The Impact of Climate Risk on Financial Markets: Evidence from Bonds and Options

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Abstract

This thesis examines how corporate environmental characteristics and market-based climate-risk exposure are associated with pricing outcomes in U.S. corporate bond and equity option markets. Three empirical essays extend research focused primarily on equities to fixed-income and derivative securities.

The first essay examines corporate environmental performance and bond yield spreads. Using Refinitiv environmental (ENV) scores, it finds that greener firms have lower bond spreads. Portfolio differences are economically substantial, while controlled regression estimates are more modest. Carbon-intensity tests provide narrower emissions-based evidence, particularly for direct Scope 1 emissions. ENV measures broad environmental performance rather than climate-risk exposure, and the results do not establish causality.

The second essay relates bond spreads to firms' historical sensitivity to climate-attention and climate-news indices. Higher climate betas are associated with wider spreads. Transition- or policy-related exposure produces the largest and most consistent portfolio differentials, although physical-risk causes remain economically meaningful in some controlled specifications. These findings indicate that climate-related information is incorporated into spreads without establishing whether climate risk is fully or correctly priced.

The third essay studies equity options using firm-level climate betas estimated from standardized option-premium returns and the Media Climate Change Concerns index. Higher lagged climate beta is associated with higher subsequent call and put returns. Their common positive pattern is consistent with volatility and tail-risk repricing, but the analysis does not distinguish risk compensation from underpricing, hedging demand, or other explanations.

Together, the essays document associations across markets with distinct payoff structures, while leaving the underlying economic mechanisms unidentified causally.

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Declaration

I declare that this thesis is my own work and has not been submitted, in whole or in part, for any other degree or qualification at any university or other institution.

Where material has been derived from other sources, I confirm that this has been appropriately acknowledged in the thesis. Except where explicit attributions are made, the work presented in this thesis is entirely my own and has been carried out under the supervision of my supervisors.

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1 Introduction

Recently, climate change has emerged as a serious concern for global economies, as it arguably affects all walks of life in many ways. Many governments have undertaken decisive steps to reduce their carbon emissions by revising environmental regulations. At the same time, climate-related risks, including both physical and transition risks, have gained increasing attention in financial markets. Physical risks, such as extreme weather events and rising temperatures, can disrupt production and lead to the destruction or impairment of physical assets. At the same time, transition risks, stemming from environmental policies, carbon pricing, and technological change, can affect firm stability and introduce substantial uncertainty into future cash flows, operating costs, and regulatory conditions. Importantly, these risks also affect asset prices and risk premia; it does not come as a surprise that investors are nowadays more concerned about how various climate-related risks may affect the valuation of financial assets, such as equities, bonds, and derivatives. Academic research in this area is relatively under-explored, albeit growing, and this PhD thesis is motivated to provide the insights. This chapter briefly discusses recent developments in the literature and their relation to the research.

1.1 Recent Finance Research on Climate Risk

Several recent studies attempt to explore how climate risk is priced in financial markets, but this strand of literature has focused mainly on equities. These studies document that climate risk affects stock returns, firm valuations, and investors' actions. For instance, Bansal et al. (2017) develop a long-run risks framework in which climate change affects economic growth and financial valuations, showing that climate-related exposure can be associated with equity valuations and expected returns. Building on this, Bolton and Kacperczyk (2021, 2023) show that firms with higher carbon emissions tend to earn higher expected returns, consistent with investors requiring compensation for bearing transition risk. The results support a risk-based explanation in which carbon-intensive firms are seen

as more exposed to adverse regulatory and market shocks.

Subsequent studies further refine the measurement of climate risk and its transmission channels. Faccini et al. (2023) construct climate risk indices based on textual analysis of news and show that regulatory climate risk is particularly important in explaining the cross-section of equity returns. Similarly, Ardia et al. (2023) develop a media-based climate concern index and find that increases in climate attention lead to positive (negative) abnormal returns for green (brown) firms. These results indicate that investor attention and sentiment drive short-term price dynamics.

In addition to risk-based explanations, another strand of literature emphasizes the role of investor preferences and non-pecuniary motives. Pástor et al. (2021) propose a model in which investors derive utility from holding green assets, leading to a "greenium" in asset prices. Empirically, Pástor et al. (2022) show that changes in climate concerns affect the relative valuation of green versus brown firms, suggesting that shifts in green tastes can influence expected returns independently of traditional risk factors. This preference-based channel implies that asset prices may reflect both risk compensation and investors' environmental values.

More recent work also explores firm-level transmission mechanisms. Climate risk has been shown to affect firm investment, financing, and disclosure decisions (e.g., Sautner et al., 2023), as well as corporate policies related to emissions and sustainability (e.g., Flammer, 2021). These channels ultimately influence firm cash flows, discount rates, and risk exposures, thereby linking climate risks to equity valuation.

The heavy focus of the existing literature on equity markets provides only a fractional understanding of how climate risks may affect financial markets. Particularly, much less attention has been devoted to fixed-income securities and derivative markets. Filling this gap is key to developing a more thorough understanding of the role of climate risk in asset pricing.

The central difference concerns the channels through which climate risk affects underlying eco-

nomic drivers across asset classes. In corporate bond markets, climate risk primarily operates through firms' fundamentals. Both physical and transition risks can increase uncertainty in future cash flows, reduce asset values, and increase default risk. For example, stricter environmental regulations or carbon pricing may raise operating costs for carbon-intensive firms, while physical climate events may disrupt production. These effects weaken firms' financial stability and increase the probability of default, leading investors to demand higher yield spreads as compensation. Therefore, in bond markets, climate risk is expected to be priced mainly through credit risk and cash-flow uncertainty.

On the other hand, in equity option markets, climate risk may be reflected more directly in expectations about future uncertainty. Options derive their value from the distribution of future stock returns, and are particularly sensitive to changes in expected volatility, downside risk, and tail events. Climate-related shocks, such as policy announcements, regulatory changes, or sudden increases in climate concerns, can alter not only the level of expected cash flows, but also the uncertainty surrounding them. Therefore, climate risk may influence option prices by affecting implied volatility and tail-risk pricing, rather than default risk. In this sense, options provide a prospective measure of how markets perceive climate-related uncertainty.

These differences suggest that climate-related information may be associated with financial-market outcomes through different economically relevant features: credit risk and cash-flow uncertainty in bond markets, and volatility and tail risk in option markets. Motivated by these considerations, this thesis aims to provide a comprehensive analysis of how climate-related risks are priced in the U.S. corporate bond and equity option markets. The central research question throughout this thesis is: How are firm-level environmental performance and market-based climate-risk exposure associated with corporate bond spreads and equity option returns, and how do these associations differ across asset classes?

To provide an answer to the above important question, this thesis conducts a comprehensive em-

pirical test of commonly used methods in empirical asset pricing to investigate whether climate risks and corporate sustainability are priced in the cross-section of bond spreads and option returns. The analyses integrate firm-level environmental characteristics with market-wide climate risk measures and use a consistent set of methodologies—including portfolio sorting, Fama–MacBeth regressions, and panel fixed-effects models—to investigate and compare pricing effects across markets. The thesis is structured around three closely related essays that collectively examine how climate-related factors are priced across asset classes, moving from firm-level characteristics to aggregate climate risk, and from bonds to derivative markets. The following provides a brief introduction to the motivations and contributions of each study.

1.2 Thesis Structure and Contributions

Taken together, the three essays provide a connected analysis of environmental characteristics and climate-related exposure across corporate bond and equity option markets. The empirical results show that these measures contain information associated with financial-market outcomes, although the strength and interpretation of the associations differ across essays and asset classes.

The thesis contributes in three main ways. First, it distinguishes broad firm-level environmental performance from market-based exposure to aggregate climate-related attention and news. Second, it examines these measures in the relatively understudied settings of corporate bond spreads and equity option returns. Third, it compares the economic interpretations suggested by the payoff structures of bonds and options. The bond results are consistent with credit-risk and cash-flow considerations, whereas the option results are more consistent with volatility and tail-risk repricing. These interpretations are economically plausible, but the empirical designs do not identify the underlying mechanisms causally.

1.2.1 Corporate Greenness and Bond Yield Spreads (Essay 1)

The first essay focuses on whether firm-level environmental performance is priced in corporate bond markets. In particular, we examine how sustainability characteristics affect fixed-income securities. Prior studies argue that bond prices reflect mostly firms' credit risk and financing conditions. Therefore, bond pricing factors are less studied, and thus, this essay investigates whether corporate bond yield spreads are associated with firms' environmental performance.

Moreover, the existing literature on climate risk and bond markets remains limited in several respects. First, most studies focus on aggregate climate risk or market-wide shocks, rather than firm-level environmental characteristics. However, this essay argues that firm-level greenness captures the differences in firms' exposure to environmental issues and their capacity to adjust to regulatory and technological changes. Second, much of the literature examines bond returns, which include both expected and unexpected components. In contrast, bond yield spreads provide a clearer interpretation, as they directly reflect the compensation investors require for bearing credit risk. Therefore, bond spreads are used to explore a more direct link between environmental performance and firms' financing costs.

Motivated by the above considerations, this first essay examines the association between corporate greenness and bond yield spreads. From an economic perspective, several channels may help explain the association between corporate greenness and bond spreads. For example, firms with poorer environmental performance might face higher compliance costs, greater exposure to environmental liabilities, and less effective operations, all of which can adversely affect profitability and increase cash flow volatility. These effects increase uncertainty about future cash flows and weaken firms' financial positions. In contrast, greener firms may face lower regulatory pressure, lower transition risk, and more stable cash flows, consequently reducing default risk. In addition, such firms may be better prepared for the transition to a low-carbon economy, which further improves their long-term financial

stability. As a result, investors may require lower compensation for holding bonds from greener firms. At the same time, investor preferences for sustainable assets may also play a role. If investors derive non-pecuniary benefits from holding environmentally friendly assets, they may be willing to accept lower returns, which leads to lower bond yield spreads. Therefore, the ENV–spread association in bond markets may reflect both risk-based and preference-based channels.

This essay tests the relationship between corporate greenness and bond spreads within a standard empirical asset pricing framework and reaches several important findings: first, bonds are sorted into portfolios based on ENV scores to provide an overall view of the relationship between greenness and bond spreads. This approach allows us to examine whether there is a monotonic pattern across different levels of environmental performance. Second, we employ Fama–MacBeth regressions to examine the cross–sectional relationship between greenness and bond spreads over time. Third, panel fixed-effects models are employed to control for unobserved heterogeneity across firms and time. Together, these complementary methods assess whether the relationship is robust across alternative empirical specifications and not driven by specific empirical choices.

The essay also explores plausible economic channels associated with the relationship between corporate greenness and bond spreads. In particular, it examines whether greener firms display lower cash-flow uncertainty, lower leverage, and lower default risk, which could explain the observed pricing effects. By linking environmental performance to firm fundamentals, this analysis provides a better understanding of how corporate sustainability affects credit risk.

We contribute to the existing literature in three main ways. First, we document a negative association between corporate environmental performance and the cross-section of corporate bond spreads. Bonds issued by firms with higher ENV scores tend to have lower yield spreads, even after controlling for observable firm characteristics and systematic bond-factor exposures. Second, the essay extends the existing climate-finance literature beyond equity markets by examining whether corporate envi-

ronmental performance contains information associated with firms' borrowing costs in the corporate bond market. Finally, the essay examines whether cash-flow uncertainty and credit-risk characteristics provide plausible explanations for the ENV–spread association. Firms with higher ENV scores tend to exhibit lower cash-flow volatility and more favourable credit-risk characteristics. These findings are consistent with, but do not causally establish, an internal cash-flow uncertainty channel.

Overall, the evidence indicates that corporate environmental performance contains incremental information associated with corporate bond spreads beyond the firm- and bond-level characteristics included in the analysis. The findings concern broad environmental performance rather than direct physical or transition climate-risk exposure. They therefore provide evidence on the relationship between corporate environmental characteristics and borrowing costs, rather than direct evidence that climate risk is priced in the corporate bond market.

1.2.2 Climate Change Risk and Bond Yield Spreads (Essay 2)

Building on the first essay, the second essay shifts the focus to aggregate climate risk and its impact on corporate bond markets. While firm-level environmental performance captures persistent differences in sustainability characteristics, it does not fully reflect time-varying climate-related uncertainty that affects all firms simultaneously. This essay, therefore, examines how exposure to aggregate climate risk is priced in corporate bond spreads.

Climate-related risks are frequently associated with policy uncertainty, regulatory changes, technological changes, and shifts in public attention. These factors are able to generate systematic shocks that affect a broad set of firms across industries. As a result, even firms with similar environmental characteristics may be affected differently depending on their exposure to these aggregate climate risks.

Existing studies have shown that aggregate climate risk affects stock returns. However, relatively

little is known about whether such risks impact bond markets. This is an important gap, as bond investors are particularly sensitive to downside risks and adverse shocks that may impair firms' ability to meet their debt obligations (Merton, 1974). In this context, aggregate climate risk may directly affect bond pricing by increasing uncertainty about future cash flows and raising the likelihood of financial distress.

To capture this effect, the second essay adopts a firm-level approach to examine how sensitive individual firms are to climate risk. Specifically, the second essay constructs a climate risk index based on climate-related news and public attention, capturing time-varying fluctuations in climate concern and policy uncertainty. In addition, this essay employs existing climate risk indices, including the Climate Risk Index of Faccini et al. (2023), to ensure robustness and comparability with the literature. Firm-level exposure to climate risk is then estimated using a rolling-window regression framework. For each firm, bond spreads are regressed on the climate risk index within a moving time window, yielding a time-varying climate beta for each firm-month observation. This procedure allows the estimated exposure to evolve over time, capturing changes in firms' sensitivity to climate-related shocks. Importantly, the resulting climate beta is treated as a firm-level characteristic rather than a conventional risk factor. This procedure enables us to examine whether firms with higher exposure to climate risk are associated with higher bond yield spreads in the cross-section. In this sense, the analysis associates time-varying climate risk exposure to credit risk and bond pricing.

Empirically, the analysis moves forward in several steps. First, bonds are sorted into portfolios based on their estimated climate risk exposure to examine whether there is a systematic pattern in bond yield spreads. Second, Fama–MacBeth regressions are used to test whether climate beta is priced in the cross-section of bond spreads. Third, panel fixed-effects models are employed to control for firm and bond characteristics, as well as time effects. These methods verify that the results are robust and not driven by specific empirical choices.

This essay further explores the economic mechanisms underlying the pricing of climate risk exposure. In particular, the essay examines whether higher exposure to climate risk is associated with greater cash-flow uncertainty, higher financing costs, and increased credit risk. Special attention is given to distinguishing between physical and transition risk, as these two dimensions may affect firms through different channels (e.g., Faccini et al., 2023).

The main contribution of this essay is threefold. First, it provides new evidence that exposure to aggregate climate risk is priced in corporate bond markets. Bonds with higher climate risk exposure are associated with higher yield spreads, indicating that this pattern is consistent with investors requiring additional yield compensation for climate-related exposure. Second, the essay extends the literature by showing that time-varying, market-wide climate risk has an important role in bond pricing. Third, the essay shows that transition- or policy-related exposure produces the largest and most consistent portfolio evidence, although physical-risk causes also remain relevant in some controlled specifications of credit risk.

Overall, this essay demonstrates that firm-level sensitivity to aggregate climate-related attention contains information associated with corporate bond spreads beyond the included controls. It complements the findings of Essay 1 by showing that both firm-level environmental characteristics and market-wide climate risk are relevant to understand how climate-related factors are incorporated into bond pricing.

1.2.3 Climate Change Risk and the Cross-Section of Option Returns (Essay 3)

The third essay examines the association between firm-level climate sensitivity and subsequent equity option returns. While the first two essays focus on corporate bond markets, this essay explores the relationship between climate risk and equity options.

Unlike bonds, which mainly capture downside risk through default probabilities, options derive

their value from the entire distribution of future stock returns. As a result, they are well-suited to capture higher-order risks, such as volatility, skewness, and extreme downside risks. Climate-related shocks, such as policy announcements, regulatory changes, or sudden increases in climate concern, can greatly alter investors' expectations about future uncertainty. Therefore, option markets provide a natural setting to study how climate risk affects forward-looking expectations.

Existing studies have mainly focused on stock returns or firm valuations, while how climate risk affects expected volatility and tail risk is still underexplored. This research attempts to fill an important gap, as derivatives markets are often more sensitive to uncertainty and are widely used by investors to hedge downside risk.

This essay measures firms' exposure to climate risk using a rolling-window approach, similar to the approach used in the previous essay. Specifically, aggregate climate concerns are proxied by the Media Climate Change Concerns (MCCC) index developed by Ardia et al. (2023). Firm-level exposure is estimated by regressing option returns on the MCCC index over a rolling window, producing a time-varying climate beta for each firm. As in Essay 2, the estimated climate beta is treated as a firm-level characteristic that captures the sensitivity of option returns to climate-related shocks.

Empirically, option portfolios are constructed based on their estimated exposure to climate risk, enabling an initial assessment of whether this exposure is systematically related to option returns. This is followed by Fama–MacBeth regressions to test the cross-sectional pricing of climate beta, and panel fixed-effects models that account for option-specific characteristics and firm-level controls. This unified framework enables a direct comparison with the results from bond markets.

Our research makes two important findings. First, the essay documents a positive association between lagged climate beta and subsequent option returns. This pattern is consistent with risk compensation, although underpricing and demand-based explanations cannot be excluded. Second, the

common positive results for calls and puts are more consistent with volatility and tail-risk repricing than with a purely directional stock-price channel. The analysis does not separately identify these mechanisms.

Overall, the essay provides evidence that lagged climate beta is positively associated with subsequent call and put returns. The common positive pattern across the two option types is more consistent with volatility and tail-risk repricing than with a purely directional stock-price channel. However, the analysis does not establish an equilibrium climate risk premium or separately identify risk compensation, underpricing, and option-demand explanations.

1.2.4 Structure of the Thesis

The remainder of this thesis is organized as follows: Essay 1 is Corporate Greenness and Bond Yield Spreads. Essay 2 is Climate Change Risk and Bond Yield Spreads. Essay 3 is Climate Change Risk and the Cross-Section of Option Returns. The final chapter concludes.

