	(4.88)		(2.71)	(-1.29)		(-1.90)
$Unc(\beta CC)^{MAD}$		0.05***	0.05***		0.06***	0.06***
		(4.39)	(4.32)		(2.91)	(3.30)
$Med(\beta CC) \times Unc(\beta CC)^{MAD}$			0.01			0.02
			(0.68)			(0.93)
Obs.	284263	284263	284263	62176	62176	62176
Adj. R^2	0.342	0.342	0.343	0.482	0.482	0.483
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents the results from the panel regressions of one-month-ahead bond (Total and Duration-Adjusted) returns, examining the interaction between median climate beta, $Med(\beta CC)$, and climate beta uncertainty, $Unc(\beta CC)^{MAD}$. Columns 1 to 3 report the regression results for the US sample. Columns 4 to 6 report the regression results for the EU sample. Definitions of all variables are provided in the Appendix. All models include issuer, industry, and time fixed effects. t-statistics are presented in parentheses using issuer-level clustered standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. Model specifications are presented at the bottom of the table.

For total returns, the coefficients range from 0.09 to 0.13, indicating a higher premium in the EU market. For duration-adjusted returns, the coefficients are somewhat lower, 0.05 to 0.06.

The results are consistent with Hypothesis 2, indicating that a bond's climate risk uncertainty $Unc(\beta CC)$ is positively related to its future returns. As climate risk uncertainty increases, investors demand higher compensation for bonds with uncertain climate risks, leading to higher future returns.

3.4. Climate beta uncertainty interactions

Columns 3 and 6 of Table 6 investigate how the interaction between the median climate beta $Med(\beta CC)$ and the climate beta uncertainty $Unc(\beta CC)^{MAD}$ influences the bond returns. Understanding this interaction is critical, as it helps assess whether climate beta uncertainty and aggregated climate beta exposure amplifies or mitigates the impact bond performance. Significant and positive results are found only in column 3 for the total returns of the US sample, where the interaction term $Med(\beta CC) \times Unc(\beta CC)^{MAD}$ is positive and significant (0.04). This suggests that as both the median climate beta and its uncertainty increase, the relationship with bond returns becomes less negative. The negative median climate beta suggests that bonds with a higher median climate beta generally offer hedging benefits (although lower returns/higher prices), but this effect is partially offset when uncertainty increases, as shown by the positive interaction term. Higher aggregated climate betas coupled with increased climate beta uncertainty diminish the hedging benefits of bonds, reflecting a classic risk-return trade-off.

The findings reveal a nuanced interplay between aggregated climate beta and uncertainty in bond returns. While the median climate beta negatively impacts returns, climate change uncertainty exhibits a positive effect. The inconsistent interaction suggests that markets potentially price these factors separately—climate beta reflecting direct climate risk exposure, and uncertainty capturing the deviation of climate risk exposures, thereby driving higher returns as investors demand compensation for increased ambiguity.

3.5. Climate beta uncertainty and climate change shocks

This part investigates the impacts of climate change shocks on the coefficients of climate uncertainty. Previous findings indicate differences between expected risks of climate change and the materialization of such risks (Balvers et al., 2017; Barnett, 2023; Baker et al., 2024a). The aim is to understand how different climate change shocks affect this relationship. To explore these

Table 7: **The impact of climate change shocks on climate change exposures**

	US				EU			
	1	2	3	4	5	6	7	8
Panel A: Total Returns								
$Unc(\beta CC)^{MAD}$	0.11***	0.27***	0.09***	0.10***	0.28***	0.22	0.15**	0.12
	(5.85)	(6.64)	(6.10)	(6.48)	(2.89)	(1.61)	(2.13)	(1.51)
$Paris \times Unc(\beta CC)^{MAD}$	-0.02				-0.25***			
	(-1.08)				(-4.94)			
$Reg_{(grant)} \times Unc(\beta CC)^{MAD}$		-0.21***				-0.10		
		(-4.46)				(-1.14)		
$Reg_{(unpri)} \times Unc(\beta CC)^{MAD}$			-0.00				-0.11*	
			(-0.03)				(-1.66)	
$Phy \times Unc(\beta CC)^{MAD}$				-0.00				0.08*
				(-0.18)				(1.75)
Obs.	287092	287092	287092	287092	63546	63546	63546	63546
Adj. R^2	0.402	0.403	0.402	0.402	0.502	0.501	0.501	0.501
Panel B: Duration-Adjusted Returns								
$Unc(\beta CC)^{MAD}$	0.03*	0.27***	0.06***	0.07***	0.10***	0.12**	0.06***	0.05**
	(1.67)	(6.66)	(4.65)	(5.30)	(3.64)	(2.57)	(2.82)	(2.11)
$Paris \times Unc(\beta CC)^{MAD}$	0.05**				-0.08***			
	(2.49)				(-3.37)			
$Reg_{(grant)} \times Unc(\beta CC)^{MAD}$		-0.25***				-0.07*		
		(-5.73)				(-1.72)		
$Reg_{(unpri)} \times Unc(\beta CC)^{MAD}$			-0.05**				-0.02	
			(-2.05)				(-0.40)	
$Phys \times Unc(\beta CC)^{MAD}$				-0.07***				0.06**
				(-3.37)				(2.43)
Obs.	284263	284263	284263	284263	62176	62176	62176	62176
Adj. R^2	0.342	0.344	0.342	0.342	0.483	0.482	0.482	0.482
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Issuer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table presents regression results examining the impact of climate change uncertainty and the moderating role of climate change shocks on one-month ahead bond returns. The climate change shocks consist of dummy variables for the Paris Agreement (post-December 2015), regulatory shocks from Grantham $reg_{(grant)}$ or UNPRI $reg_{(unpri)}$, and physical disasters from EM-Data *Phys*. Panel A presents total returns, and Panel B reports duration-adjusted returns. Columns 1 to 4 report results for the US sample, while columns 5 to 8 show results for the EU sample. Definitions of all variables are provided in the Appendix. All models include issuer, industry, and time fixed effects. t-statistics clustered at the issuer-level are reported in parentheses. Statistical significance is indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

effects, the analysis focuses on the interaction terms between climate change shocks, such as regulatory and physical disasters, climate uncertainty, and future bond returns. The results are presented in Table 7, which shows the extent to which the bonds' returns react to climate change shocks in relation to their climate change exposures.

Data on climate disasters are sourced from the Center for Research on the Epidemiology of Disasters (CRED), covering over 15,000 extreme weather events. The analysis filters for events causing 100+ deaths or damages exceeding 0.1% of GDP, then aggregates monthly disaster counts for the EU and US, following Baker et al. (2024b). Climate regulation data comes from the Grantham Research Institute and UNPRI, with manual verification of signing months, focusing on EU and US regulations. Here, $Reg_{(grant)}$ and $Reg_{(unpri)}$ represent regulations from these sources, while Phy denotes physical climate shocks.

The findings indicate that climate beta uncertainty $Unc(\beta CC)^{MAD}$ generally increases both total and duration-adjusted bond returns in the US and EU markets, with coefficients ranging from 0.03 to 0.28. However, various climate-related shocks can significantly alter these effects. For example, the Paris Agreement has differing impacts across regions (insignificant in US total returns but significantly negative in the EU at -0.25). Furthermore, regulatory shocks $Reg_{(grant)}$ and $Reg_{(unpri)}$ show primarily negative effects (especially pronounced for Grantham in the US at -0.21 to -0.25), while physical climate shocks exhibit contrasting effects in the US (-0.07 for duration-adjusted returns) compared to the EU (positive effects ranging from 0.06 to 0.08).

According to hypothesis 3, the findings indicate that as climate uncertainty decreases, the positive impact of climate risk exposure on future returns weakens, supporting the hypothesis that predictability reduces the market's reaction to climate risks.

3.6. Economic implications

To assess the economic significance of $Unc(\beta CC)^{MAD}$ in estimates of 0.13 (total) and 0.06 (duration-adjusted) for the US, a one-standard-deviation increase in climate beta uncertainty 0.61 (0.52) leads to a rise in next month's bond excess return of 7.93 bps (3.12 bps). Similarly for the EU, with estimates of 0.09 (0.05), a one-standard-deviation increase 0.60 (0.26) results in a 5.4 bps (1.3 bps) increase in bond excess returns.

This can also be interpreted in terms of the dollar cost of debt issuance by assuming that an average firm issues a new corporate bond with the same characteristics as the average bond. For the US, given the average bond price of \$106.77 and the average offer amount of \$820,763, an increase in total bond returns of 7.93 bps results in a higher debt cost of \$6.94 million ($106.77 \times 820,763 \times 0.0108$). In contrast, an increase in duration-adjusted returns of 3.12 bps leads to a cost of \$2.73 million which reflects the cost of debt when isolating long-term interest risks. For the EU, the average bond price is €104.88, and the offering amount is €773,561. With an increase of 5.4 bps (1.3 bps), this results in a higher cost of debt of €4.38 million for total returns and €1.05 million for duration-adjusted returns.