2 Essay 1: Corporate Greenness and Bond Yield Spreads

2.1 Introduction

The profound impact of climate change on both human life and financial markets is now widely recognized. The 2015 Paris Agreement underscored the urgent need for decisive policy actions to mitigate climate change. Additionally, it heightened global awareness of the associated risks, which stem from physical events, such as extreme weather, as well as changes in climate-related regulations. The growing need for transition toward a greener economy has, in turn, spurred significant interest in sustainable investments in recent years.[1] For instance, BlackRock reports that sustainable assets have more than tripled since 2015, reflecting the rapid rise in demand for sustainability-oriented strategies.[2] The significant role of ESG, particularly its environmental (E) dimension, is widely acknowledged by regulators, market participants, and academics. However, new debates continue to surface. In her AFA presidential address, Starks (2023) explores the nuanced distinction between the "*value*" and "*values*" motivations behind ESG investing. Specifically, whether the ESG investing motivation arises from potential pecuniary benefits (i.e., related to financial value) or from non-pecuniary benefits (i.e., someone's personal values), is still unclear.[3]

These differing motivations raise an important question: to what extent do investor preferences for corporate greenness influence asset prices? Clarifying this relationship is crucial for understanding how sustainability considerations are priced in financial markets. Inspired by the above considera-

[1] Bloomberg Intelligence predicts that "*ESG market could surpass $40 trillion by 2030, based on our scenario analysis, anchoring the $140 trillion of projected assets under management globally, despite 70% slower growth and polarized sentiment.*"

[2] Morgan Stanley reports that more than half of individual investors intend to expand their allocations to sustainable investments in 2024 (https://www.morganstanley.com/about-us/sustainability-reports-archive). Additionally, more than 70% believe that robust ESG practices contribute to higher returns.

[3] More specifically, a *values investor* is primarily motivated by the intention to generate positive social impact. Such investors typically avoid companies whose activities are environmentally harmful or ethically questionable, thereby aligning closely with Corporate Social Responsibility (CSR) principles. In contrast, a *value investor* seeks superior risk-adjusted returns, incorporating Environmental, Social, and Governance (ESG) criteria into their investment decision-making process.

tions, this essay systematically explores the relationship between corporate greenness and bond yield spreads. Specifically, we aim to answer, among others, the following questions: Is corporate greenness, measured by firms' environmental (ENV) scores, priced in the cross-section of U.S. corporate bond spreads? If so, which plausible economic channels may help explain this relationship? We posit that if investors are motivated by non-pecuniary preferences for ESG/environmental sustainability, and if prevailing market sentiment favours green corporate practices, the bond yields of greener firms are likely to be lower. This, in turn, implies that corporate greenness is negatively associated with bond spreads in the cross-section of corporate bonds, as greener firms face, on average, lower financing costs. Nonetheless, the extent to which sustainability preferences are consistently priced into bond markets remains an open question in the literature.

The corporate bond market provides an ideal empirical context for disentangling financial (pecuniary) and non-financial (non-pecuniary) motivations behind green-oriented investment choices. In a frictionless market, default risk is the main determinant of bond value (excluding green-related factors), while other bond characteristics, such as coupon rate and maturity, are treated as exogenous and unrelated to financial value. However, due to the fixed-income nature of bond payoffs, bondholders are less sensitive than shareholders to further increases in firm value once debt repayment is sufficiently secure. [4] Nevertheless, they remain sensitive to financial conditions that affect default probability and recovery value. Therefore, after accounting for these credit-risk channels, any remaining relation between corporate greenness and bond spreads may partly reflect investors' non-pecuniary preferences.

We employ a large cross-section of U.S. corporate bonds from the TRACE database for the period 2008-2021,[5] matched with environmental (ENV) scores from LSEG Workspace (formerly Asset4).

[4]Indeed, a firm's financial performance affects the probability that the firm will be able to pay back its debt. This effect diminishes significantly as the firm's distance to default increases.

[5]The sample choice reflects a tradeoff between maximizing the time-series length and ensuring, at the same time, sufficient cross-sectional observations within each time period.

We adopt a standard empirical asset pricing approach. Specifically, at the end of each month, we sort all available bonds by their ENV scores and construct portfolios based on the tertiles of the empirical distribution of these scores. For each portfolio, we compute equal-weighted (and volume-weighted) average bond spreads (i.e., bond yields in excess of the risk-free rate), as well as the average spread differential between the top and bottom portfolios (i.e., the high-minus-low portfolio). Our findings reveal a negative and highly significant cross-sectional relationship between corporate bond spreads and ENV scores, suggesting that corporate greenness is negatively priced in the cross-section of corporate bond spreads. Furthermore, this relationship remains robust after controlling for key systematic bond factors, including a bond market factor, credit risk, downside risk, and bond liquidity risk factors in time series tests. These findings indicate that the observed ENV–spread association is not absorbed by exposure to common risk factors.

Moving a step further, we examine the financial characteristics of portfolios formed by sorting bonds according to their ENV scores. This analysis provides additional insights into the relationship between corporate greenness and firm-level characteristics. Specifically, we find that greener firms tend to exhibit greater profitability, lower leverage, higher market-to-book ratios, greater distance to default, and greater liquidity (lower illiquidity). However, these attributes alone do not fully account for the observed effect of corporate greenness on bond yield spreads. This conclusion is supported by bivariate portfolio sorts based on ENV scores, as well as cross-sectional and panel regression analyses. Taken together, the results indicate that corporate environmental performance contains incremental information associated with bond spreads beyond the conventional firm- and bond-level characteristics included in the analysis.

What economic mechanism underlies the above findings? One potential explanation is that brown firms, i.e., those with a lower ENV score, face a higher cost of borrowing. Empirical research has shown that brown firms tend to pay higher loan spreads, reflecting lenders' concerns about transition

risk, regulatory uncertainty, and potential shifts in investor preferences (Ginglinger and Moreau, 2023; Altavilla et al., 2024; Demetriades and Politsidis, 2025). Ge et al. (2025) find that firms exposed to abnormal temperature-related climate risks face higher bank loan costs, but voluntary climate risk disclosures in conference calls by borrowers can mitigate this effect. Another plausible explanation is that brown firms experience greater uncertainty in their fundamentals, leading to heightened credit risk. Their exposure to climate-related policy changes, carbon pricing, or market shifts favouring greener alternatives increases earnings or cash-flow volatility and weakens their financial stability. As a result, investors and creditors demand higher compensation for bearing the additional risk, which manifests in wider credit spreads. Given the substantial evidence supporting the former channel, we focus on the latter as one plausible economic channel, which we term *the internal cash-flow uncertainty channel*. Portfolio sorts and panel regressions indicate that firms with higher ENV scores experience lower cash flow uncertainty and greater distance to default, providing evidence consistent with the internal cash-flow uncertainty channel.

Most existing research on the relationship between corporate environmental performance and financial outcomes has focused predominantly on equities (e.g., Engle et al., 2020; Bolton and Kacperczyk, 2021, 2023; Ardia et al., 2023; Faccini et al., 2023; Ginglinger and Moreau, 2023; Sautner et al., 2023; Aswani et al., 2024), while the corporate bond market has received comparatively less attention. Notable exceptions include Seltzer et al. (2022) and Huynh and Xia (2021), which highlight the growing influence of environmental factors in fixed-income markets. Seltzer et al. (2022) offer valuable insights into the interaction between climate and regulatory risks. In contrast, our study adopts a pure asset pricing perspective, examining potential explanations for the relationship between corporate greenness and bond spreads. Rather than challenging the findings of Seltzer et al. (2022), our results are complementary, contributing new evidence on how environmental performance is associated with bond spreads in the cross-section of corporate bonds. Huynh and Xia (2021) examine

whether climate change news is priced in bond returns. Our approach differs in three key respects. First, we focus on corporate bond spreads rather than bond returns, which allows for a more direct interpretation of investor-required compensation for credit risk. Second, our empirical approach is based on firms' environmental performance, measured by ENV scores, rather than the bonds' sensitivity (betas) to a climate news index. This approach has the clear advantage that the measure of greenness is defined at the firm level, allowing us to capture persistent environmental attributes of the issuer rather than transient market reactions to climate-related news. Third, while their study emphasizes climate risk, our analysis focuses more broadly on overall environmental performance, which reflects a firm's sustainability orientation and long-term environmental strategy.

Our research also relates to the rapidly growing stream of literature on the impact of climate risk on financial markets. For instance, Bolton and Kacperczyk (2021, 2023) find that firms with higher carbon emissions earn higher returns after controlling for various firm characteristics, consistent with a risk–based asset pricing explanation. Faccini et al. (2023) document that among several climate risk dimensions, only climate regulatory risk is priced in the cross-section of stock returns. Ardia et al. (2023) construct a new Media Climate Change Concerns index, and find that on days with heightened climate change concerns, the prices of green firms tend to increase, while those of brown firms tend to decline. This finding is consistent with the evidence of Pástor et al. (2022).[6] Recent papers have explored the impact of climate-related uncertainties on options markets. For example, Sautner et al. (2023) document that the cost of option protection against downside tail risks is higher for firms with more carbon-intensive business models. We contribute to this literature by focusing on the role of firm-level greenness, which is arguably the most important dimension of ESG investing. Corporate greenness, as measured by the ENV score, is related to climate considerations but is conceptually distinct from direct physical or transition climate-risk exposure. The main ENV analysis therefore concerns broad corporate environmental performance, while the supplementary carbon-intensity tests

[6]For an excellent review on *Climate Finance* the interested reader can look at Giglio et al. (2021).

provide narrower emissions-based evidence. Therefore, our analysis provides valuable insights that further enrich ongoing climate finance research.

Our research also contributes to the body of literature that explores the impact of climate-induced uncertainties on the firm's cost of debt and external financing. Examples of studies that examine the impact of climate change on the firm's cost of debt include, among many others, Jung et al. (2018), Palea and Drogo (2020), Apergis et al. (2022), Ali et al. (2023), Francis et al. (2025). In a recent study, Ginglinger and Moreau (2023) find that firms that are more exposed to climate risks have significantly lower leverage in the post-Paris Agreement (COP21) period. The authors explore the channels that drive the documented decrease in leverage and find that the results are due to a demand effect (the firm's optimal leverage decreases) as well as a supply effect (bankers and bondholders increase the interest rate that they charge to high-climate risk firms). Feng et al. (2024) document that firms with greater climate risk exposure face significantly higher bankruptcy risk, particularly those with low operating cash flows or tight financial constraints. The effect is mitigated by stronger creditor protections and varies across regions and firm characteristics. Ozkan et al. (2023) explore how corporate social responsibility (CSR) moderates the negative impact of climate risk on firm performance, finding that higher CSR levels can significantly mitigate climate-related performance declines. Our study builds on the above studies in several ways. First, we demonstrate that firms' environmental performance, measured by their ENV score, is negatively associated with bond yield spreads, offering new insights into the role of greenness in bond pricing. Second, we move beyond documenting this relationship by investigating whether internal cash-flow uncertainty provides one plausible explanation for the observed ENV–spread association. Specifically, we examine whether stronger environmental performance is associated with lower cash-flow volatility, suggesting that greener firms may be perceived as more financially stable or resilient. This highlights the role of sustainability in shaping investor expectations and capital allocation decisions in fixed-income markets.

The remainder of this essay is organized as follows. Section 2.2 develops the theoretical background underpinning our research hypotheses. Section 2.3 presents the data and variable construction. Section 2.4 discusses the results. Section 2.5 presents the additional analyses, and, finally, Section 2.6 concludes.

2.2 Hypothesis Development

2.2.1 Theoretical Motivation: Bond Pricing with ENV

In this section, we describe the theoretical background underpinning our research hypotheses. To build intuition, consider a one-period, zero-coupon defaultable corporate bond whose payoff at maturity (i.e., at $t = 1$) is fixed:

$$\text{payoff}_1 = \widetilde{F} \tag{1}$$

where F is the bond's face value (the overhead tilde indicates that F is a random variable in the presence of default risk). A defaultable bond implies that the issuer may fail to repay the full face value in the event of default. The *probability of default* is exogenously given and denoted by q, where $0 \leq q \leq 1$. In the case of default, the bondholder recovers a constant fraction R of the face value, i.e., $0 \leq R < 1$.

Then, the *expected bond payoff* estimated at time 0 (i.e., the present) is:

$$\begin{aligned} \text{E}_0(\widetilde{F}) &= (1-q)\ F + q\ R\ F \\ &= [1-(1-R)q]\ F \\ &\equiv (1-\lambda)\ F, \end{aligned} \tag{2}$$

where $\lambda = (1-R)q$ is the *recovery-adjusted probability of default*. The bond price at time 0 is the discounted expectation of the bond's face value (Cochrane, 2009). If $\widetilde{m}$ is the *stochastic discount*

factor, then from a bond buyer's perspective, the *price of the bond* at time 0 (P_0) is given by:

$$\begin{aligned} P_0 &= \mathrm{E}_0(\widetilde{m}\ \ \widetilde{F}) \\ &= \mathrm{E}_0(\widetilde{m})\ \ \mathrm{E}_0(\widetilde{F}) + \mathrm{Cov}_0(\widetilde{m}, \widetilde{F}) \end{aligned} \tag{3}$$

Dividing both sides of Eq. (3) by P_0 and assuming that the expected discount factor equals the inverse of the *gross risk-free rate of return* (R_f),[7] we can rewrite Eq. (3) as

$$1 = \mathrm{E}_0\left(\frac{\tilde{F}/P_0}{R_f}\right) + \mathrm{Cov}_0\left(\widetilde{m}, \frac{\widetilde{F}}{P_0}\right) \tag{4}$$

Combining Eq. (4) with Eq. (2) and taking natural logarithms on both sides, we have:

$$\begin{aligned} Y_0 &= F/P_0 \\ &= \frac{R_f}{1-\lambda}[1 - \mathrm{Cov}_0(\widetilde{m}, \widetilde{Y})], \\ \Leftrightarrow \log(Y_0) &= \log(R_f) + \log(1 - \mathrm{Cov}_0(\widetilde{m}, \widetilde{Y})) - \log(1-\lambda). \end{aligned} \tag{5}$$

where Y_0 is the *gross yield to maturity* of the one-period bond.[8] For small x, it holds that $\log(1+x) \approx x$. Then, we can rewrite Eq. (5) as follows:

$$y_0 \approx \underbrace{r_f}_{\text{risk-free rate}} + \underbrace{\lambda}_{\text{credit risk premium}} + \underbrace{\mathrm{Cov}_0(-\widetilde{m},\ \widetilde{Y})}_{\text{risk-adjustment}} \tag{6}$$

where y_0 is the logarithm of the bond's yield to maturity, λ is the investor's compensation due to default (credit premium), and $Cov_0(-\widetilde{m},\ \widetilde{Y})$ represents the covariance of the bond's gross return

[7] This follows from the fact that for a risk-free asset paying \$1 one period later, we have $1 = E(\widetilde{m}R_f)$. Given that R_f is known in advance (i.e., is non-stochastic), the risk-free rate is linked to the stochastic discount factor by $R_f = 1/E(\widetilde{m})$.

[8] Specifically, starting from $1 = \mathrm{E}_0\left(\frac{\tilde{F}}{P_0}\right)\frac{1}{R_f} + \frac{\mathrm{Cov}_0(\widetilde{m},\widetilde{F})}{P_0}$ and using the result from Eq. (2) $E_0(\widetilde{F}) = (1-\lambda)\ F$, we can write $1 = (1-\lambda)\frac{F}{P_0}\frac{1}{R_f} + \mathrm{Cov}_0(\widetilde{m}, \widetilde{F}/P_0)$. Using the fact that $Y_0 = F/P_0$, we have $1 = (1-\lambda)\frac{F}{P_0}\frac{1}{R_f} + \mathrm{Cov}_0(\widetilde{m}, \widetilde{Y}) = (1-\lambda)Y_0\frac{1}{R_f} + \mathrm{Cov}_0(\widetilde{m}, \widetilde{Y})$. Solving for Y_0 we get $Y_0 = \frac{R_f}{1-\lambda}[1 - \mathrm{Cov}_0(\widetilde{m}, \widetilde{Y})]$

with the stochastic discount factor. As we will show below, the covariance term is directly related to the investor's risk aversion. Therefore, the bond's yield in excess of the risk-free rate (*bond spread*) is a linear function of *credit risk premium* (λ) and the investor's aversion to other systematic risks. If these risks do not co-move with the SDF, then the excess bond yield is driven only by credit risk.

Including the non-pecuniary ENV factor

If investors are compensated solely for a firm's default risk exposure, the covariance term, $\text{COV}_0(-\widetilde{m}, \widetilde{Y})$, in Eq. (6) should theoretically be zero. However, Pástor et al. (2022, Section 2, p. 406) provide compelling evidence that greenness represents an independent risk dimension, distinct from default risk. The authors analyze German twin bonds, i.e., green bonds issued by the German government that are structurally identical to their non-green counterparts, sharing the same coupon rate, payment dates, and maturity. These twin bonds provide identical cash flow streams and exhibit similar credit risk, yet they differ exclusively in their level of greenness, offering a natural experiment for isolating the pricing impact of ESG/environmental factors. Interestingly, the authors identified a significant yield spread between green and non-green bonds, commonly referred to as the greenium. Their findings strongly suggest that the covariance term in Eq. (6) is potentially non-zero, indicating that greenness may serve as a pricing factor in the cross-section of bond spreads.

To characterize $\text{COV}_0(-\widetilde{m}, \widetilde{Y})$ in the previous equation, we borrow from Pástor et al. (2021, Corollary 2) and set $\text{COV}_0(-\widetilde{m}, \widetilde{Y}) = -(\bar{d}/a) \times g$, where $\bar{d}$ is the overall market preference for greenness,[9] a is the investor's level of risk aversion, and g is the individual firm's green characteristic. Pástor et al. (2021) provide unique insights on the pricing of sustainability in equity markets. The authors argue that there are non-pecuniary benefits the investor derives from holding green assets (i.e., those with a high ENV score). In their model, $-(\bar{d}/a) \times g$ is the CAPM-style abnormal return driven

[9]Specifically, if d_i is agent i's green preference, $\bar{d} = \int_i \omega_i d_i di$ is the wealth-weighted mean of green tastes across agents (see Pástor et al., 2021, Eq. (5)), where ω_i is agent i's share of aggregate wealth.

by corporate greenness but not captured by the market risk. Although their framework was originally developed for equities, the underlying mechanism whereby investor preferences for greenness generate return premia can be applied to bond markets, as long as investors value environmental attributes regardless of asset class.

Following our discussion, we rewrite Eq. (6), and the bond spread (bond yield in excess of the risk-free rate) becomes:[10]

$$SPR \equiv y_0 - r_f = \lambda - \frac{\bar{d}}{a} g. \tag{7}$$

In what follows, we present the model's implications regarding how a firm's greenness (as measured by its ENV score) affects its bond yield. Let $a > 0$ be the parameter of absolute risk aversion. The variable g corresponds to corporate greenness. Firms with $g > 0$ have positive ENV impact, i.e., generate positive environmental externalities, whereas firms with $g < 0$ have negative environmental impact and generate negative externalities (i.e., brown firms). Here, we assume the firm's ENV score is observable via ESG rating agencies. Importantly, the impact of corporate greenness (g) on bond yields is not uniform, as it depends on the prevailing market sentiment toward greenness, represented by $\bar{d}$. A larger and positive $\bar{d}$ reflects a strong, favourable market preference for green attributes in the bond market, amplifying the effect of greenness on bond pricing.

Therefore, when societal preferences favor green investing (i.e., $\bar{d} > 0$), we expect lower bond yields for greener firms than their brown counterparts, ceteris paribus. It is important to note, though, that ENV preferences are not universally positive. A prominent counterexample is the Friedman doctrine,[11] which asserts that a firm's sole responsibility is to maximize shareholder value. If such a view dominates societal sentiment, then the market preference parameter $\bar{d}$ may be negative, implying

[10] Throughout the essay, we occasionally use the terms bond spread and excess bond yield interchangeably to refer to the bond yield in excess of the risk-free rate.

[11] See Milton Friedman's commentary in The New York Times (1970): "The Social Responsibility of Business is to Increase Its Profits" Available at: https://www.nytimes.com/1970/09/13/archives/a-friedman-doctrine-the-social-responsibility-of-business-is-to.html.

that greener firms could face higher bond yields due to a lack of investor demand for environmental attributes.

2.2.2 Hypotheses

We investigate the cross-sectional relationship between corporate greenness and corporate bond spreads. This focus is motivated by the following considerations. First, bond yields are closely linked to the default risk of a firm's bonds. This makes them a more fundamental measure of how firm characteristics (like greenness) affect borrowing costs. As such, analyzing bond yields allows us to examine how corporate greenness is associated with credit-risk outcomes and borrowing costs, offering direct implications for bond pricing. Second, we opt to examine bond yields rather than bond returns because the latter incorporate both expected and unexpected components (Elton, 1999). While expected returns reflect compensation for risk, unexpected returns can be influenced by market volatility, liquidity shocks, or other transient factors that may obscure the underlying relationship of interest. This approach is consistent with the structural credit risk framework of Merton (1974), which links bond yields to the firm's asset value and default probability, reinforcing the relevance of yields as a proxy for credit risk.

Corporate environmental performance may matter to creditors because bondholders receive fixed coupon and principal payments but may suffer losses if the issuer defaults. For creditors, the key issue is whether environmental problems make these promised payments less certain or reduce the value recovered after default. Weak environmental performance may affect both components of the recovery-adjusted default probability introduced in Eq. (2). Compliance and remediation expenditures, environmental fines or litigation, additional capital expenditures, and shifts in demand away from environmentally intensive products may reduce or destabilise operating cash flows, thereby increasing the probability of default, q. Environmental liabilities and the impairment or stranding of

environmentally intensive assets may also reduce the value available to creditors following default, thereby lowering the recovery rate, R. Consequently, creditors may require a higher yield spread from firms whose environmental characteristics indicate greater potential pressure on debt-servicing capacity or recovery values.

This argument does not require the ENV score to be interpreted as a direct measure of climate risk. Rather, the ENV score may summarise environmental characteristics that creditors consider relevant to expected credit losses. A separate investor-demand channel may also operate. Institutional investors subject to sustainability mandates or exclusionary screens may have lower demand for bonds issued by firms with weak environmental performance, potentially narrowing these firms' investor base and increasing their required yields. Conversely, stronger demand for bonds issued by greener firms may raise their prices and reduce their yield spreads. The observed ENV–spread relationship may therefore reflect both differences in credit fundamentals and differences in investor preferences or demand.

We formulate the following hypotheses:

H1: Corporate greenness is priced in the cross–section of corporate bond spreads

H1 follows directly from the definition of corporate bond yield in Eq. (6), which associates bond investors' risk sensitivity to firms' greenness (ENV) through the final term on the right-hand side of the equation.

We further develop a hypothesis concerning the direction of ENV's impact on bond spreads. As shown in Eq. (7), this direction is contingent upon the prevailing investment climate. In light of the current societal emphasis on corporate social responsibility (CSR), we assume a positive investor preference for ESG-aligned investments. Accordingly, we formulate our second hypothesis:

H2: Corporate environmental performance is negatively associated with corporate bond spreads.

If *H2* is true, then we expect that the yield spread of green firms is, on average, lower than that of brown firms. We test the above two hypotheses within a standard empirical asset pricing framework, employing portfolio sorting, cross-sectional, and panel regressions. Our primary analysis uses firms' ENV scores as a proxy for greenness, while we also assess the robustness of our results when ESG scores are used instead. We discuss specific details about methodology in Section 2.4 below.

2.3 Data and Variable Construction

We quantify firms' greenness using their environmental (ENV) score. Rather than focusing on a single environmental dimension, the ENV score integrates various themes, including emissions, biodiversity, and resource utilization. This not only makes it a comprehensive measure of corporate greenness and sustainability but also aligns closely with the objectives of our study. Moreover, this approach aligns with prior studies (e.g. Alessi et al., 2021). The firm's ENV score is available at the annual frequency and ranges from 0 to 100. The data is obtained from Refinitiv and covers the period from 2008 to 2021.

For the supplementary analysis, we also obtain carbon-intensity measures from Refinitiv. Scope 1 covers direct emissions from sources owned or controlled by the firm. Scope 2 covers indirect emissions from purchased electricity and energy. Scope 3 covers other indirect emissions in the firm's value chain. We examine each scope separately and also construct Scope 1+2 and Scope 1+2+3 measures. Carbon intensity is narrower than ENV because it focuses more directly on firms' emissions and their potential exposure to carbon prices, environmental regulation, and transition costs. By contrast, ENV also captures broader information about environmental policies, management, disclosure, and resource use.

We also collect data on corporate bond yields from the Enhanced TRACE database, accessed via WRDS. Unlike the standard TRACE corporate bond data, the Enhanced TRACE database provides

detailed transaction reports for all intraday activities. To refine the bond quotes in our sample, we closely follow the methodology of Dick-Nielsen (2014). Specifically, we implement the following filters: (i) We remove trades with cancellation and correction reported within the same reporting date, (ii) we remove reversal reports (i.e., cancellations reported on a later date than the date on which the original transaction took place) and delete the original trades that are identified in the reports, (iii) we delete transactions by agency and inter-dealer where the principal transaction has the same price as the agency transaction in order to avoid potential double counting.[12] We further remove "when-issued" trades, namely trades that are not in the secondary market, trades under special circumstances or non-standard settlement, commissioned trades, and automatic-give-up trades. Finally, we remove negative bond yields and winsorize the bond yields at the 5/95% levels.[13] After cleaning the bond data, we obtain the last daily quotes of each bond and consider the simple average across all available bonds if multiple bond quotes are available. We employ the month-end bond yields for our empirical analysis. For the construction of certain variables (e.g., bond illiquidity), the daily yields are used in order to obtain more accurate estimates.

We merge the Refinitiv and TRACE datasets using firms' CUSIP identifiers. The empirical analysis is conducted at a monthly frequency. For each firm-month observation in month t, the dependent variable is the month-end corporate bond spread observed in that month and is not lagged. All firm- and bond-level explanatory variables used in the portfolio sorts and cross-sectional and panel regressions, including the annual ENV/ESG scores and control variables, are lagged by 12 months. Annual and quarterly variables are first assigned to the relevant months when constructing the monthly panel, after which the 12-month lag is applied. Consequently, the bond spread observed in month t is matched with explanatory-variable values from month $t-12$. This timing convention ensures that the explanatory information predates the dependent variable and mitigates potential look-ahead bias. The

[12] We also remove special transactions such as commissioned transactions, odd number of days to settlement as suggested in Dick-Nielsen (2014).

[13] The results remain robust when a 1st-99th percentile winsorization is applied.

systematic bond factors used solely in the time-series risk-adjustment regressions enter contemporaneously or with a one-month lag, as specified separately in the relevant regressions. The same timing rule is applied in the carbon-intensity tests. Each bond spread in month t is matched with the issuing firm's carbon intensity in month $t - 12$ using an exact firm-month match. The control-variable fields in the dataset already contain their 12-month-lagged values and are therefore used without applying a second lag. After the exact carbon-intensity match, the sample contains 40,522 firm-month observations over 156 months from January 2009 to December 2021. The controlled regressions use 30,321 observations with complete data for all included variables.

We exclude observations for which the ENV score is reported as unavailable (N/A). Missing ENV scores are treated as missing observations and are not recoded as zero. The baseline sample is therefore restricted to firms covered by Refinitiv for which both a valid ENV score and a corresponding corporate bond spread are available. This screening procedure results in a final sample of 820 distinct firms and 56,132 firm-month observations over the period 2008–2021. For the ESG robustness analysis, we similarly require a non-missing ESG score.

This coverage requirement may introduce sample-selection concerns because firms covered by Refinitiv may differ systematically from firms without ENV or ESG coverage. In particular, covered firms may be larger, more visible, and provide more extensive corporate disclosures. Consequently, the sample may not be representative of smaller or less transparent bond issuers. Accordingly, we cannot rule out sample-selection bias if Refinitiv coverage is correlated with unobserved determinants of corporate bond spreads. The estimates should therefore be interpreted as conditional on Refinitiv coverage and may not generalize to smaller or less transparent issuers without ENV or ESG coverage.

Table 2.1 presents summary statistics for the cross-section of excess bond yields and ENV scores, calculated across all available firm-month observations. The average annualized bond spread is 3.188%, while the mean annual ENV score is approximately 44.198. ENV scores exhibit relatively

high volatility, indicating substantial variation and heterogeneity in sustainability performance across firms.

[Insert Table 2.1 here]

Table 2.2 presents yearly cross-sectional summary statistics for corporate bond spreads. Average spreads exhibit a modest downward trend over the sample period. The number of observations increases from 1,646 in 2008 to 5,805 in 2021, reflecting a steady expansion in firm-bond coverage by Refinitiv. This growth is likely driven by the broader availability of ESG data over time. The heightened interest in environmental (ENV) ratings, particularly following the Paris Agreement in 2015, aligns with the surge in green bond issuance documented by Flammer (2021).

[Insert Table 2.2 about here]

We also collect a range of firm-specific and bond-specific characteristics to serve as control variables in our subsequent estimations. Specifically, the variables include: net sales over total assets (Sales), operating cash flow over total assets (CF), leverage (Lev), cash holdings (Cash), net operating income scaled by net sales (Inc), return on assets (ROA), firm size (Size), the market-to-book ratio (MB), the bond's coupon rate (CPN), time to maturity (TTM), illiquidity (Illiq), distance to default (DD), and asset volatility (AV). Definitions and detailed descriptions of all variables are provided in Table A1 of the appendix. The DD and AV measures are derived using the KMV model, with further details provided in the appendix.

2.4 Empirical Results

This section presents the empirical findings on the relationship between corporate greenness and corporate bond spreads. We start with portfolio sorts (e.g., sorting bonds on ENV score). We then

employ Fama and MacBeth (1973) and panel regressions to control for firm- and bond-level characteristics. We then attempt to investigate the mechanisms underlying the observed relationships. Specifically, we first examine how firm characteristics vary with ENV scores. More importantly, we examine plausible economic channels associated with the relationship between corporate greenness and bond spreads.

2.4.1 Univariate Portfolio Sorts on ENV

We begin our analysis with univariate sorts on the firm's ENV score. Each month, we sort all available U.S. corporate bonds on their ENV score lagged by 12 months. We then form three portfolios using the tertiles of the empirical distribution of the ENV scores: a "Low" portfolio which contains those firms with ENV score below the lowest tertile (brown firms), a "High" portfolio which contains the firms with ENV score above the top tertile (green firms), and a "Medium" portfolio which includes the remaining firms. We then compute the equal-weighted average bond spread for each portfolio. Refinitiv reports ENV scores as of December, though actual disclosure may occur at any point earlier in the year. To mitigate potential forward-looking bias, we lag the ENV score by one year. The above sorting procedure generates portfolios of approximately equal size, with an average of about 110 firms per portfolio, ensuring adequate diversification.

Table 2.3 presents the results from the univariate portfolio sorts. The average annualized bond spread declines monotonically from 4.058% for the "Low" ENV portfolio to 3.439% for the "Medium" portfolio and 3.021% for the "High" ENV portfolio. Consequently, the "High–Low" spread, defined as the difference between the average spreads of the High- and Low-ENV portfolios, is -1.037 percentage points, or -103.7 basis points per year. This difference is statistically significant at the 1% level (NW t-statistic = -14.83).

Because the outcome variable is a bond yield spread rather than a bond return, the "High–Low"

value should not be interpreted as a conventional long–short portfolio return. Instead, it represents the average pricing difference between bonds issued by firms with high and low environmental performance. Economically, the estimate indicates that investors require approximately 103.7 basis points less annual yield compensation from bonds issued by High-ENV firms than from those issued by Low-ENV firms. From the issuer's perspective, this finding is consistent with environmentally stronger firms facing a lower market-implied cost of debt. Nevertheless, because this is a univariate portfolio comparison, the result should be interpreted as an economically meaningful association rather than a causal effect.

[Insert Table 2.3 about here]

The baseline portfolios are equally weighted, meaning that each constituent bond contributes equally to the portfolio average irrespective of its issue size or trading volume. This construction captures the spread of the typical bond within each ENV category and prevents a small number of large or heavily traded bonds from dominating the results. A potential limitation is that equal weighting gives relatively greater influence to smaller or less actively traded bonds.

To examine whether the "High–Low" spread reflects passive exposure to systematic bond risk factors, Columns (5) and (6) of Table 2.3 report intercepts from time-series regressions of the monthly "High–Low" spread on the adjusted bond factors (*BBWadj*) proposed by Bai et al. (2018) and subsequently corrected by Dickerson et al. (2023). Column (5) uses contemporaneous factors and estimates the following specification:

$$SPR_t^{High-Low} = \alpha_x^{BBWadj} + \beta_{MKT}\, MKT_t + \beta_{DRF}\, DRF_t + \beta_{CRF}\, CRF_t + \beta_{LRF}\, LRF_t + \epsilon_t \quad (8)$$

where $SPR_t^{High-Low}$ is the month *t* value of the "High-Low" bond portfolio, computed as the spread

between the equal-weighted average excess bond yields of the top and bottom tertile portfolios. In Column (6) we estimate the above regression but use lagged instead of contemporaneous values for the factors. The regression intercept, α_x^{BBWadj}, represents the average factor-adjusted High–Low bond-spread differential, where $x = C$ denotes the specification using contemporaneous factors reported in Column (5), while $x = L$ denotes the specification using one-month-lagged factors reported in Column (6). *MKT* is the bond market factor, *DRF* is the downside risk factor, *CRF* is the credit risk factor, and *LRF* is the bond liquidity factor. The *BBWadj* factor data were obtained from Open Bond Asset Pricing. Details on the construction of the four bond factors are provided in Section 2.3.1 of Dickerson et al. (2023).

Because the dependent variable in these regressions is a yield-spread differential rather than a portfolio return, the intercept measures the average "High–Low" spread that is not explained by exposure to the four systematic bond factors. It should therefore be interpreted as a factor-adjusted spread differential rather than an abnormal investment return. The contemporaneous factor-adjusted intercept reported in Column (5) is -0.990 percentage points, equivalent to -99.0 basis points, and is statistically significant at the 1% level (NW t-statistic = -16.15). Similarly, the lagged-factor intercept in Column (6) is -0.999 percentage points, or -99.9 basis points, and remains statistically significant at the 1% level (NW t-statistic = -15.92). Both estimates are close in magnitude to the unadjusted "High–Low" spread of -103.7 basis points. Thus, the average spread differential between High- and Low-ENV firms is not accounted for by their differential exposure to the included systematic bond factors. Among the four factors, the liquidity-risk factor has the strongest association with the "High–Low" spread. Its loading is negative and statistically significant in both the contemporaneous specification (NW t-statistic = -3.15) and the lagged specification (NW t-statistic = -2.91), indicating that the "High–Low" spread co-moves negatively with the liquidity-risk factor. Importantly, however, the negative and statistically significant intercept remains after controlling for this exposure. Overall,

the portfolio-sort results reveal an economically substantial difference in bond pricing across firms with different levels of environmental performance. Bonds issued by High-ENV firms have average spreads approximately 104 basis points lower than those issued by Low-ENV firms, and the factor-adjusted difference remains approximately 100 basis points.[14]

Taken together, these findings indicate that the negative association between environmental performance and bond spreads is neither an artifact of the equal-weighting scheme nor subsumed by the four included bond-risk factors. These results do not, by themselves, establish causality or mispricing, but they show that environmental characteristics contain economically meaningful information for corporate bond pricing.

2.4.2 Fama-MacBeth & Panel Regressions

In the previous section, we examined the relationship between corporate greenness and bond spreads using univariate portfolio sorts. We next estimate Fama-MacBeth regressions of bond spreads on firms' ENV scores and various control variables:

$$SPR_{i,t} = \alpha_t + \beta_t \, ENV_{i,t-12} + \sum_{j=1}^{N} \gamma_{j,t} \, Z_{i,j,t-12} + \epsilon_{i,t} \tag{9}$$

where $SPR_{i,t}$ is the bond spread (excess bond yield) of firm *i* in month *t*, $ENV_{i,t-12}$ is the ENV score for firm *i* lagged by 12 months, and $Z_{i,j,t-12}$ denotes the month *t-12* value of control variable *j* referring to firm *i*. The set Z contains the following controls: Sales, Cash, Lev, CF, Inc, ROA, Size, MB, CPN, TTM, DD, AV, and Illiq, which are described in Section 2.3 and in Table A1 of the appendix.