Although the cost of debt due to climate change uncertainty will be the same for the issuer, the decomposition highlights two key components: the duration risk arising from changes in interest risk and the credit-specific risk. The duration-adjusted estimation isolates issuer-specific risks by removing interest rate fluctuations, revealing the impact of credit-specific climate risk uncertainty on debt costs. For the US, these credit-specific climate risks contribute about 40% of the total cost due to climate uncertainty, while for the EU, it is 23%. This underscores the need for issuers to consider climate-related uncertainties in financial planning and risk management, as these factors significantly affect their overall cost of capital.

4. Discussion & conclusion

Exposure to climate uncertainty carries a statistically significant positive price of risk. Previous research indicates that exposure to climate change correlates with future lower performance (Engle et al., 2020; Huynh and Xia, 2020), suggesting that a higher demand for assets more exposed to climate risks increases their price and reduces average returns. Therefore,tThe impact of climate beta on returns depends on the measure used. For duration-adjusted returns, climate beta is positively associated with bond returns, indicating that higher risk yields higher returns when interest effects are removed. For total returns, the link is negative—a phenomenon known as *greenium*. When climate risks rise, total returns drop because of interest rate movements. Investors treat these bonds as safe havens, much like government bonds in market stress. This flight-to-safety drives prices up and yields down, leading to a *greenium*. However, when isolating credit returns, higher climate risk degrades credit quality, lowering prices, and raising yields.

Barnett and Yannelis (2024) demonstrate that long-term climate damage expectations depress bond yields, particularly for long-maturity instruments. These results emphasize the need for further research on climate risks in corporate and sovereign bond pricing.

Multiple climate dimensions and indices prevent a unified measure of risk. However, when the exposure to these indices diverges considerably, there is a positive premium paid given the inability to hedge climate risks. This provides a compensation for being exposed to multiple climate risks; however, the compensation is small. As climate change poses systemic risks that are largely unhedgeable, traditional bond markets may not adequately reflect the true costs associated with climate change.

In examining regional differences, in the US, the sign of the climate beta estimates shifts between positive (when using duration-adjusted returns) and negative (when using total returns), consistent with the observations discussed above. In contrast, in EU, both the duration-adjusted climate betas and the total return climate betas are negative. This consistent sign in European markets suggests that bonds exposed to climate factors tend to have lower returns, even after accounting for interest rate sensitivity. The difference between the US and Europe reflects the varying dynamics in how climate risks are integrated into bond prices across these markets. European investors may have a stronger preference for climate-aligned assets, leading to lower yields (and thus lower returns) for such bonds due to higher demand. This could be influenced by Europe's more advanced ESG frameworks and stricter climate policies, such as the EU Taxonomy and Sustainable Finance Disclosure Regulation, which reinforce the effect *greenium* and indicate a more mature integration of climate risks in the pricing of European bonds (Bats et al., 2024). For climate beta uncertainties, both regions price them positively with both return measures. This pricing implies higher debt costs for issuers. It offers compensation for carrying out the risks.

In conclusion, uncertainty about climate risk matters for the corporate bond market. Climate risk spans multiple dimensions, and various proxies provide different measurements. As it remains largely undiversifiable, bonds may not effectively hedge these risks or provide adequate compensation. Initially, investors appear to pay a premium for bonds with high climate exposure. However, duration-adjusted returns show that these bonds yield higher returns after controlling for interest rate risk. This outcome reflects an increase in credit risk and debt costs due to climate sensitivity. Investors may choose these bonds based on duration factors rather than credit fundamentals.

The findings on climate beta uncertainty have key implications for investors and policymakers. For investors, understanding its impact of climate beta uncertainty on bond pricing is essential for developing climate-resilient strategies and identifying credit risks. For policymakers, integrating climate beta uncertainty into regulatory frameworks is critical to enhancing financial system resilience. This requires improving scoring systems based on emissions, decarbonization goals, and disclosures, while also accounting for climate uncertainties. This study serves as a starting point for integrating climate beta uncertainty into investment and regulatory frameworks, strengthening resilience to climate change (Danisman et al., 2025).

During the preparation of this work, the author used Writefull and Claude AI for improving the readability and clarity of the manuscript. After using these tools, the author reviewed and edited all content thoroughly and takes full responsibility for the content of the publication.

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A. Appendix

Table 8: **Variable Description**

Variable	Description	Data Source
Total Return	Bond total return (Bessembinder et al., 2008)	IBOXX / TRACE
Duration-Adjusted Return	Return adjusted for bond duration (van Binsbergen et al., 2025)	IBOXX / TRACE
VaR95	The average of the four lowest monthly return observations over the past 36 months (beyond the 10% VaR threshold), multiplied by –1 and measured as a percentage (Bai et al., 2019).	Computed
Illiq	Bond illiquidity is computed at the end of each month t for each bond the covariance of prices for the US sample, and the monthly average of daily bid-ask-spreads for the EU sample.	Computed
Duration-Adjusted Return	Bonds Duration	IBOXX/TRACE
Num Rating	A bond's credit rating as a numerical score, where 1 refers to an AAA-AA, 2 to A, and 3 to BBB.	IBOXX/TRACE
ln(AMOUNT_OU	The natural logarithm of a bond's amount outstanding.	IBOXX/TRACE
β	The bond betas are estimated from the monthly rolling regressions of individual total and duration-adjusted bond returns controlling for macroeconomic factors.	Computed
ME(log)	The natural logarithm of a firms market capitalization.	Jensen et al. (2023)
Debt/BE	Debt to Shareholders Equity Ratio (debt_be)	Jensen et al. (2023)
ROE	Return on equity (ni_be)	Jensen et al. (2023)
IdioVol	Idiosyncratic volatility from the CAPM	Jensen et al. (2023)
Term Spread	Difference between long-term and short-term interest rates	FRED/ECB
Default Spread	Spread between corporate bonds and Treasuries	FRED/IBOXX
TED Spread	Spread between LIBOR and Treasury rates	FRED/ECB