Table 2.4 reports the time-series average slope estimates and corresponding Newey and West

[14] Our baseline analysis is based on equal-weighted tertile portfolios. To assess the robustness of these findings, Table A4 of the appendix explores alternative portfolio construction methods, including volume-weighted portfolios and quintile-based sorting. We elaborate further on this in Section 2.5.3.

(1987) t-statistics (in parentheses) of the Fama–MacBeth regressions. In Model (1), which does not include any control variables, the coefficient on the *ENV* variable (multiplied by 100) is equal to -1.465 and statistically significant at the 1% level (NW t-stat. = -15.21), consistent with earlier evidence. Model (2) introduces firm-specific and bond-specific control variables. The average slope estimate of *ENV* remains negative and statistically significant at the 1% level in the augmented model, albeit with a reduced magnitude. Thus, incorporating firm- and bond-specific characteristics into the models does not alter the negative association between corporate greenness and bond spreads, which is still significant at the 1% level.

Most control variables have significant slope estimates. Their signs are meaningful too. For example, Lev enters with a positive coefficient, while *ROA* has a negative loading, implying that firms with higher leverage have wider bond spreads, whereas firms with greater profitability have lower bond spreads. Likewise, the distance-to-default (*DD*) is negatively associated with bond spreads, consistent with financially safer firms having lower borrowing costs. The attenuation of the coefficient of *ENV* in models that include controls suggests that some of the variation in bond spreads associated with corporate greenness may be partially captured by firm and bond characteristics. We delve deeper into this relationship in the sections that follow.

[Insert Table 2.4 about here]

For further robustness, we also estimate a panel regression specified as follows:

$$SPR_{i,t} = \alpha + \beta\, ENV_{i,t-12} + \sum_{j=1}^{K} \gamma_j\, Z_{i,j,t-12} + \eta_s + \tau_t + u_{i,t} \tag{10}$$

where η_s corresponds to sector fixed effects and τ_t to time (month) fixed effects, respectively. Standard errors are two-way clustered by firm and year. The rest of the notation is as defined in Eq. (9). Consistent with Eq. (9), the dependent variable is measured contemporaneously in month t, while the

ENV score and all control variables are lagged by 12 months. The estimation results are reported in Table 2.5.

[Insert Table 2.5 about here]

The slope estimate of *ENV* in Model (1) of Table 2.5, which excludes control variables, is uniformly negative and statistically significant at the 1% level. Models (3) and (5), which incorporate sector fixed effects and both time and sector fixed effects, respectively, yield consistent results. In line with earlier evidence from the Fama and MacBeth (1973) regressions, the inclusion of control variables (Models (2), (4), and (6)) attenuates the magnitude of the *ENV* coefficient. However, it remains negative and statistically significant across these specifications. Overall, the panel regression results closely mirror those obtained from the Fama–MacBeth approach, reinforcing the robustness of our findings.

To assess the economic magnitude of these estimates, the ENV score is measured on a 0–100 scale and has a standard deviation of 29.085 points, as reported in Table 2.1. Because the ENV coefficients in Tables 2.4 and 2.5 are reported after being multiplied by 100, the spread effect of a one-standard-deviation increase in ENV is obtained by multiplying the reported coefficient by $29.085/100$. In Table 2.4, the univariate coefficient of -1.465 implies a reduction in the annualized bond spread of approximately 0.426 percentage points, or 42.6 basis points (i.e., $-1.465/100 \times 29.085 \approx -0.426$ percentage points). After controlling for firm- and bond-level characteristics in Model (2), the coefficient of -0.362 implies a reduction of approximately 0.105 percentage points, or 10.5 basis points (i.e., $-0.362/100 \times 29.085 \approx -0.105$ percentage points). Similarly, the fully controlled panel specification in Model (6) of Table 2.5, which includes both month and sector fixed effects, implies a reduction of approximately 0.075 percentage points, or 7.5 basis points (i.e., $-0.259/100 \times 29.085 \approx -0.075$ percentage points).

Relative to the full-sample mean bond spread of 3.188%, or 318.8 basis points, the controlled estimates in Tables 2.4 and 2.5 represent reductions of approximately 3.3% and 2.4%, respectively (i.e., $0.105/3.188 \times 100 \approx 3.3\%$ and $0.075/3.188 \times 100 \approx 2.4\%$). These conditional one-standard-deviation effects are therefore modest but economically non-negligible. For comparison, the unconditional High–Low portfolio differential reported in Table 2.3 is 103.7 basis points, with the average spread of the High-ENV portfolio being approximately 25.6% lower than that of the Low-ENV portfolio (i.e., $(4.058 - 3.021)/4.058 \times 100 \approx 25.6\%$). The two magnitudes capture different empirical objects: the portfolio result compares the extreme ENV tertiles without regression controls, whereas the regression coefficients measure conditional marginal associations. Accordingly, neither estimate should be interpreted as a causal effect.

2.4.3 Exploring Potential Drivers

Double Portfolio Sorts

The findings thus far demonstrate a robust cross-sectional relationship between corporate greenness and bond spreads. To examine whether the association persists after conditioning on observable characteristics, we perform double portfolio sorts on *ENV* and various firm characteristics. Specifically, at the end of each month, all available bonds are independently sorted based on firms' ENV scores and the selected characteristic, yielding nine tertile portfolios. The variables under consideration correspond to those utilized in the univariate sorts and Fama-MacBeth regressions in the preceding section. These include the following: *Cash, CF, Lev, Inc, ROA, Sales, Size, MB, CPN, TTM, DD, AV, Illiq*. If the High–Low ENV spread differential becomes statistically insignificant within the tertiles of the control variable, this would suggest that the association between greenness and bond spreads may be explained by exposure to that characteristic.

Table 2.6 presents the results of double portfolio sorts. The control variable for each panel is

displayed on the left. The final column of each panel (highlighted in grey) shows the mean of the high-minus-low ("High-Low") ENV portfolio within each tertile of the control variable. To conserve space, we do not report the average for the "High-Low" spread portfolios of the control variables. Newey and West (1987) t-statistics are provided in parentheses. Overall, the results suggest that the negative and significant impact of greenness on bond spreads cannot be fully explained by any of the considered characteristics as the average of "High-Low" ENV portfolio is negative and significant in each portfolio of the control variable. In addition, the monotonic decrease in bond spreads from the "Low" to the "High" ENV-sorted bond portfolio is still present.

Our results also demonstrate that the effect of greenness on bond spreads is more pronounced among firms with low distance-to-default (*DD*), low cash holdings, high leverage (*Lev*), low return on assets (*ROA*), and low market-to-book (*MB*) ratios. These characteristics are commonly associated with financially constrained or distressed firms, as noted by Chan and Chen (1991) and Fama and French (1992). This suggests that environmental performance plays a more significant role in influencing credit risk for more financially constrained firms. At a minimum, these findings indicate that the impact of corporate environmental performance on bond pricing is heterogeneous and varies systematically with firm- and bond-level characteristics.

[Insert Table 2.6 here]

Corporate Greenness and Firm Characteristics

To better understand the underlying drivers of the credit spread differences observed across our ENV-sorted portfolios, we next examine the characteristics associated with different levels of greenness. Specifically, we construct tertile portfolios by sorting the bonds by their ENV scores, following the approach outlined in Section 2.4.1. For each of the three ENV tertile portfolios, we then compute the average value of a specific outcome variable. This analysis aims to explore whether the average

bond spread differentials across ENV-sorted portfolios are associated with systematic differences in firm and bond characteristics.

The results from the above analysis are reported in Table 2.7. Our findings provide valuable new insights. We observe that greener firms exhibit higher operating cash flow (*CF*), along with higher income (*Inc*) and profitability (*ROA*). This is reflected in the positive and significant mean of the "High-Low" spread portfolio for the respective row variables. For instance, firms in the top ENV tertile have an average *ROA* of 5.2%, compared to 2.9% for firms in the bottom ENV tertile, a difference that is statistically significant at the 1% level. Similarly, firms in the top *ENV* tertile show a significant difference in their income (*Inc*) compared to those in the bottom tertile. Furthermore, greener firms tend to have, on average, lower leverage (*Lev*) and higher market-to-book (*MB*) ratios (lower book-to-market ratios). Assuming, as Chan and Chen (1991) argue, the market-to-book ratio reflects relative distress, [15] these findings suggest that firms with stronger environmental performance exhibit lower default risk and reduced leverage compared to firms with weaker environmental performance. Indeed, as shown in Table 2.7, bonds issued by brown firms (i.e., those in the "Low" *ENV* portfolio) tend to be associated with lower average distance-to-default (*DD*), indicating higher default risk, and higher leverage ratios.

Furthermore, the results in Table 2.7 indicate that brown firms tend to exhibit higher asset volatility (*AV*) and greater illiquidity (*Illiq*). The final column of the table (i.e., "High–Low") reports the differences in average values between the top and bottom ENV tertiles, and shows that these differences are statistically significant at the 1% level. These findings are consistent with a growing body of literature documenting that green firms benefit from lower borrowing costs (Javadi and Masum, 2021; Huang et al., 2022; Altavilla et al., 2024). They also contribute to the emerging evidence on the role of climate-related risks in shaping firms' capital structure decisions (Ginglinger and Moreau,

[15] According to Chan and Chen (1991), firms with high book-to-market (or low market-to-book) ratios have poor prospects and are relatively distressed. Additional evidence on the role of the distress premium in the cross-section of stock returns is provided by Fama and French (1992) and Fama and French (1996).

2023).

[Insert Table 2.7 here]

Our findings primarily demonstrate that the difference in bond spreads between green and brown firms, as documented in earlier sections, is largely attributable to differences in firm fundamentals and bond-specific characteristics. However, as shown in our preceding analyses, these factors do not fully account for the effect of corporate greenness on bond spreads. These results indicate that the ENV–spread association is not fully accounted for by the firm- and bond-level characteristics considered here. Environmental performance therefore contains incremental information associated with the cross-section of corporate bond spreads, although the analysis does not establish a separate causal risk factor.

2.4.4 Economic Channels

What is the potential economic mechanism underlying the relationship between corporate greenness and bond spreads? In this section, we explore plausible channels that may explain this association. The extant literature has provided robust evidence on the *external financing channel*, according to which brown firms tend to pay higher loan spreads than green firms (Ginglinger and Moreau, 2023; Altavilla et al., 2024; Demetriades and Politsidis, 2025). This disparity is often attributed to heightened perceived risks, regulatory exposure, and reputational concerns associated with environmentally unfriendly practices, which in turn affect lenders' and investors' required compensation for bearing such risks. An alternative explanation is that firms with stronger environmental performance (i.e., higher ENV scores) tend to issue bonds that are more liquid and exhibit lower default risk. For example, prior research has shown that illiquid bonds generally command higher yield spreads (Chen et al., 2007). The results in Table 2.7 provide preliminary evidence consistent with this view, namely, greener firms exhibit lower leverage, stronger profitability, reduced default risk (as measured

by distance-to-default), and greater bond liquidity (i.e., lower illiquidity) on average compared to brown firms.

Another potential explanation for our findings is related to the uncertainty about the firm's internal cash flows, which may impair its debt repayment ability, therefore leading to higher yield spreads (He et al., 2025). This economic explanation draws from Chen et al. (2007), who focus on the role of internal liquidity (see He et al., 2025, for an application in the Chinese bond market). For ease of exposition, we will call this the *internal cash–flow uncertainty channel*. To empirically examine this channel, we begin by conducting bivariate independent portfolio sorts based on firms' environmental (*ENV*) scores and cash flow volatility (*CFVol*) and income volatility (*IncVol*). The former corresponds to the volatility of the firm's net operating cash flow, while the latter is the volatility of the net operating income. Both measures are calculated as the rolling standard deviation over the past five years of quarterly data. These measures are similar to those used in Titman and Wessels (1988) and Strebulaev and Yang (2013).

Table A2 reports the ENV High–Low bond-spread differential within portfolios formed on cash-flow volatility (CFVol) and income volatility (IncVol). The High–Low differential is negative and statistically significant within every CFVol and IncVol subgroup, indicating that the negative association between ENV and bond spreads persists across different levels of cash-flow uncertainty. The differential is more negative in the High-volatility portfolios. For example, in Panel A, the ENV High–Low spread differential is -1.223 percentage points in the High-CFVol portfolio, compared with -0.795 percentage points in the Low-CFVol portfolio. These comparisons do not estimate the unconditional relationship between CFVol or IncVol and bond spreads. Instead, they show that the ENV–spread association remains present, and is descriptively stronger, among firms with greater cash-flow uncertainty. The FM regressions are specified as follows:

$$Q_{i,t} = \alpha_t + \beta_t \, ENV_{i,t-12} + \sum_{j=1}^{N} \gamma_{j,t} Z_{i,j,t-12} + u_{i,t} \tag{11}$$

where: $Q_{i,t}$ is the value of variable *Q* for firm *i* in month *t*, where $Q = \{CFVol$, or $IncVol\}$, $ENV_{i,t-12}$ is the environmental score of firm *i* at the end of month *t-12*, and $Z_{i,j,t-12}$ is the end-of-month *t-12* value of the control variable *j*, referring to firm *i*. We estimate both the univariate Fama–MacBeth regressions and specifications that include the full set of controls.

[Insert Table 2.8 here]

The results from the above cross-sectional regressions are reported in Table 2.8. The coefficient estimate of *ENV* is consistently negative and statistically significant at the 5% level across all regressions. These results indicate that greenness is negatively associated with cash flow uncertainty. Taken together, these findings are consistent with the internal cash-flow uncertainty channel: firms with higher ENV scores tend to exhibit lower cash-flow and income volatility. Because the analysis is observational, the results do not establish that environmental performance itself stabilizes firms' operations.

The cash-flow uncertainty channel is particularly relevant to bondholders because coupon and principal payments are fixed. Greater cash-flow volatility makes the funds available for these payments less predictable and may increase refinancing and default risk. Unlike shareholders, bondholders do not participate fully in the upside generated by riskier corporate strategies, while remaining exposed to losses if cash-flow deterioration leads to default. The evidence in Table 2.8 is therefore consistent with one creditor-specific explanation for the wider spreads of low-ENV firms. Nevertheless, it should not be interpreted as establishing a causal mechanism or as ruling out other channels, including differences in recovery values, bond liquidity, and investor demand.

2.5 Additional Results

2.5.1 Does ESG matter?

In our baseline analysis, corporate greenness was proxied by firms' *ENV* scores. While the environmental (E) dimension of ESG is arguably of paramount importance, in light of climate change, it is worthwhile to examine whether the broader ESG score, which incorporates environmental, social (S), and governance (G) dimensions, can also explain the cross-section of corporate bond spreads. To investigate this, we replicate the portfolio sorting exercise from Section 2.4.1, replacing firms' ENV scores with their ESG scores.

The results, presented in Table A3, reveal a negative and highly significant cross-sectional relationship between ESG scores and excess bond yields. Specifically, the average value of the "High–Low" spread portfolio is -1.081 and statistically significant at the 1% level (Newey-West t-stat. = -15.75). Importantly, controlling for contemporaneous (Column 5) or lagged (Column 6) bond market factors, as identified by Dickerson et al. (2023), does not materially affect the results, thereby reinforcing the robustness of our findings. Consistent with our portfolio sorting results, the findings from both the Fama–MacBeth and panel regression analyses (unreported to save space; available upon request from the authors) also reveal a negative and statistically significant association between ESG scores and excess bond yields.

Economically, the ESG-sorted High–Low spread differential of -1.081 percentage points, or -108.1 basis points, is close to the corresponding ENV-sorted differential of -1.037 percentage points, or -103.7 basis points, reported in Table 2.3. The factor-adjusted ESG differentials are also similar to their ENV counterparts. This similarity indicates that the negative association with bond spreads is also present when firms are classified using a broader measure of environmental, social, and governance performance, rather than ENV scores alone.

The ESG score provides a broader measure of firm ESG quality because it combines environ-

mental, social, and governance performance. Since the ENV score forms part of the composite ESG score, the two measures contain overlapping information. Investors may therefore use the aggregate ESG score as a simple and readily observable proxy for a firm's overall greenness and sustainability performance. The similarity between the ESG- and ENV-sorted results indicates that the negative association with bond spreads is not specific to the ENV measure, but is also present when firms are classified using this broader ESG proxy. Accordingly, this robustness result should not be interpreted as evidence that the environmental pillar alone drives the ESG finding; rather, it confirms that the main relationship remains when broader firm ESG quality is used to represent overall greenness.

2.5.2 Carbon Intensity as a Narrower Climate-Exposure Measure

The ENV score measures broad environmental performance, but it is not a direct measure of climate risk. To examine whether the main conclusion is also supported by a narrower emissions-based measure, we repeat the portfolio-sorting, Fama–MacBeth, and panel analyses using Scope 1, Scope 2, Scope 3, Scope 1+2, and Scope 1+2+3 carbon intensity.

Table A7 reports the portfolio-sorting results. For all five measures, bonds issued by firms in the High carbon-intensity portfolio have higher average spreads than bonds in the Low portfolio. The High–Low differences range from 23.7 to 36.6 basis points and are statistically significant at the 1% level. The unconditional portfolio evidence therefore indicates that more carbon-intensive firms generally face higher borrowing-cost spreads.