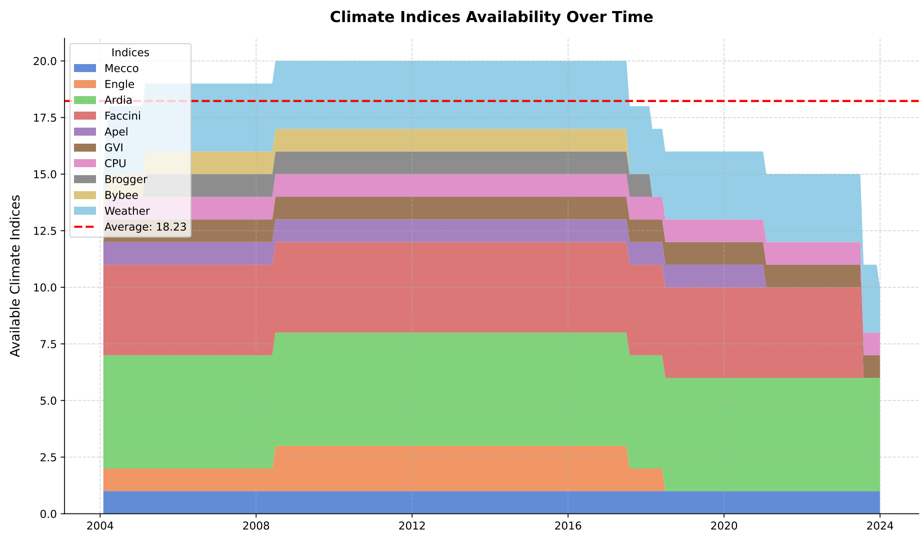

Figure 3: **Climate change indices over time**

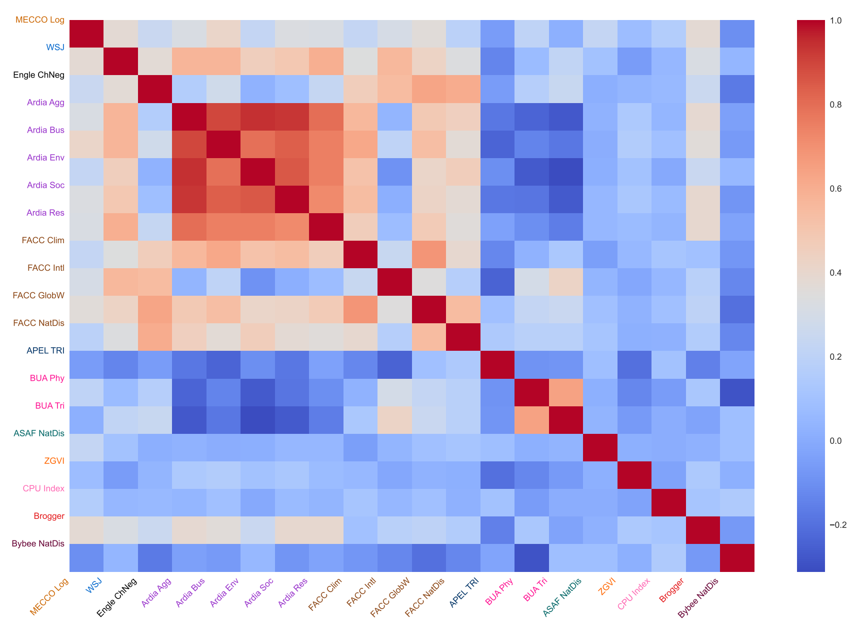

Figure 4: **Heatmap climate change indices**

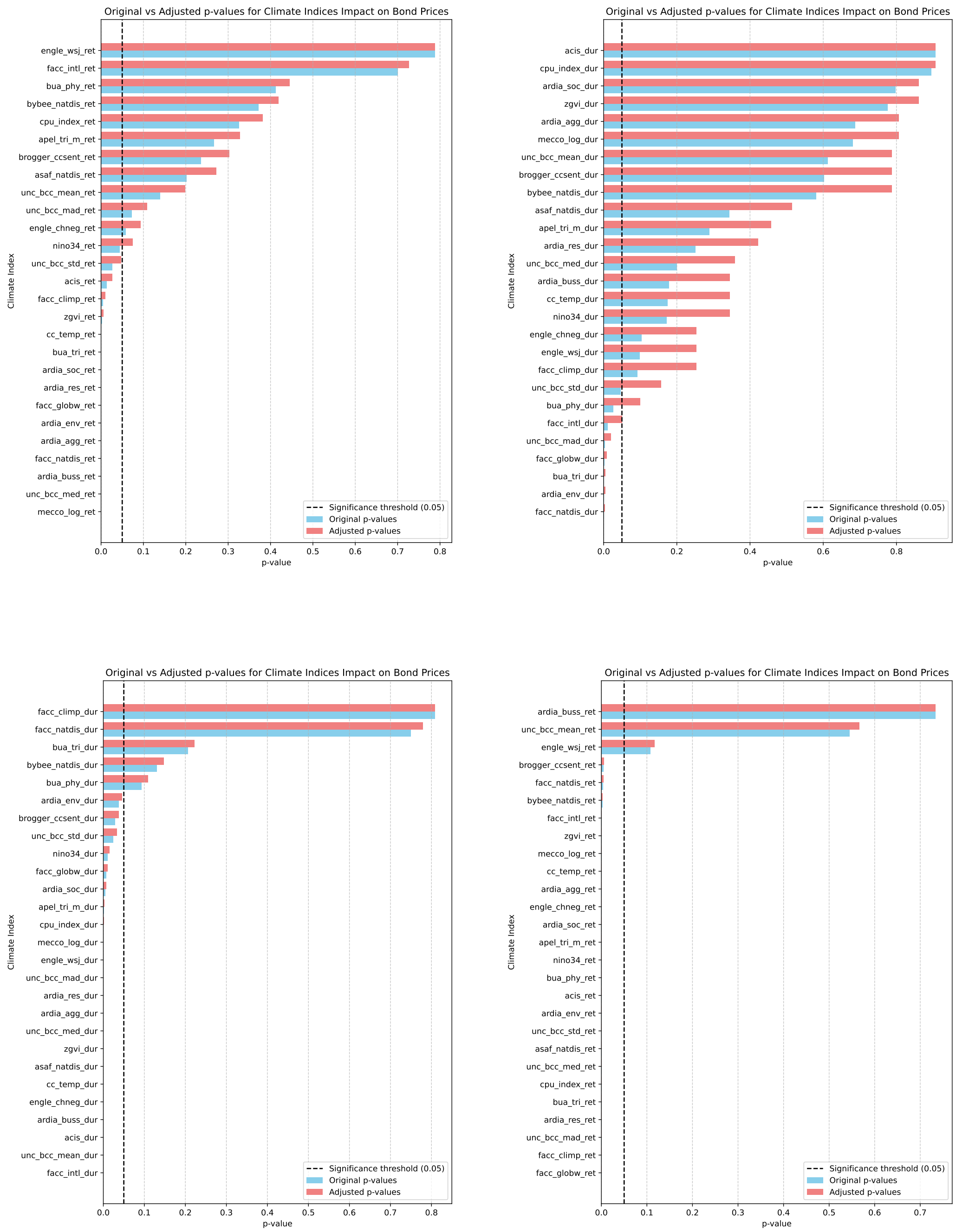

Figure 5: **P-values controlling for multiple hypothesis testing**

B. Online Appendix for climate beta uncertainty in corporate bonds

The online appendix contains details on the construction of the MeCCO climate index and supplementary results not reported in the main manuscript.

Climate Change Media Attention Index (MeCCO).