Table A8 reports the Fama–MacBeth results. The univariate carbon-intensity coefficients are positive for all five measures. After the firm- and bond-level controls are included, the coefficients remain positive for Scope 1, Scope 2, Scope 1+2, and Scope 1+2+3. The Scope 3 coefficient becomes negative, indicating that its conditional relationship is sensitive to the included controls. For Scope 1 and Scope 1+2, the controlled coefficients are both reported as 0.004 in Table A8 after rounding to three

decimal places. The corresponding unrounded regression estimates are 0.0039255 and 0.0039773. The standard deviations of Scope 1 and Scope 1+2, calculated from the same controlled regression sample of 30,321 firm-month observations, are 1,266.741 and 1,282.087, respectively. Because the carbon-intensity variables are divided by 100 in the regressions, the one-standard-deviation effects are

$$0.0039255 \times \frac{1{,}266.741}{100} = 0.0497 \text{ percentage points} = 4.97 \text{ basis points}$$

for Scope 1 and

$$0.0039773 \times \frac{1{,}282.087}{100} = 0.0510 \text{ percentage points} = 5.10 \text{ basis points}$$

for Scope 1+2. Thus, a one-standard-deviation increase in either measure is associated with an increase of approximately 5 basis points in the annualized bond spread. When ENV and carbon intensity are included together, ENV remains negative and statistically significant in every specification.

The panel results in Table A9 are more mixed. In the fully controlled specification with both month and sector fixed effects, Scope 1 remains positive and statistically significant at the 5% level, while the Scope 1+2 estimate is close to the 5% significance boundary. Although both coefficients are reported as 0.004 in Column (6) after rounding to three decimal places, their unrounded estimates are 0.0036201 and 0.0036137, respectively. Using the same controlled-sample standard deviations, the corresponding one-standard-deviation effects are

$$0.0036201 \times \frac{1{,}266.741}{100} = 0.0459 \text{ percentage points} = 4.59 \text{ basis points}$$

for Scope 1 and

$$0.0036137 \times \frac{1{,}282.087}{100} = 0.0463 \text{ percentage points} = 4.63 \text{ basis points}$$

for Scope 1+2. Thus, both effects are approximately 4.6 basis points. However, Scope 2 and Scope 1+2+3 are not statistically significant, while the Scope 3 coefficient is negative. The negative Scope 3 coefficient should not be interpreted as evidence that value-chain emissions reduce credit risk. It may reflect reporting differences, measurement error, industry composition, or the inclusion of correlated firm characteristics.

Overall, the carbon-intensity tests provide supplementary evidence that direct emissions, especially Scope 1 emissions, are associated with higher corporate borrowing costs. However, the results are not equally strong across all emission scopes. Moreover, ENV remains negative and statistically significant when it is included together with carbon intensity. These findings suggest that ENV captures broader environmental information and should not be treated as a direct measure of climate-risk exposure. As with the main results, these estimates represent associations rather than causal effects.

2.5.3 Sorting Procedure and Weighting Scheme

A natural question is whether our results are sensitive to (i) the sorting procedure used to construct the High–Low spread differentials and (ii) the equal-weighting of bonds within each portfolio. First, we apply trading-volume weights instead of equal weights. As reported in Panel A of Table A4, the volume-weighted High–Low spread differential is -0.968 percentage points, or -96.8 basis points per year, which is close to the equal-weighted baseline estimate of -1.037 percentage points. This similarity indicates that the baseline result is not driven by the equal-weighting scheme.

Second, we replicate the analysis using quintile rather than tertile portfolios. Panel B of Table A4 shows that the average bond spread declines monotonically from the bottom to the top quintile. The High–Low spread differential is -1.095 percentage points, or -109.5 basis points per year, and is statistically significant at the 1% level (NW t-statistic = -16.52). The factor-adjusted spread differentials remain negative and significant. Thus, the findings are robust to both the portfolio-weighting scheme

and the choice of sorting breakpoints.

2.5.4 Sub-sample Analysis

Recent studies suggest that climate-induced uncertainties have increasingly shaped financial markets, particularly following the Paris Agreement. For example, Monasterolo and De Angelis (2020) found that after its introduction in 2015, stock markets adjusted their risk perception, leading to lower systematic risk for low-carbon indices and a greater allocation to optimal portfolios. Similarly, Tolliver et al. (2020) demonstrated that in the years following 2015, the Paris Agreement significantly boosted green bond allocations to renewable energy. Motivated by these findings, we examine whether the relationship between corporate greenness and bond spreads differs before vs. after the Paris Agreement. Since the Paris Agreement officially entered into force in November 2016, we set January 2017 as the breakpoint for our analysis.

Table A5 reports the results from the Fama-MacBeth regressions of Eq. (9) for the sub-periods pre- (2008–2016) and post-Paris Agreement (2017–2021). The results show that corporate greenness is negatively and significantly associated with bond spreads in both sub-periods, whereas there is little to suggest that this relationship differs substantially after the Paris Agreement. However, we do observe a much higher t-statistic in the post-Paris Agreement period.

2.5.5 Evidence across Sectors

Is the negative relationship between corporate greenness and bond spreads driven by specific sectors? To address this question, we replicate the univariate portfolio sorting exercise from Section 2.4.1, conducting the analysis separately for each sector using the Refinitiv Eikon sector classification. The results, presented in Table A6 of the appendix, provide evidence on the relationship between firms' (*ENV*) scores and their bond spreads for each sector. While the negative association is particularly pronounced in certain sectors, such as energy, where environmental risks are more salient, we

observe a broadly consistent pattern across the majority of sectors. In most cases, firms with higher *ENV* scores tend to exhibit lower bond spreads, suggesting that investors reward environmental performance across a wide range of industries. Therefore, we do not find compelling evidence that the relationship is driven by a specific sector. This suggests that the negative association between environmental performance and bond spreads is broadly present across sectors rather than being confined to one particular sector.

2.6 Conclusion

In this essay, we examine the relationship between corporate greenness and corporate bond spreads. Our empirical analysis draws on a large cross-section of U.S. corporate bonds. Using portfolio sorts and cross-sectional regressions that control for a range of firm- and bond-level characteristics, we find that greenness is negatively priced in the corporate bond market; namely, greener firms, on average, exhibit lower credit spreads. We further examine the relationship between corporate greenness and firm- and bond-specific characteristics, and find that greener firms generally exhibit higher operating cash flow, stronger profitability, lower leverage, higher market-to-book ratios, greater distance to default, and greater liquidity. However, these attributes do not fully account for the observed link between greenness and bond yield spreads. These findings suggest that firm-level environmental performance contains incremental information associated with corporate bond yield spreads beyond the included controls.

Taken together, the economic magnitudes vary across the empirical specifications. The univariate portfolio results indicate a substantial unconditional pricing difference: bonds issued by High-ENV firms have average spreads 103.7 basis points lower than those issued by Low-ENV firms, while the factor-adjusted differentials remain close to 100 basis points in absolute magnitude. By contrast, in the most fully controlled regressions, a one-standard-deviation increase in ENV is associated with an

approximately 7.5–10.5-basis-point reduction in bond spreads (i.e., $-0.259/100 \times 29.085 \approx -0.075$ percentage points and $-0.362/100 \times 29.085 \approx -0.105$ percentage points), equivalent to about 2.4–3.3% of the full-sample mean spread (i.e., $0.075/3.188 \times 100 \approx 2.4\%$ and $0.105/3.188 \times 100 \approx 3.3\%$). Thus, although the statistical evidence is consistently strong, the estimated effects are not uniformly large. The extreme-portfolio difference is economically substantial, whereas the conditional marginal association is more modest but remains economically non-negligible. These estimates capture associations rather than causal effects. The supplementary carbon-intensity tests further refine this interpretation. High carbon-intensity portfolios have higher average bond spreads, but the controlled evidence is strongest for direct Scope 1 emissions and is less consistent for Scope 2, Scope 3, and the combined measures. ENV remains negative and statistically significant when it is included together with carbon intensity. Therefore, ENV and carbon intensity appear to contain different information about corporate bond spreads: ENV captures broader environmental performance, while carbon intensity provides a narrower emissions-based measure.

We also examine whether cash-flow uncertainty provides one plausible explanation for the main findings. Firms with higher ENV scores tend to exhibit lower cash-flow and income volatility than firms with lower ENV scores. This evidence is consistent with an internal cash-flow uncertainty channel, but it does not establish a causal mechanism. The ENV results are also robust to alternative portfolio constructions and weighting schemes.

Table 2.1: Descriptive Statistics for Bond Spreads and ENV Scores

This table presents cross-sectional summary statistics for bond spreads and ENV scores over the period 2008–2021. Reported statistics include the sample mean, 25th percentile, median (50th percentile), 75th percentile, standard deviation, skewness, and kurtosis. The final two rows report the number of unique firms and the total number of firm-month observations.

	Bond Spread (%)	ENV Score
Mean	3.188	44.198
25^{th} Percentile	1.846	18.568
50^{th} Percentile	2.768	45.410
75^{th} Percentile	4.108	70.215
Max.	13.058	98.546
Min.	0.142	0.000
St. Dev.	1.914	29.085
Skewness	1.447	-0.039
Kurtosis	6.223	1.716
# Firms	820	820
# Firm–month obs.	56,132	56,132

Table 2.2: Per Year Summary Statistics for Bond Spreads

This table reports the per year summary statistics for the monthly cross-section of U.S. corporate bond spreads. The sample period is from January 2008 to December 2021. Descriptive statistics include the sample mean, standard deviation, skewness, and kurtosis for each year. The mean and standard deviation are annualized. Bond spreads are expressed in percentage terms. The last column reports the total number of firm-month observations per year.

Year	Mean	STD	Skewness	Kurtosis	# Obs
2008	4.926	2.452	1.007	3.404	1,646
2009	6.188	2.722	0.956	3.382	2,382
2010	4.418	1.642	0.198	2.097	2,633
2011	4.129	1.669	0.392	2.362	2,968
2012	3.334	1.593	0.626	2.633	3,216
2013	3.306	1.305	0.286	2.317	3,417
2014	3.221	1.204	0.418	2.560	3,495
2015	3.565	1.461	0.933	3.361	3,818
2016	3.523	1.691	1.098	3.620	4,568
2017	2.715	1.128	0.738	2.792	5,026
2018	2.532	1.030	0.871	3.039	5,447
2019	1.642	1.282	1.301	4.128	5,689
2020	3.024	2.545	1.651	5.034	6,022
2021	2.454	1.134	1.108	3.719	5,805

Table 2.3: Portfolio Sorting on Firms' ENV Scores

This table presents the average bond spread, defined as the bond yield in excess of the risk-free rate, for portfolios sorted by firms' ENV scores. At the end of each month, all available bonds are sorted by their ENV score lagged by 12 months, and three portfolios are constructed based on the tertiles of the empirical ENV score distribution. The "Low" portfolio includes bonds below the bottom tertile, the "High" portfolio includes those bonds above the top tertile, and the "Med" portfolio includes the remaining bonds. The table reports the average bond spread (i.e., excess yield) for each portfolio. The "High–Low" column shows the mean spread differential between the "High" and "Low" portfolios. The final two columns display intercept estimates from time-series regressions of the "High–Low" portfolio on contemporaneous ($\alpha_C^{BBW_{adj}}$) and lagged ($\alpha_L^{BBW_{adj}}$) values of the bond factors of Dickerson et al. (2023). Portfolios are equally weighted, so each constituent bond receives the same weight. Because the reported outcome is a yield spread rather than a bond return, the High-minus-Low portfolio should be interpreted as the difference in average annualized spreads between the High- and Low-ENV portfolios, expressed in percentage terms. All portfolio means and alpha estimates are annualized and expressed in percentage terms. Newey and West (1987) t-statistics with four lags are reported in parentheses. The sample spans January 2008 to December 2021.

	(1)	(2)	(3)	(4)	(5)	(6)
	Low	Med	High	High–Low	$\alpha_C^{BBW_{adj}}$	$\alpha_L^{BBW_{adj}}$
Port. Mean / α	4.058	3.439	3.021	-1.037	-0.990	-0.999
	(17.550)	(17.215)	(15.414)	(-14.825)	(-16.149)	(-15.923)
MKT_t					-7.497	
					(-2.395)	
DRF_t					5.549	
					(1.861)	
CRF_t					1.377	
					(0.870)	
LRF_t					-14.195	
					(-3.152)	
MKT_{t-1}						-7.445
						(-1.832)
DRF_{t-1}						5.512
						(1.708)
CRF_{t-1}						2.406
						(1.516)
LRF_{t-1}						-12.928
						(-2.906)
R^2	-	-	-	-	0.131	0.108
# Months	168	168	168	168	168	167

Table 2.4: Fama-MacBeth Regression Results

This table presents the results from monthly Fama and MacBeth (1973) regressions, where bond spreads are regressed on ENV scores and a set of control variables, which are all lagged by 12 months. Column (1) presents estimates from a univariate regression using ENV as the sole explanatory variable. Column (2) adds firm-level and bond-level controls. The third-to-last row (Mean R^2) reports the average R-squared coefficient across regressions. The second-to-last row (Mean Obs/Month) reports the average number of firms per month, while the final row (# Months) indicates the total number of months in the sample. Newey and West (1987) t-statistics (with four lags) are reported in parentheses. The sample period spans January 2008 to December 2021.

	(1)	(2)
Env × 100	-1.465	-0.362
	(-15.213)	(-8.511)
Sales		-0.123
		(-3.150)
Cash		0.027
		(0.114)
CF		-0.426
		(-1.122)
Lev		0.823
		(8.474)
Inc		-0.542
		(-1.956)
ROA		-3.581
		(-7.243)
Size		-0.236
		(-16.526)
MB		-0.012
		(-1.774)
DD		-0.030
		(-7.029)
AV		0.959
		(7.636)
CPN		0.430
		(14.240)
TTM		0.081
		(11.139)
ILLIQ		41.970
		(7.836)
Intercept	4.145	6.166
	(18.417)	(13.921)
Mean R^2	0.076	0.657
Mean Obs/Month	334	246
# Months	168	168

Table 2.5: Panel Regression Results

This table presents the results from the following panel regressions:

$$SPR_{i,t} = \alpha + \beta ENV_{i,t-12} + \sum_{j=1}^{K} \gamma_j Z_{i,j,t-12} + \eta_s + \tau_t + u_{i,t}$$

where $SPR_{i,t}$ is the corporate bond spread for firm i in month t, $ENV_{i,t-12}$ is the environmental score for firm i lagged by 12 months, and $Z_{i,j,t-12}$ is the value of control variable j for firm i at the end of month $t-12$. η_s and τ_t denote sector and time (month) fixed effects, respectively. Columns (1)–(2) include month fixed effects only, Columns (3)–(4) include sector fixed effects only, and Columns (5)–(6) include both month and sector fixed effects. The reported ENV coefficients are multiplied by 100 for presentation; this does not affect their t-statistics. Standard errors are two-way clustered by firm and calendar year in all columns, and the resulting t-statistics are reported in parentheses. The sample spans January 2008 to December 2021.

	(1)	(2)	(3)	(4)	(5)	(6)
Env × 100	-1.458	-0.338	-1.481	-0.568	-1.351	-0.259
	(-6.381)	(-3.455)	(-5.959)	(-3.763)	(-6.179)	(-2.408)
Sales		-0.070		0.004		-0.060
		(-1.164)		(0.064)		(-0.960)
Cash		-0.218		0.284		-0.064
		(-0.605)		(0.638)		(-0.209)
CF		0.663		0.852		-0.134
		(0.691)		(1.131)		(-0.210)
Lev		0.892		0.660		1.091
		(3.287)		(2.164)		(3.597)
Inc		0.169		0.599		0.566
		(0.383)		(1.037)		(1.209)
ROA		-5.216		-6.109		-5.334
		(-4.014)		(-4.677)		(-4.101)
Size		-0.229		-0.166		-0.263
		(-7.034)		(-2.646)		(-6.347)
MB		-0.019		-0.019		-0.020
		(-1.361)		(-1.733)		(-1.398)
DD		-0.023		-0.011		-0.020
		(-4.762)		(-2.520)		(-4.380)
AV		0.724		0.212		0.610
		(2.679)		(0.464)		(2.559)
CPN		0.402		0.516		0.385
		(8.958)		(7.389)		(8.664)
TTM		0.070		0.063		0.068
		(5.076)		(4.726)		(4.773)
Illiq		42.851		77.653		43.165
		(2.778)		(5.781)		(2.793)
Intercept	3.832	5.958	3.842	3.819	3.785	6.717
	(34.039)	(7.957)	(12.187)	(2.297)	(35.631)	(7.096)
Time F.E.	Yes	Yes	No	No	Yes	Yes
Sector F.E.	No	No	Yes	Yes	Yes	Yes
Firm-Month Obs.	56,132	41,402	56,132	41,402	56,132	41,402
R^2	0.367	0.672	0.102	0.545	0.416	0.678

Table 2.6: Bivariate Portfolio Sorts

This table reports the results from double independent portfolio sorts on ENV and the variable specified in each panel (all lagged by 12 months). At the end of each month, we form nine portfolios from the intersection of three tertile ENV portfolios and three tertile portfolios of the other variable. This sorting procedure is repeated monthly, resulting in a time series of monthly portfolio spreads for each of the nine portfolios. The final column of the table shows the average bond spread of the high-minus-low ("High-Low") ENV portfolio calculated as the difference between the average spreads of bonds in the High- and Low-ENV portfolios. Newey and West (1987) t-statistics with four lags are reported in parentheses. The sample period is from January 2008 to December 2021.