The aggregation takes inspiration from previous methodologies Gavriilidis (2021); Brøgger and Kronies (2020); Baker et al. (2016); Ardia et al. (2023); Engle et al. (2020). Formally, the $ClimateIndex_t^{(MeCCO)}$ index is computed as follows. The newspaper s publishes $n_{s,t}$ articles discussing topics about *climate change* & *global warming* in month $t = \{1, \ldots, T\}$. Barkemeyer et al. (2018) show that the media coverage exhibits a deterministic trend, low signal-to-noise ratio, and seasonal patterns in some newspapers.

Table 9 provides the list of newspapers in MeCCO. To address heterogeneity between sources, we standardize media coverage by newspaper source, as done by Ardia et al. (2023); Da et al. (2011). In month t, we first demean the news volume for each newspaper, $n_{s,t}$, using its rolling average of 36 months, then divide by its rolling standard deviation of 36 months. Next, we construct $ClimateIndex_t^{(MeCCO)}$ by aggregating the source-specific data and scaling by the number of sources, S_t.

$$ClimateIndex_t^{(MeCCO)} = h\left(\frac{1}{S_t}\sum_{s=1}^{S}\frac{n_{s,t} - \overline{n}_{s,t}}{\sigma_{s,t}}\right) \tag{B.1}$$

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., 2023).[21]

This construction ensures that the index in month t the available data is up to month t (and does not have 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 $ClimateIndex_t^{(MeCCO)}$ relative to its window values. This

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

Table 9: **Newspapers from MeCCO database**
This table 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 December 2023.

Newspaper	Country	Total	Yearly Avg.	Monthly			
				Avg.	SD	Min	Max
Jyllandsposten	Denmark	7935	33.17	32.79	18.37	6	165
Politiken	Denmark	9694	39.98	40.06	20.50	6	184
Berlingske Tidende	Denmark	6735	27.58	27.83	19.23	4	202
Daily Mail and Mail on Sunday	England	11463	48.60	47.37	34.19	7	167
Guardian and Observer	England	54696	225.64	226.02	146.10	40	981
Telegraph and Telegraph on Sunday	England	22225	91.92	91.84	46.49	14	305
The Daily Mirror and Sunday Mirror	England	11423	47.97	47.20	41.39	4	268
Times and The Sunday Times	England	47261	195.82	195.29	130.63	20	812
Sun and News of the World or Sunday Sun	England	11965	49.21	49.44	42.23	1	330
Helsingin Sanomat	Finland	12789	53.13	52.85	36.89	4	202
Ilta-Sanomat	Finland	3642	15.80	15.05	15.61	0	87
Agence France Presse	France	38032	156.36	157.16	110.77	15	735
Le Monde	France	10377	43.78	42.88	23.39	2	123
Le Figaro	France	6841	28.69	28.27	18.80	3	101
Süddeutsche Zeitung	Germany	20967	87.92	86.64	50.80	1	278
Die Tageszeitung	Germany	9197	38.20	38.00	24.91	2	156
Irish Times	Ireland	14979	62.32	61.90	36.35	12	207
La Repubblica	Italy	4156	18.31	18.55	15.37	0	110
Corriere della Sera	Italy	5036	21.25	20.81	18.29	0	92
Associated Press	North America	31807	131.85	131.43	86.59	12	439
The Canadian Press	North America	45908	194.56	189.70	159.31	15	1202
Globe & Mail	North America	18602	76.65	76.87	41.66	18	236
National Post	North America	22090	90.40	91.28	154.86	0	933
Toronto Star	North America	18256	74.77	75.44	44.53	14	301
United Press International	North America	9068	36.68	37.47	18.65	9	144
Los Angeles Times	North America	13671	56.97	56.49	27.36	8	129
New York Times	North America	42994	182.67	177.66	146.28	21	646
USA Today	North America	3856	16.39	15.93	8.55	0	55
Wall Street Journal	North America	3978	16.16	16.44	11.20	1	93
Washington Post	North America	16782	69.57	69.35	39.66	8	239
Aftenposten	Norway	6159	24.94	25.45	14.96	5	86
Dagbladet	Norway	3174	12.93	13.12	9.61	2	70
VG	Norway	3208	13.01	13.26	8.76	1	64
Correio da Manhã	Portugal	3065	17.55	16.93	20.56	0	165
Izvestiya	Russia	799	3.43	3.43	3.21	0	21
Rossiskaya Gazeta	Russia	2160	8.89	8.93	6.50	0	42
Nezavisimaya Gazeta	Russia	1728	7.33	7.14	5.31	0	31
Komsomolskaya Pravda	Russia	662	3.14	3.04	2.37	0	16
El País	Spain	16580	68.53	68.51	45.57	7	281
El Mundo	Spain	14773	60.57	61.05	41.87	7	218
La Vanguardia	Spain	10399	43.59	42.97	26.93	5	144
Expansión	Spain	6033	25.85	24.93	20.36	1	137
Dagens Nyheter	Sweden	6235	25.87	25.76	17.14	2	91
Aftonbladet	Sweden	3019	12.71	12.63	10.73	1	60
Expressen	Sweden	2706	11.23	11.42	11.63	1	76
Total		617125	57.15	56.81	40.77	6	254
Total European		390113	47.80	47.60	32.23	5	206
Total North American		227012	86.06	85.28	67.15	10	402

normalization accounts for a possible evolution in the news coverage of the media.