		ENV			
Sales	Low	Low	Med	High	High-Low
		4.164	3.456	2.978	-1.186
		(16.030)	(13.157)	(14.566)	(-13.144)
	Med	3.845	3.385	3.104	-0.741
		(19.691)	(18.560)	(14.446)	(-10.733)
	High	4.098	3.448	2.956	-1.141
		(18.014)	(19.498)	(16.881)	(-12.045)

		ENV			
Cash	Low	Low	Med	High	High-Low
		4.215	3.547	2.960	-1.255
		(18.551)	(16.182)	(15.409)	(-13.097)
	Med	3.955	3.287	3.023	-0.932
		(19.817)	(19.802)	(17.016)	(-11.495)
	High	3.912	3.470	3.114	-0.798
		(16.193)	(15.863)	(14.150)	(-13.568)

		ENV			
CF	Grade	Low	Med	High	High-Low
	Low	4.238	3.936	3.350	-0.888
		(16.238)	(14.949)	(14.224)	(-12.238)
	Med	3.952	3.349	3.120	-0.832
		(17.494)	(17.674)	(15.311)	(-10.197)
	High	3.846	3.101	2.688	-1.158
		(19.670)	(18.177)	(16.744)	(-17.303)

		ENV			
Lev	Low	Low	Med	High	High-Low
		3.798	3.188	2.944	-0.854
		(17.718)	(16.769)	(17.127)	(-12.413)
	Med	3.993	3.376	3.001	-0.992
		(17.796)	(18.567)	(14.879)	(-11.115)
	High	4.279	3.784	3.227	-1.051
		(21.074)	(19.844)	(14.597)	(-10.029)

		ENV			
Inc	Low	Low	Med	High	High-Low
		4.642	4.111	3.675	-0.966
		(19.471)	(19.634)	(14.597)	(-10.801)
	Med	3.650	3.173	2.874	-0.776
		(16.402)	(17.203)	(15.440)	(-13.498)
	High	3.644	3.003	2.670	-0.975
		(15.448)	(14.156)	(16.149)	(-11.246)

		ENV			
ROA	Low	Low	Med	High	High-Low
		4.504	4.172	3.487	-1.017
		(17.357)	(15.715)	(13.675)	(-12.364)
	Med	3.807	3.234	3.022	-0.785
		(17.496)	(18.086)	(15.773)	(-10.842)
	High	3.519	2.993	2.697	-0.822
		(16.736)	(16.947)	(16.312)	(-12.758)

		ENV			
Size	Low	Low	Med	High	High-Low
		4.301	3.774	3.644	-0.657
		(20.147)	(20.133)	(14.785)	(-6.943)
	Med	3.784	3.409	3.049	-0.735
		(15.559)	(16.900)	(15.928)	(-9.356)
	High	3.616	3.105	2.817	-0.799
		(13.221)	(14.086)	(15.125)	(-7.682)

		ENV			
MB	Grade	Low	Med	High	High-Low
	Low	4.470	3.917	3.507	-0.963
		(17.145)	(16.853)	(14.672)	(-11.818)
	Med	3.690	3.232	2.979	-0.711
		(15.587)	(16.697)	(15.727)	(-9.743)
	High	3.503	3.058	2.706	-0.797
		(16.784)	(17.979)	(15.338)	(-14.044)

		ENV			
DD	Grade	Low	Med	High	High-Low
	Low	4.889	4.500	3.759	-1.130
		(17.385)	(16.905)	(16.451)	(-11.640)
	Med	3.657	3.344	3.089	-0.568
		(15.941)	(15.755)	(14.379)	(-14.349)
	High	3.099	2.688	2.515	-0.584
		(16.924)	(16.669)	(15.705)	(-11.095)

		ENV			
AV	Grade	Low	Med	High	High-Low
	Low	4.045	3.184	2.847	-1.198
		(19.122)	(16.127)	(15.272)	(-12.792)
	Med	3.403	3.013	2.798	-0.605
		(15.159)	(15.425)	(14.528)	(-11.488)
	High	4.504	4.034	3.693	-0.811
		(17.265)	(17.727)	(16.567)	(-9.188)

		ENV			
CPN	Low	Low	Med	High	High-Low
		2.976	2.508	2.341	-0.635
		(14.877)	(13.955)	(14.629)	(-7.973)
	Med	3.730	3.281	3.124	-0.606
		(14.068)	(15.463)	(15.181)	(-8.217)
	High	4.935	4.462	4.009	-0.927
		(19.376)	(20.423)	(17.880)	(-10.274)

		ENV			
TTM	Grade	Low	Med	High	High-Low
	Low	3.733	2.944	2.465	-1.268
		(15.390)	(14.357)	(13.041)	(-14.277)
	Med	4.323	3.637	3.040	-1.284
		(16.856)	(17.391)	(14.646)	(-16.668)
	High	4.163	3.712	3.346	-0.817
		(19.105)	(17.901)	(16.313)	(-14.461)

		ENV			
Illiq	Grade	Low	Med	High	High-Low
	Low	3.626	2.930	2.571	-1.055
		(15.737)	(15.817)	(14.727)	(-13.308)
	Med	3.774	3.189	2.825	-0.949
		(16.044)	(16.657)	(15.762)	(-13.282)
	High	4.587	4.223	3.748	-0.840
		(18.509)	(17.517)	(16.706)	(-11.568)

Table 2.7: Characteristics of ENV-Sorted Portfolios

This table presents results from univariate portfolio sorts using ENV as the sorting variable and the row-specific variables as outcomes. For instance, the "Sales" row reports the average firm sales across portfolios sorted by ENV. At the end of each month, all available bonds are sorted by their ENV score lagged by 12 months, and three portfolios are formed based on the tertiles of the empirical distribution of the ENV scores. The "Low" ("High") portfolio includes bonds with ENV scores below (above) the bottom (top) tertile, while the "Med" portfolio contains the remaining bonds. The final column reports the average high-minus-low ("High-Low") difference in the outcome variable between the "High" and "Low" portfolios. Newey and West (1987) t-statistics with four-month lags are reported in parentheses. The sample period spans January 2008 to December 2021.

	(1) Low	(2) Med	(3) High	(4) High-Low
Sales	0.603	0.733	0.709	0.106
				(14.315)
Cash	0.070	0.070	0.072	0.003
				(2.785)
CF	0.079	0.091	0.096	0.016
				(13.436)
Lev	0.529	0.498	0.495	-0.034
				(-8.420)
Inc	0.073	0.080	0.097	0.024
				(7.027)
ROA	0.029	0.044	0.052	0.023
				(15.246)
Size	22.982	23.594	24.283	1.301
				(52.395)
MB	2.596	2.984	3.583	0.987
				(11.211)
DD	18.250	23.312	24.240	5.990
				(16.707)
AV	0.327	0.317	0.267	-0.060
				(-11.301)
CPN	5.280	5.026	4.758	-0.523
				(-14.234)
TTM	9.328	10.616	11.627	2.300
				(12.583)
Illiq ($\times$ 100)	0.699	0.598	0.590	-0.109
				(-4.858)

Table 2.8: Corporate Greenness and Internal Cash Flow Volatility

This table reports the results from Fama-MacBeth regressions to explore the internal cash flow uncertainty channel. In particular, we estimate the following regressions:

$$Q_{i,t} = \alpha_t + \beta_t ENV_{i,t-12} + \sum_{j=1}^{N} \gamma_{j,t} Z_{i,j,t-12} + u_{i,t}$$

where: $Q_{i,t}$ is the month t value of the cash flow volatility (CFVol, Panel A) or net income volatility (IncVol, Panel B). Both measures are calculated as the rolling standard deviation over the past five years of quarterly data. $ENV_{i,t-12}$ is the environmental score of firm i at the end of month t-12, and $Z_{i,j,t-12}$ is the value of control variable j for firm i at the end of month t-12. Newey and West (1987) standard errors (with a lag length of four) are employed in the estimations. NW t-statistics are reported in parentheses below each coefficient estimate. The sample period spans January 2008 to December 2021.

Panel A. Cash-Flow Volatility															
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Env × 100	-1.465	-1.361	-1.458	-1.428	-1.312	-1.385	-1.341	-1.212	-1.361	-1.464	-1.377	-1.627	-1.518	-1.498	-0.791
	(-5.268)	(-4.418)	(-4.493)	(-4.709)	(-4.045)	(-4.662)	(-4.257)	(-3.631)	(-4.332)	(-5.491)	(-4.612)	(-5.729)	(-5.399)	(-5.368)	(-2.047)
Sales		-0.494													-0.917
		(-5.076)													(-5.495)
Cash			5.750												6.962
			(9.752)												(7.734)
CF				1.412											2.803
				(1.619)											(2.062)
Lev					-2.953										-0.177
					(-6.603)										(-0.499)
Inc						1.089									-0.139
						(2.948)									(-0.120)
ROA							-0.073								-0.896
							(-0.057)								(-0.228)
Size								-0.092							-0.078
								(-3.019)							(-1.701)
MB									-0.105						-0.197
									(-2.699)						(-3.377)
DD										0.003					0.010
										(0.638)					(1.287)
AV											0.679				0.467
											(2.039)				(0.880)
CPN												-0.191			-0.098
												(-4.716)			(-2.017)
TTM													0.009		0.011
													(1.405)		(1.197)
Illiq														-12.273	-14.341
														(-1.180)	(-0.837)
Intercept	-4.948	-4.649	-5.405	-5.074	-3.530	-5.072	-5.029	-2.861	-4.642	-5.011	-5.215	-3.979	-5.011	-4.878	-2.779
	(-45.861)	(-32.236)	(-42.857)	(-42.713)	(-16.345)	(-46.335)	(-46.345)	(-4.253)	(-40.704)	(-32.454)	(-32.262)	(-14.034)	(-35.461)	(-54.795)	(-2.354)
R^2	0.010	0.014	0.017	0.012	0.020	0.012	0.014	0.012	0.020	0.012	0.012	0.014	0.011	0.013	0.084
Firm-Month obs.	53,608	53,011	50,288	53,043	43,468	53,157	53,025	53,058	50,772	52,408	52,408	53,608	53,608	52,939	39,659
# Months	168	168	168	168	168	168	168	168	168	168	168	168	168	168	168

Table 2.9: *Table 2.8 continued*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
							Panel B. Income Volatility								
Env (× 100)	-1.645	-1.370	-1.638	-1.396	-1.466	-1.599	-1.198	-2.217	-1.263	-1.354	-1.717	-1.568	-1.800	-1.623	-0.971
	(-9.829)	(-6.616)	(-8.177)	(-7.400)	(-7.068)	(-9.244)	(-5.977)	(-10.490)	(-7.108)	(-7.292)	(-10.026)	(-9.506)	(-9.755)	(-9.733)	(-4.293)
Sales		-2.429													-2.405
		(-21.862)													(-11.665)
Cash			0.007												4.318
			(0.012)												(6.421)
CF				-8.757											1.848
				(-8.896)											(1.816)
Lev					-4.267										-1.049
					(-19.642)										(-3.678)
Inc						2.283									0.158
						(3.305)									(0.138)
ROA							-12.328								-4.544
							(-13.299)								(-2.108)
Size								0.301							0.181
								(8.301)							(4.172)
MB									-0.182						-0.047
									(-6.697)						(-1.763)
DD										-0.046					-0.014
										(-7.125)					(-3.033)
AV											-1.197				-1.818
											(-4.815)				(-5.891)
CPN												0.123			0.261
												(3.630)			(5.209)
TTM													0.039		0.009
													(6.392)		(1.096)
Illiq														15.458	7.908
														(1.392)	(0.442)
Intercept	-3.191	-1.672	-3.268	-2.519	-1.253	-3.463	-2.892	-10.051	-2.749	-2.476	-2.887	-3.899	-3.520	-3.307	-6.358
	(-45.368)	(-15.616)	(-36.008)	(-32.158)	(-10.386)	(-54.431)	(-34.710)	(-11.872)	(-30.651)	(-25.924)	(-30.461)	(-15.493)	(-42.239)	(-44.279)	(-5.392)
R^2	0.008	0.064	0.012	0.019	0.021	0.016	0.023	0.014	0.020	0.020	0.010	0.011	0.011	0.012	0.125
Firm-Month obs.	53,371	52,782	50,059	52,814	43,260	52,928	52,796	52,829	50,488	52,174	52,174	53,371	53,371	52,705	39,394
# Months	168	168	168	168	168	168	168	168	168	168	168	168	168	168	168

Calculation of Illiquidity, Asset Volatility and Distance-to-Default

Monthly bond illiquidity (Illiq) is calculated using Amihud's measure (Amihud, 2002), defined as follows:

$$Illiq_{i,t} = \frac{1}{D_t} \sum_{d=1}^{D_t} \frac{|Ret_{i,d,t}|}{Volume_{i,d,t}} \tag{12}$$

where $Illiq_{i,t}$ is the illiquidity of bond *i* in month *t*, $Ret_{i,d,t} = log\left(\frac{P_{i,d,t}}{P_{i,d-1,t}}\right)$ is the return of bond *i* on day *d* of month *t*, $Volume_{i,d,t}$ is the trading volume of bond *i* on day *d* of month *t*, and D_t is the number of days in month *t*.

To estimate a firm's asset volatility (*AV*) and distance-to-default (*DD*), we employ the KMV model by Moody's which builds upon Merton's structural credit risk model (Merton, 1974). Under a structural credit risk modelling framework equity (*E*) is treated as a European call option on the firm's assets (*A*), with strike price equal to the value of its debt, and maturity at time *T*. The option's payoff (i.e., payoff of the firm's equity) at maturity *T* can be expressed as: $E_T = max[A_T - \widetilde{D}; 0]$, where $\widetilde{D}$ is the promised debt payment, and A_T is the value of the company's assets at time T.[16]

Using the Black-Scholes model (Black and Scholes, 1973), the current value of equity is:

$$E_0 = A_0 N(d_1) - \widetilde{D} e^{-rT} N(d_2) \tag{13}$$

where $d_1 = \frac{\ln(A_0/\tilde{D}) + (r + \frac{1}{2}\sigma_A^2)T}{\sigma_A \sqrt{T}}$ and $d_2 = d_1 - \sigma_A \sqrt{T}$

where $N(\cdot)$ denotes the cumulative standard normal distribution function, A_0 is the present value of the company's assets, r is the risk–free rate, and σ_A is the volatility of the company's asset value.

[16] Specifically, $\widetilde{D}$ is the payment on a discount bond of the company with maturity at time *T*.

It can be shown that the relationship between equity volatility (σ_E) and asset volatility (σ_A) is:

$$\sigma_E = \sigma_A N(d_1) \frac{A}{E} \tag{14}$$

In the KMV model *A* and σ_A are treated as unknowns. Thus, the above two equations form a nonlinear system with two unknowns *A* and σ_A, respectively. We solve these equations iteratively using the Newton-Raphson method. More specifically, we start with an initial guess for A and σ_A. Then, at each iteration, using the system of Equations (13) & (14), we compute the equity value and equity volatility using the current estimates. Next, we compute the error between the modelled and observed equity values and volatilities. The objective is to minimize these errors. The iterative procedure continues until the absolute values of the changes in the estimates of *A* and σ_A between successive iterations fall below predefined convergence thresholds.

Once *A* and σ_A have been estimated, the Distance to Default (*DD*) is calculated. *DD* measures how many standard deviations the firm's asset value is away from the default point over the time horizon T.

$$DD = \frac{\ln(A/D) + (r - 0.5\sigma_A^2)T}{\sigma_A \sqrt{T}} \tag{15}$$

This expression captures the expected drift in asset value relative to the default threshold, normalized by the asset's standard deviation. A higher *DD* indicates a lower likelihood of default.

Table A1: Definition of Variables

Variable	Symbol	Definition
Sales	*Sales*	Firm's net sales scaled by total assets.
Cash	*Cash*	Firm's cash and cash equivalent items scaled by total assets.
Cash flow	*CF*	Firm's net operating cash flow scaled by total assets.
Leverage	*Lev*	Firm's sum of current liabilities and long-term debt scaled by total assets.
Income	*Inc*	Firm's income before extraordinary items scaled by net sales.
Return-on-assets	*ROA*	Operating Income before depreciation as a fraction of average total assets based on the two most recent periods
Firm size	*Size*	Firm size measured by the logarithm of total assets.
Market-to-book ratio	*MB*	Market value of equity over the book value of equity.
Coupon rate	*CPN*	Bond's coupon rate
Time to maturity	*TTM*	Bond's time to maturity
Bond illiquidity	*Illiq*	Bond's illiquidity (Amihud)
Distance-to-default	*DD*	Distance to default computed using the KMV model
Asset volatility	*AV*	Asset volatility estimated using the KMV model.

Table A2: Bivariate Sorts on ENV Score and Cash-Flow and Income Volatility

This table reports the results from double independent portfolio sorts on ENV scores and cash flow volatility (CFVol, Panel A) or income volatility (IncVol, Panel B) (all lagged by 12 months). At the end of each month, we form nine portfolios from the intersection of tertile ENV portfolios and tertile portfolios of CFVol (IncVol). This sorting procedure is repeated monthly, resulting in a time series of monthly portfolio spreads for each of the nine portfolios. The final column of the table shows the average bond spread of the high-minus-low ("High-Low") ENV portfolio calculated as the difference between the average spreads of bonds in the High- and Low-ENV portfolios within each tertile of the CFVol (IncVol). Newey and West (1987) t-statistics with four lags are reported in parentheses. The sample period is from January 2008 to December 2021.

Panel A. Cash-flow Volatility

		ENV			
		Low	Med	High	High-Low
CFVol	Low	3.714	3.293	2.919	-0.795
		(15.831)	(14.330)	(16.478)	(-7.869)
	Med	4.078	3.325	3.111	-0.967
		(19.366)	(18.715)	(14.557)	(-11.657)
	High	4.249	3.634	3.025	-1.223
		(17.096)	(18.405)	(15.132)	(-15.463)

Panel B. Income Volatility

		ENV			
		Low	Med	High	High-Low
IncVol	Low	3.621	3.100	2.903	-0.718
		(18.302)	(17.613)	(16.090)	(-12.964)
	Med	3.774	3.191	2.812	-0.963
		(16.173)	(17.086)	(13.511)	(-16.111)
	High	4.463	4.042	3.456	-1.007
		(17.779)	(15.669)	(16.708)	(-10.633)

Table A3: Portfolio Sorting on Firms' ESG Scores

This table presents the average bond spread, defined as the bond yield in excess of the risk-free rate, for portfolios sorted by firms' ESG scores. At the end of each month, all available bonds are sorted by their ESG score lagged by 12 months, and three portfolios are constructed based on the tertiles of the empirical ESG score distribution. The "Low" portfolio includes bonds below the bottom tertile, the "High" portfolio includes those bonds above the top tertile, and the "Med" portfolio includes the remaining bonds. The table reports the average bond spread (i.e., excess yield) for each portfolio. The "High–Low" column shows the mean spread differential between the "High" and "Low" portfolios. The final two columns display intercept estimates from time-series regressions of the "High–Low" portfolio on contemporaneous ($\alpha_C^{BBW_{adj}}$) and lagged ($\alpha_L^{BBW_{adj}}$) values of the bond factors of Dickerson et al. (2023). All portfolio means and alpha estimates are annualized and expressed in percentage terms. Newey and West (1987) t-statistics with four lags are reported in parentheses. The sample spans January 2008 to December 2021.

	(1) Low	(2) Med	(3) High	(4) High–Low	(5) $\alpha_C^{BBW_{adj}}$	(6) $\alpha_L^{BBW_{adj}}$
Port. Mean / α	4.082	3.440	3.001	-1.081	-1.048	-1.055
	(19.017)	(15.999)	(15.069)	(-15.750)	(-17.089)	(-17.270)
MKT_t					-8.076	
					(-3.335)	
DRF_t					5.439	
					(1.869)	
CRF_t					2.767	
					(2.121)	
LRF_t					-10.850	
					(-2.189)	
MKT_{t-1}						-4.599
						(-1.154)
DRF_{t-1}						3.781
						(1.084)
CRF_{t-1}						3.193
						(2.217)
LRF_{t-1}						-11.536
						(-2.480)
R^2					0.095	0.090
# Months	168	168	168	168	168	167

Table A4: Robustness to Sorting and Portfolio Weighting Schemes

This table presents robustness checks related to the weighting scheme within portfolios (Panel A) and the sorting methodology used for constructing High–minus-Low portfolios (Panel B). In Panel A, all available bonds are sorted at the end of each month by their ENV scores lagged by 12 months, and three portfolios are formed based on the tertiles of the empirical distribution. The "Low" portfolio includes bonds below the bottom tertile, the "High" portfolio comprises bonds above the top tertile, and "Med" includes the remaining bonds. Portfolio averages are weighted by trading volume. The "High–Low" column reports the average difference in excess bond yields between the "High" and "Low" portfolios. The final two columns show intercept estimates from regressing the High–Low portfolio's time series on contemporaneous ($\alpha_C^{BBW_{adj}}$) and lagged ($\alpha_L^{BBW_{adj}}$) values of the bond factors from Dickerson et al. (2023). Panel B explores an alternative sorting specification using quintiles instead of tertiles, based on equally spaced percentiles of ENV scores. The "High–Low" column shows the spread differential between the top and bottom quintiles. The portfolios in Panel B revert to equal-weighting, consistent with the main analysis in Table 2.3. All portfolio means and alphas are annualized and expressed in percentage terms. Newey and West (1987) t-statistics with four lags are employed in the estimations (reported in parentheses). The sample period is from January 2008 to December 2021.

Panel A: Trading Volume Weights

	Low	Med	High	High–Low	$\alpha_C^{BBW_{adj}}$	$\alpha_L^{BBW_{adj}}$
Port. Mean / α	4.067	3.480	3.099	-0.968	-0.916	-0.926
	(17.804)	(17.481)	(16.076)	(-13.377)	(-14.456)	(-14.569)

Panel B: Sorting into 5 portfolios

	Low	2	3	4	High	High-Low	$\alpha_C^{BBW_adj}$	$\alpha_L^{BBW_adj}$
Port. Mean / α	4.072	3.906	3.438	3.119	2.976	-1.095	-1.053	-1.068
	(18.435)	(16.811)	(17.571)	(15.963)	(14.541)	(-16.518)	(-17.632)	(-18.016)

Table A5: Fama-MacBeth Regressions - Sub-sample Analysis

This table presents the results of monthly Fama and MacBeth (1973) regressions, where bond spreads are regressed on ENV scores and a set of control variables. ENV scores and all control variables are lagged by 12 months. Column (1) reports the results using the full sample. Columns (2) and (3) present results for two sub-periods: before and after the Paris Agreement. As the agreement came into effect around the end of 2016, we use December 2016 as the breakpoint. The second-to-last row ("Mean Obs/Month") reports the average number of observations per month, while the final row ("# Months") indicates the total number of months in the sample. Newey and West (1987) t-statistics with four lags are reported in parentheses. The sample period spans January 2008 to December 2021.

	(1)	(2)	(3)
	Full sample	Pre-Paris	Post-Paris
Env × 100	-0.362	-0.376	-0.337
	(-8.511)	(-5.972)	(-9.494)
Sales	-0.123	-0.106	-0.152
	(-3.150)	(-1.831)	(-5.176)
Cash	0.027	0.301	-0.465
	(0.114)	(0.871)	(-2.722)
CF	-0.426	-1.306	1.158
	(-1.122)	(-3.438)	(2.011)
Lev	0.823	0.590	1.241
	(8.474)	(5.532)	(10.871)
Inc	-0.542	-0.779	-0.116
	(-1.956)	(-1.907)	(-0.576)
ROA	-3.581	-3.524	-3.685
	(-7.243)	(-6.609)	(-3.710)
Size	-0.236	-0.251	-0.207
	(-16.526)	(-13.397)	(-11.223)
MB	-0.012	0.002	-0.037
	(-1.774)	(0.202)	(-6.444)
DD	-0.030	-0.036	-0.019
	(-7.029)	(-5.897)	(-7.479)
AV	0.959	1.134	0.643
	(7.636)	(6.526)	(5.511)
CPN	0.430	0.463	0.371
	(14.240)	(11.311)	(10.336)
TTM	0.081	0.094	0.057
	(11.139)	(10.221)	(7.200)
Illiq	41.970	28.755	65.756
	(7.836)	(7.309)	(6.504)
Intercept	6.166	6.829	4.972
	(13.921)	(11.336)	(11.945)
Mean R^2	0.657	0.674	0.627
Mean Obs/Month	246	191	346
# Months	168	108	60

Table A6: Bond Spread Sorted on ENV by Sector

This table reports bond spread sorting results by sector from January 2008 to December 2021. Each month, the 33rd and 66th percentiles of 12-month-lagged ENV scores in the full sample are used as common portfolio breakpoints across sectors. Low, Med, and High denote the portfolios with low, medium, and high ENV scores, respectively. Within each sector, portfolio means use the available months for each portfolio, while the High–Low mean and its t-statistic use only months in which both the High and Low portfolios have observations. Consequently, the reported High–Low mean may differ from the difference between the separately reported High and Low means. Newey and West (1987) t-statistics with four lags are reported in parentheses.

Sector	(1) Low	(2) Med	(3) High	(4) High–Low
Communication Services	4.541	2.894	2.828	-1.623
	(20.947)	(12.774)	(21.739)	(-12.865)
Consumer Discretionary	4.347	3.770	3.607	-0.740
	(15.298)	(16.058)	(16.696)	(-7.886)
Consumer Staples	4.709	2.747	2.375	-2.377
	(17.111)	(17.367)	(16.578)	(-12.374)
Energy	5.313	4.142	3.083	-2.229
	(22.666)	(21.575)	(19.118)	(-12.179)
Financials	3.999	3.334	2.814	-1.185
	(13.439)	(11.210)	(12.333)	(-12.612)
Health Care	3.505	3.047	2.678	-0.828
	(16.476)	(17.429)	(14.384)	(-6.956)
Industrials	3.888	3.044	3.016	-0.873
	(19.674)	(20.608)	(15.142)	(-7.682)
Information Technology	3.175	3.671	3.012	-0.164
	(14.418)	(11.852)	(12.808)	(-2.552)
Materials	4.233	4.155	3.563	-0.669
	(15.618)	(17.639)	(17.046)	(-5.890)
Real Estate	3.622	2.876	4.056	0.430
	(13.374)	(15.806)	(11.384)	(2.151)
Utilities	3.366	3.266	2.788	-0.578
	(11.341)	(13.750)	(14.004)	(-4.029)

Table A7: Portfolio Sorting on Firms' Carbon Intensity

This table reports monthly portfolio sorts based on firms' carbon intensity lagged by 12 months. The five sorting measures are Scope 1, Scope 2, Scope 3, Scope 1+2, and Scope 1+2+3 carbon intensity. Scope 1 covers direct emissions from sources owned or controlled by the firm. Scope 2 covers indirect emissions from purchased electricity and energy. Scope 3 covers other indirect emissions in the firm's value chain. At the end of each month, all available bonds are sorted separately into three portfolios using the tertiles of each carbon-intensity measure. The Low, Medium, and High columns report equal-weighted average bond spreads. High–Low is the average spread of the High portfolio minus that of the Low portfolio. All spreads are annualized and expressed in percentage terms. Newey and West (1987) t-statistics with four lags are reported in parentheses. Carbon intensity is matched using an exact 12-month firm-month lag. The sample spans January 2009 to December 2021.

Carbon-intensity measure	(1) Low	(2) Medium	(3) High	(4) High–Low
Scope 1	3.104	3.204	3.450	0.346
	(14.346)	(16.923)	(18.676)	(5.145)
Scope 2	3.221	3.077	3.459	0.238
	(13.669)	(18.838)	(18.019)	(3.071)
Scope 3	3.175	3.171	3.412	0.237
	(14.314)	(18.009)	(17.774)	(4.934)
Scope 1+2	3.113	3.167	3.478	0.366
	(13.811)	(17.858)	(18.500)	(5.004)
Scope 1+2+3	3.121	3.202	3.435	0.314
	(14.491)	(16.252)	(19.253)	(4.587)
Mean Obs/Month		260		
# Months		156		

Table A8: Fama–MacBeth Regressions Using Carbon Intensity

This table reports the time-series average coefficients from monthly Fama and MacBeth (1973) cross-sectional regressions of bond spreads on five alternative carbon-intensity measures. Carbon intensity is lagged by 12 months and divided by 100, so its coefficient is the percentage-point change in the annualized bond spread associated with a 100-unit increase in carbon intensity. Panel A reports univariate regressions. Panel B adds the firm- and bond-level controls used in Table 2.4. Panel C includes both carbon intensity and ENV together with the full set of controls; coefficients on the controls are not repeated in Panel C to save space. ENV coefficients are reported after being multiplied by 100. Newey and West (1987) t-statistics with four lags are reported in parentheses. The sample spans January 2009 to December 2021.

	(1) Scope 1	(2) Scope 2	(3) Scope 3	(4) Scope 1+2	(5) Scope 1+2+3
Panel A: Univariate regressions					
Carbon intensity (per 100 units)	0.005	0.196	0.033	0.006	0.006
	(6.854)	(6.104)	(3.952)	(7.019)	(7.098)
Intercept	3.236	3.168	3.196	3.231	3.220
	(16.510)	(16.148)	(15.956)	(16.470)	(16.355)
Mean R^2	0.005	0.018	0.007	0.006	0.007
Mean Obs/Month	260	260	260	260	260
# Months	156	156	156	156	156
Panel B: Regressions with firm- and bond-level controls					
Carbon intensity (per 100 units)	0.004	0.041	-0.016	0.004	0.003
	(8.704)	(2.869)	(-3.577)	(8.719)	(7.302)
Sales	-0.096	-0.109	-0.103	-0.095	-0.100
	(-3.245)	(-3.734)	(-3.754)	(-3.217)	(-3.357)
Cash	-0.208	-0.258	-0.352	-0.201	-0.212
	(-1.548)	(-2.099)	(-2.750)	(-1.498)	(-1.594)
CF	-0.997	-1.066	-1.100	-0.998	-0.985
	(-2.324)	(-2.420)	(-2.481)	(-2.323)	(-2.268)
Lev	0.798	0.836	0.792	0.802	0.809
	(9.335)	(9.768)	(9.254)	(9.375)	(9.481)
Inc	-0.217	-0.216	-0.291	-0.214	-0.205
	(-1.070)	(-1.119)	(-1.439)	(-1.059)	(-1.010)
ROA	-3.081	-3.136	-3.037	-3.080	-3.108
	(-6.397)	(-6.427)	(-6.434)	(-6.404)	(-6.430)
Size	-0.250	-0.244	-0.250	-0.250	-0.248
	(-16.012)	(-16.128)	(-16.043)	(-16.037)	(-16.214)
MB	-0.008	-0.009	-0.010	-0.008	-0.008
	(-0.995)	(-1.123)	(-1.336)	(-1.009)	(-1.042)
DD	-0.027	-0.027	-0.027	-0.027	-0.027
	(-6.026)	(-5.900)	(-5.849)	(-6.020)	(-6.027)
AV	1.021	0.990	1.012	1.020	1.020
	(7.977)	(7.503)	(7.653)	(7.979)	(7.964)
CPN	0.373	0.373	0.375	0.373	0.373
	(15.297)	(15.021)	(15.171)	(15.299)	(15.254)
TTM	0.087	0.087	0.087	0.087	0.087
	(12.425)	(12.509)	(12.524)	(12.424)	(12.383)
Illiq	50.471	50.015	50.803	50.436	50.462
	(7.605)	(7.530)	(7.615)	(7.597)	(7.592)
Intercept	6.287	6.159	6.349	6.282	6.238
	(13.154)	(13.172)	(13.259)	(13.158)	(13.249)
Mean R^2	0.696	0.696	0.696	0.696	0.696
Mean Obs/Month	194	194	194	194	194
# Months	156	156	156	156	156
Panel C: Joint regressions with ENV and full controls					
Carbon intensity (per 100 units)	0.004	0.061	-0.011	0.004	0.004
	(9.434)	(4.092)	(-2.502)	(9.602)	(8.374)
ENV × 100	-0.328	-0.347	-0.294	-0.331	-0.332
	(-10.026)	(-11.580)	(-8.653)	(-10.122)	(-9.992)

Table A9: Panel Regression Results Using Carbon Intensity

This table presents panel regression results corresponding to the specifications used in Table 2.5. Each panel replaces ENV with one of five carbon-intensity measures. Carbon intensity is matched using an exact 12-month firm-month lag and divided by 100, so its coefficient represents the percentage-point change in the annualized bond spread associated with a 100-unit increase in carbon intensity. The other control variables are already lagged by 12 months. Columns (1)–(2) include time (month) fixed effects, Columns (3)–(4) include sector fixed effects, and Columns (5)–(6) include both time and sector fixed effects. The even-numbered columns include the firm- and bond-level controls used in Table 2.5. Coefficients on the controls and intercepts are not reported to save space. Standard errors are two-way clustered by firm and calendar year, and the resulting t-statistics are reported in parentheses. The sample spans January 2009 to December 2021.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Scope 1 carbon intensity						
Carbon intensity (per 100 units)	0.005	0.003	0.017	0.006	0.012	0.004
	(1.077)	(1.870)	(3.181)	(2.491)	(2.405)	(1.972)
Firm and bond controls	No	Yes	No	Yes	No	Yes
Time F.E.	Yes	Yes	No	No	Yes	Yes
Sector F.E.	No	No	Yes	Yes	Yes	Yes
Firm-Month Obs.	40,522	30,321	40,522	30,321	40,522	30,321
R^2	0.321	0.697	0.064	0.568	0.386	0.703
Panel B: Scope 2 carbon intensity						
Carbon intensity (per 100 units)	0.130	0.017	0.005	0.001	0.010	0.008
	(1.995)	(0.825)	(0.094)	(0.070)	(0.230)	(0.480)
Firm and bond controls	No	Yes	No	Yes	No	Yes
Time F.E.	Yes	Yes	No	No	Yes	Yes
Sector F.E.	No	No	Yes	Yes	Yes	Yes
Firm-Month Obs.	40,522	30,321	40,522	30,321	40,522	30,321
R^2	0.324	0.697	0.057	0.567	0.383	0.703
Panel C: Scope 3 carbon intensity						
Carbon intensity (per 100 units)	0.033	-0.013	0.031	-0.040	0.023	-0.028
	(1.268)	(-1.189)	(0.917)	(-3.007)	(0.737)	(-2.089)
Firm and bond controls	No	Yes	No	Yes	No	Yes
Time F.E.	Yes	Yes	No	No	Yes	Yes
Sector F.E.	No	No	Yes	Yes	Yes	Yes
Firm-Month Obs.	40,522	30,321	40,522	30,321	40,522	30,321
R^2	0.321	0.697	0.058	0.568	0.383	0.703
Panel D: Scope 1+2 carbon intensity						
Carbon intensity (per 100 units)	0.006	0.003	0.017	0.006	0.012	0.004
	(1.210)	(1.896)	(3.167)	(2.504)	(2.382)	(1.956)
Firm and bond controls	No	Yes	No	Yes	No	Yes
Time F.E.	Yes	Yes	No	No	Yes	Yes
Sector F.E.	No	No	Yes	Yes	Yes	Yes
Firm-Month Obs.	40,522	30,321	40,522	30,321	40,522	30,321
R^2	0.321	0.697	0.064	0.568	0.386	0.703
Panel E: Scope 1+2+3 carbon intensity						
Carbon intensity (per 100 units)	0.006	0.002	0.016	0.004	0.011	0.003
	(1.308)	(1.670)	(3.196)	(2.364)	(2.452)	(1.587)
Firm and bond controls	No	Yes	No	Yes	No	Yes
Time F.E.	Yes	Yes	No	No	Yes	Yes
Sector F.E.	No	No	Yes	Yes	Yes	Yes
Firm-Month Obs.	40,522	30,321	40,522	30,321	40,522	30,321
R^2	0.322	0.697	0.064	0.567	0.386	0.703

3 Essay 2: Climate Change Risk and Bond Yield Spreads

3.1 Introduction

As we discussed in the first essay, climate change denotes a significant, long-term alteration in the planet's weather patterns and average global temperatures, primarily driven by human activities. This phenomenon leads to the emergence of climate change risks, which pertain to the potential harm inflicted on human and ecological systems by these changes.

Green finance has become increasingly crucial as climate change continues to pose increasing challenges. Several studies have explored the relationship between climate change risks and financial instruments. For instance, Ardia et al. (2023) find that when there is an unexpected increase in climate change risk, the stock prices of green firms tend to rise, while those of brown firms decline. Similarly, Bansal et al. (2017) indicate that climate change risk, as proxied by temperature rise, adversely affects stock market valuations, suggesting that financial markets do price in climate change risks. On the other hand, Faccini et al. (2023) highlight that it is the regulatory risks stemming from government interventions rather than the physical risks from climate change that are priced in the U.S. stock market. Despite these insights into stocks, there is a notable lack of research on the impact of climate change risk on corporate bonds. This naturally raises the question: Would bonds be affected by climate risk in the same manner as stocks?