Figure 6 shows the evolution of the aggregated $MeCCO_t$ index (level, from Jan. 2004 to July 2024) with European newspapers and combined with American newspapers. The index spikes at major climate events. Looking over the 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 after the 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.

Table 10: **Climate News Indices: Description**

Indices	Authors	Sources	Frequency	Period
Attention				
Climate salience	Brøgger and Kronies (2020)	Google Trends	Monthly	2005/01 - 2017/12
Google Search Volume Index (GSVI)	Google	Google Trends	Monthly	2004/01 - 2023/12
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. (2023)	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. (2023)	Dow Jones Newswires, Reuters, NY Times, The Washington Post, BBC, WSJ, MSN, and CNN.	Monthly/Weekly	2000/01 - 2020/12
Transition & Physical Risk Indices	Bua et al. (2024)	Reuters News (Europe)	Daily	2005/01 - 2023/12
Nat. Dis.	Manela and Moreira (2017)	Wall Street Journal (Front-page articles)	Monthly/Daily	2002/01 - 2016/03
Nat. Dis.	Bybee et al. (2023)	Wall Street Journal	Monthly/Daily	2002/01 - 2017-06
Uncertainty				
Climate Policy Uncertainty Index (CPU)	Gavriilidis (2021)	Boston Globe, Chicago Tribune, LA Times, Miami Herald, NY Times, Tampa Bay Times, USA Today, WSJ.	Monthly	2000/01 - 2021/12

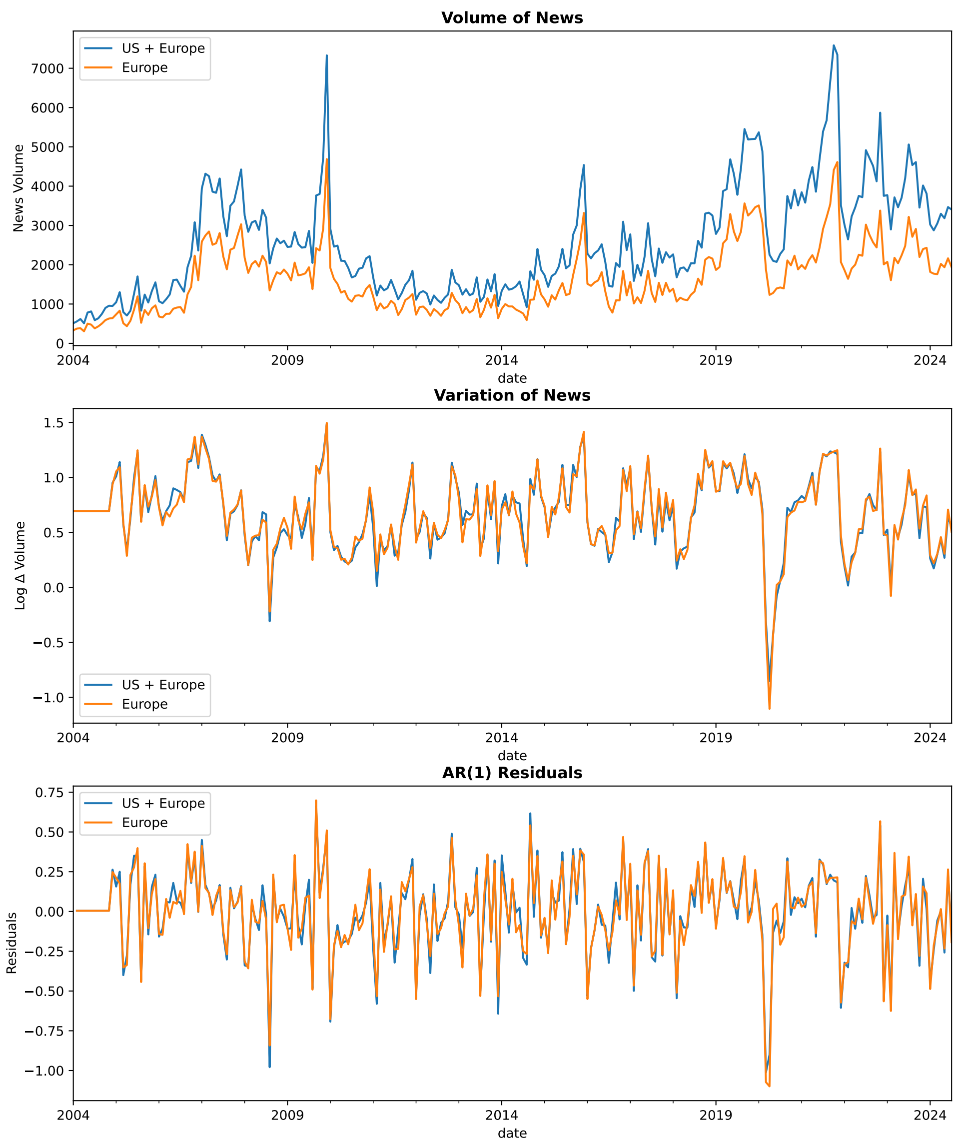

Figure 6: **MeCCO Climate Index**
Aggregate media coverage of climate change or global warming articles in Europe and US, from January 2004 through July 2024.

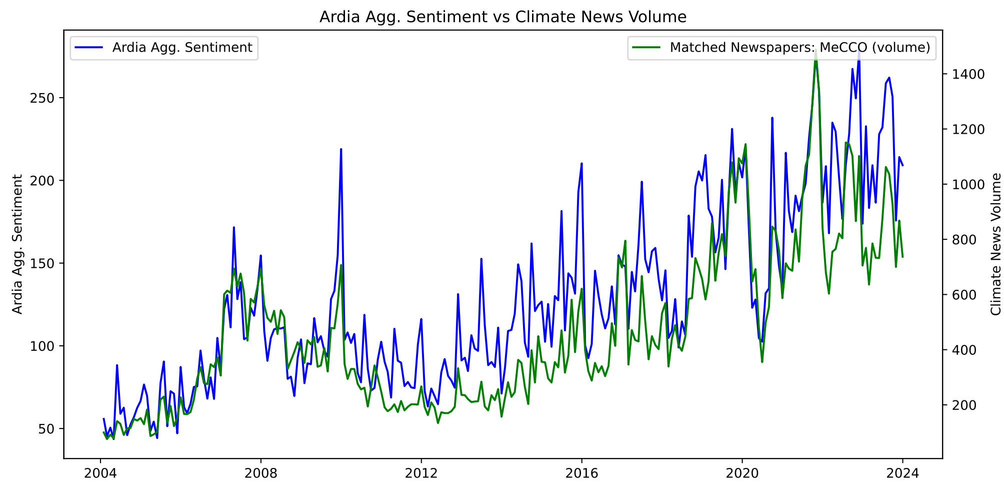

Figure 7: **Ardia vs. MeCCO.**
Selected newspapers are: New York Times (US), Washington Post (US), Los Angeles Times (US), Wall Street Journal (US), USA Today (US), Associated Press

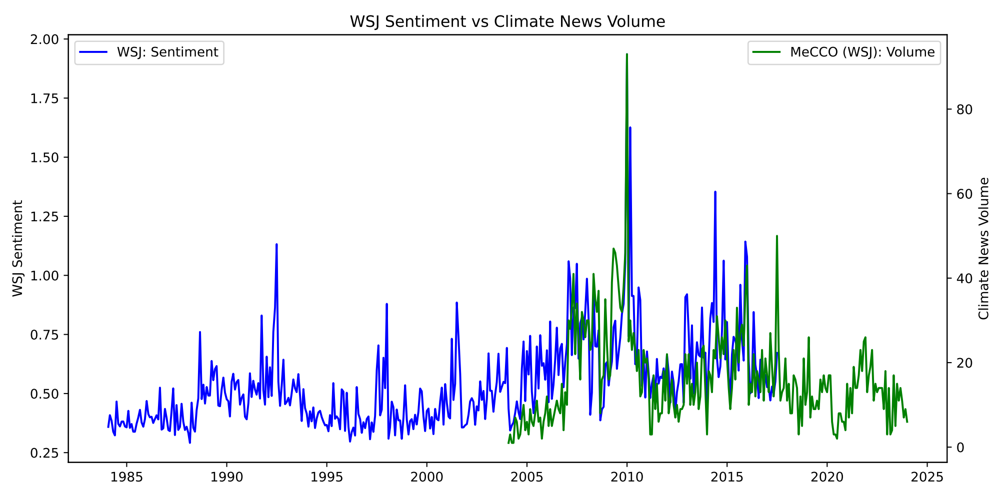

Figure 8: **Engle (WSJ) vs. MeCCO (WSJ)**