This essay studies whether climate risk is priced in the cross-section of corporate bond spreads. In particular, we ask whether bonds with greater exposure to climate risk command higher yield spreads, and which dimensions of climate risk are most relevant for bond investors. While prior studies mainly focus on equities, the consequences for corporate bonds remain unclear. Therefore, we focus on bond spreads, which more effectively capture the expected compensation required by debt holders and allow us to isolate the pricing effect of climate risk from other sources of variation in realized bond

returns.

We measure climate risk using two complementary indices: the Attention to Climate News Index, constructed from Google Trends data, and the Faccini Climate Risk Index (Faccini et al., 2023), based on textual analysis of news sources. Using rolling regressions, we estimate firm-level climate betas that reflect the sensitivity of bond spreads to changes in climate risk. We then examine the pricing of climate risk using portfolio sorts, Fama–MacBeth, and panel regressions, while controlling for a comprehensive set of firm- and bond-level characteristics.

Our findings show a robust positive association between firms' climate-risk exposure and corporate bond spreads. Bonds with greater climate betas consistently exhibit wider spreads, and this relationship remains after controlling for traditional credit-risk factors and firm- and bond-level characteristics. The evidence is therefore consistent with climate-related information being incorporated into bond spreads. However, it does not establish that investors fully or correctly price the future losses associated with climate risk.

Importantly, we find substantial heterogeneity across the different dimensions of climate risk. Transition or policy-related exposure produces the largest and most consistent High–Low portfolio spread differentials. However, some physical-risk measures, particularly physical-risk causes, also remain significant in the controlled regressions. The evidence therefore points to a particularly strong role for transition risk rather than an exclusive role.

This essay contributes to the climate-finance literature in three ways. First, it provides evidence on the relationship between firm-level climate-risk exposure and corporate bond yield spreads. Second, it directly compares transition and physical climate risk within the same corporate bond setting. Previous studies show that climate-risk dimensions can have different effects in equity, option, and bond markets (e.g., Faccini et al., 2023; Ilhan et al., 2021; Huynh and Xia, 2021; Seltzer et al., 2022). This essay extends that literature by estimating firm-level exposure to separate climate-risk dimen-

sions and examining them using the same portfolio and regression methods. The comparison is also repeated using both attention-based and news-based climate indices. The contribution is therefore not the first evidence that regulatory risk matters for bonds, but a systematic comparison of transition and physical exposure in the cross-section of corporate bond spreads. Third, the essay develops a novel attention-based climate risk index using Google Trends data, which provides a flexible and accessible measure of changes in public climate attention.

The remainder of the essay is structured as follows. Section 3.2 reviews the related literature. Section 3.3 describes the data and variable construction. Section 3.4 presents the empirical results. Section 3.5 provides additional robustness tests. Section 3.6 concludes.

3.2 Literature Review

3.2.1 Background on Corporate Climate Risk

Climate risk refers to the potential damage to human or ecological systems caused by climate change. It essentially encompasses the various risks caused by climate change and its effects on human life. Usually, there are two broad types of climate risk: (i) Physical climate risk, which materializes in the form of financial losses/increased costs from the impact of chronic and acute physical events, and (ii) Transition risk, which arises from the costly adjustment towards a low-carbon economy and is typically prompted by changes in climate and/or environmental policy, technological advances, and/or shifts in public preferences (Bua et al., 2024).

Physical climate risk reflects losses arising from acute and chronic physical consequences of climate change, including extreme heat, floods, storms, droughts, wildfires, and sea-level rise. Research to date has documented severe economic consequences due to physical climate risk. For instance, Cosemans et al. (2022) show that rising temperatures affect asset prices by increasing the likelihood of climate-driven disasters that can have a negative impact on economic growth. Ozturk et al. (2022)

argue that climate uncertainty, associated with climate policy and natural hazards, is a significant driver of the dynamics of the prices of carbon emission allowances. Besides the physical risks, i.e., those stemming from natural disasters and rising temperatures, transition risks, i.e., those stemming from government intervention via carbon taxation and incentives to develop green technologies, are also highly important and have recently attracted special attention (Faccini et al., 2023).

Climate transition risk is the risk for businesses that stems from changes in environmental policies, since there is expected to be business risk for firms to transition their usual business to one with a lower gas-emitting level. It is related to the process of adjustment to a low-carbon economy (Collender et al., 2023). Again, Bolton and Kacperczyk (2023) find that short-term transition risk is greater for firms located in countries with lower economic development, greater reliance on fossil energy, and less inclusive political systems. Importantly, they argue that climate transition risk is different from physical climate risk.

In terms of general impact due to transition risk, Reboredo and Ugolini (2022) find that firms with low exposure to transition risk have better financial performance. They also find that European firms are more sensitive to climate transition risks than those in the US, implying that the sensitivity to climate transition risk exhibits geographical heterogeneity. The findings in Reboredo and Ugolini (2022) are consistent with Bolton and Kacperczyk (2023) in the sense that short-term transition risk is greater for firms located in less developed countries that rely more on fossil-fuel energy, while long-term transition risk is greater in countries with stricter domestic climate policies. Similarly, Dumrose and Höck (2023) show that firms in more restrictive regulatory environments have higher credit spreads, better carbon-risk performance leads to lower credit spreads, a higher exposure leads to larger credit spreads, while good management can reduce credit spreads.

The strand of literature on climate risk impact on the financial market has grown rapidly recently, and the distinction between physical and transition risk is central to the broader climate-finance lit-

erature (Giglio et al., 2021). Existing evidence suggests that their relative importance differs across markets. In equity markets, Bolton and Kacperczyk (2023) document the pricing of carbon-transition risk, while Faccini et al. (2023) find that the U.S. climate-policy factor is more strongly priced than their physical-risk measures. In European markets, however, Bua et al. (2024) find evidence of both transition and physical risk premiums. In the option market, Ilhan et al. (2021) show that climate-policy uncertainty is reflected in the cost of downside protection for carbon-intensive firms. In fixed-income markets, Huynh and Xia (2021) examine climate-news exposure and corporate bond returns, while Seltzer et al. (2022) show that climate regulatory risk affects corporate credit ratings and yield spreads.

These studies show that climate risk cannot be treated as a single and uniform source of financial risk. However, relatively limited evidence directly compares transition and physical exposure within the same corporate bond spread framework. This essay contributes to the literature by estimating firm-level betas for separate climate-risk dimensions and examining their associations with bond spreads under the same portfolio construction, regression controls, and sample period. This approach provides a direct comparison of which dimensions are more relevant to creditors.

3.2.2 Background on Climate Risk Indices

With the increasing awareness of climate change, the concept of a climate risk index has gained significant attention. Developing a reasonable and effective climate risk index is crucial due to the variety of possible methods used to construct it, potentially leading to diverse results. Ardia et al. (2023) demonstrate that by analyzing climate change-related news articles from U.S. newspapers and newswires, green firms are more profitable and earn higher returns, a finding consistent with Pástor et al. (2022). Conversely, Bolton and Kacperczyk (2021) report that firms with higher carbon emissions tend to earn higher returns. In the options market, Ilhan et al. (2021) show that climate

policy uncertainty is factored into prices, with the cost of protection against tail risks being higher for firms with more carbon-intensive business models. This cost increases further during periods of heightened public attention to climate change. In European markets, Bua et al. (2024) observe that climate risk premiums for both transition and physical climate risks have risen since the Paris Agreement. Additionally, Jiang et al. (2019) compute a monthly manager sentiment index based on the aggregated tone in 10-Ks, 10-Qs, and conference call transcripts, reflecting sentiments toward climate risks.

Carbon Risks

Several studies have utilized carbon emission data to represent climate change risk. For instance, Duan et al. (2025) examine the relationship between climate risk and expected corporate bond returns by employing carbon emission intensity (CEI) as a measure of a firm's carbon risk. Their findings indicate that bonds issued by firms with higher carbon intensity tend to earn significantly lower future returns. This effect remains robust even after accounting for a comprehensive set of bond and firm characteristics, as well as exposure to established stock and bond risk factors.

Similarly, Bansal et al. (2017) leverage empirical estimates and the temperature-augmented long-run risks model to quantify the social cost of carbon. This metric, which calculates the present value of damages resulting from a marginal increase in carbon emissions, plays a crucial role in the economic analysis of global warming and in informing policy decisions. Moreover, Seltzer et al. (2022) demonstrate that higher carbon emissions generally correlate with lower credit ratings and higher bond yield spreads. This suggests that firms with significant carbon emissions may face higher costs of borrowing.

Search Volume and Textual Analysis

Recent studies have increasingly focused on how financial markets respond to news events. For

example, Naughton et al. (2019) observe that announcements related to green activities lead to positive abnormal returns, particularly when investors value sustainability highly. Similarly, Flammer (2013) reports positive market reactions to eco-friendly initiatives, while Capelle-Blancard and Petit (2019) find negative stock market reactions to adverse climate news. Consequently, there is a growing interest in quantifying climate change risks through search volume metrics and textual analysis, reflecting public concerns and sentiment. Essential to these studies are two critical inputs: search volume data and lexicons.

Google Trends provides anonymized, categorized, and aggregated information on the relative frequency of Google search queries. Its non-real-time series are available from 2004 onwards and have been widely used as measures of public and investor attention. Numerous studies have explored methodologies for leveraging Google Trends data (e.g., Curme et al., 2014; Choi and Varian, 2012; Choi et al., 2020; El Ouadghiri et al., 2021). Vlastakis and Markellos (2012) show a positive relationship between search volume for specific stocks, trading volume, and return volatility. Bank et al. (2011) extend this by tracking not only individual stock tickers, but also general public names of specific companies, finding that increases in search queries for specific stocks indicate an increase in attention from stock market investors, and that these increases in queries precede a temporary increase in future returns. Beyond the realm of the stock market, Han et al. (2018) show that investor attention proxied through Google Trends data was statistically significant in driving currency returns. Aliano et al. (2023) construct Google Search Volume Indices for the term "climate change" across multiple countries and languages. They find that greater public attention to climate change is associated with relatively higher returns for stocks with high ESG scores than for stocks with low ESG scores.

Textual analysis is another pivotal approach in evaluating climate risks. Faccini et al. (2023) extract articles from the Thomson Reuters News Archive for Machine Readable News and conduct textual analysis by employing the Latent Dirichlet Allocation (LDA, Blei et al., 2003), which is one

of the most commonly employed topic models in textual analysis (Zhao et al., 2016). LDA is a textual method that takes a collection of articles and the number of unique words (termed vocabulary) contained in these articles as inputs, which is also used by Curme et al. (2014). Engle et al. (2020) construct climate-news measures using two sources: climate-related coverage in The Wall Street Journal (WSJ) and content collected by the data analytics provider Crimson Hexagon (CH). The latter covers more than 1,000 news outlets, including The New York Times, The Washington Post, Reuters, BBC, CNN, and Yahoo News. El Ouadghiri et al. (2021) quantified US media attention to climate change and pollution with the weekly number of articles about climate change and pollution that are released in four major US newspapers (i.e., The New York Times, The Wall Street Journal, The Washington Post, and USA Today). Ardia et al. (2023) further construct a daily Media Climate Change Concerns index using climate change-related news articles from U.S. newspapers and newswires. In another approach, Bollen et al. (2011) demonstrated that constructing a statistical model using Twitter mood as an indicator could generate a directional forecast for movements in the Dow Jones Industrial Average index (DJIA) at an extremely high accuracy level.

Lexicon also plays a crucial role that varies from study to study. Media can influence a population's perceptions in two ways: (i) via the informational content communicated in news articles and (ii) by the level of news coverage or attention on a particular subject. Ardia et al. (2023) define concerns as "the perception of risk and related negative consequences associated with this risk." From this definition, they design a score that measures concerns from the informational content of news articles, which relies on two lexicons: (i) a risk lexicon to determine the level of discussion about (future) risk events and (ii) a sentiment lexicon to assess the increase in (the perception of) risk. These lexicons are retrieved from the LIWC2015 software (Pennebaker et al., 2015). The number of risk words, positive words, negative words, and total words in a news article published on a certain day by a certain source is considered and analyzed in the process. The risk lexicon of this software is

also used in Stecula and Merkley (2019) to analyze how the news media shape public opinion about climate change, while for El Ouadghiri et al. (2021), when they consider the weekly Google Search Volume Index (GSVI), it refers to the two keywords "climate change" and "pollution" in the USA.

3.2.3 Research Hypotheses

In this study, our research objective is to examine the relationship between climate risk and corporate bond spreads. Specifically, we aim to answer the following important question: Is the effect of climate risk significantly priced in the cross-section of excess corporate bond spreads? Our research fills a gap in the literature, as the impact of climate risk on corporate bonds remains underinvestigated. As discussed earlier, mainstream studies primarily focus on equities, leaving the effect on corporate bonds unclear. As realized bond returns include both expected and unexpected components (Elton, 1999), we examine corporate bond spreads, which capture the expected return required by debt holders at a given point in time. Thus, using bond spreads allows us to better isolate the pricing effect of climate risk.

In addition, we will separately explore which dimensions of climate risk are priced in the cross-section. Climate risk can be divided into several dimensions, such as physical risk and transition (regulatory) risk. Faccini et al. (2023) document that different dimensions of climate risk have different effects in the stock market. However, there is limited evidence on which dimension is most important for corporate bonds. Given the wide range of climate risk proxies proposed in the literature, it is important to identify which measures are most relevant for bond investors.

Based on the above discussion, we develop the following hypotheses.

First, climate risk increases uncertainty about future cash flows and policy changes. In the bond market, higher risk leads investors to require higher spreads as compensation. Therefore, if climate risk is priced, bonds with higher exposure to climate risk should have higher excess spreads.

H1: Climate risk is positively priced in the cross-section of corporate bond spreads.

Second, there are several reasons why transition risk may have a stronger association with corporate bond spreads. Environmental policies often have identifiable announcement or implementation dates and may create costs within the remaining life of a bond. Carbon taxes, compliance costs, required capital expenditure, and possible impairment of carbon-intensive assets can reduce cash flows and recovery values and increase default risk. Policy changes may also affect many firms at the same time and are highly visible to investors. In contrast, physical risk is often location-specific and more uncertain in its timing and severity. Some physical losses may occur beyond the maturity of current bonds, while firms may partly reduce their exposure through insurance, adaptation, or geographic diversification. These differences provide the economic basis for H2, but they do not imply that physical climate risk is unimportant (Faccini et al., 2023; Seltzer et al., 2022; Giglio et al., 2021).

H2: Transition (policy-related) climate risk has a stronger association with corporate bond spreads than physical climate risk.

3.3 Data and Variable Construction

To explore the relationship between climate risk and corporate bond spreads, we employ two different indices, the Attention to Climate News Index and the Faccini Climate Risk Index, to quantify climate risk. We do not follow other studies in using carbon emissions as a measure of climate risk, although carbon emissions data are also a popular proxy for corporate greenness. We argue that carbon emissions capture only part of climate risk, reflecting primarily firms' exposure to regulatory and transition-related risks associated with carbon-intensive activities, but do not account for broader sources of climate risk, such as changes in investor attention, policy uncertainty, and prospective market expectations.

Corporate bond yield data is collected from Enhanced TRACE via WRDS. The Enhanced TRACE corporate bond data is an alternative to the standard TRACE corporate bond data, but it contains transaction reports for all intra-day transactions. Therefore, we follow Dick-Nielsen (2014) closely to clean the bond quotes in the sample. Briefly speaking, three types of transactions are cleaned: (i) we remove original trades due to same-day cancellation and correction; (ii) we follow reversal reports and delete the original trades that are identified in the reports. Reversal reports are used to cancel trades, but, different from a cancellation report, which is done on the same trade day, it is done on a later day; (iii) we delete transactions by agency and inter-dealer, as these transactions are duplicates, and impose additional filters.[17] After cleaning the bond data, we obtain the last trade quotes of each bond entity each day. The TRACE sample includes US bond quotes in terms of price and yield since 2002, and in this study, we use the month-end yields to produce key empirical analysis. Note that at any given time, a firm can have multiple bonds traded in the bond market. To obtain an effective bond yield for firm i at month t, we consider equal–weighted constructions. We follow prior studies to use the one-month US Treasury bill rate as the risk-free rate.[18]

The Attention to Climate News Index is constructed from search volume in Google Trends from January 2004 to December 2021, using a lexicon similar to that provided by Gong et al. (2023). We group words into five different categories representing public climate attention and build a vocabulary for each aspect based on Table B10. We searched these words on Google Trends and collected monthly data for each keyword, scaled from 0 to 100. We then calculated the category-level monthly values by taking the equal-weighted average of the keywords within each category. Finally, we constructed the overall monthly Google Trends index by averaging across categories using equal weights. Faccini Climate Risk Index utilizes articles from the Thomson Reuters News Archive from January

[17] After we clean the bond data, we further remove 'when-issued' trades, trades that are not in the secondary market, trades under special circumstances or non-standard settlement, commissioned trades, and automatic-give-up trades. Finally, we remove negative bond yields and winsorize the bond yields at 5/95% levels. These are additional filters suggested by Dick-Nielsen (2014) or based on our needs for empirics.

[18] The risk-free rate is obtained from Kenneth French Data Library: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library.html.

2000 to December 2021 [19]. These diverse sources for the two indices ensure a comprehensive examination of climate risk, with each index serving as a control for the other.

The Attention to Climate News Index and the Faccini Climate Risk Index are market-wide time-series measures. Therefore, each index has the same value for all firms in a given month and cannot directly measure differences in firm-level exposure. To convert the aggregate index into a firm-level measure, we estimate how strongly each firm's bond spread has historically moved with the climate index. For each firm-month, we re-estimate the following time-series regression using the most recent 48 months of data and require at least 24 valid monthly spread observations:

$$\text{SPR}_{i,t} = \alpha_i + \beta_{i,t}^{\text{climate}} ClimateIndex_t + \epsilon_{i,t} \tag{16}$$

where $SPR_{i,t}$ is the equal-weighted average bond spread of firm i in month t, and $ClimateIndex_t$ is either the Attention to Climate News Index or the Faccini Climate Risk Index. We repeat this procedure for each firm and every month to obtain the firm-month estimated slope coefficient, $\beta_{i,t}^{\text{Climate}}$, which is the firm's climate beta.

The economic interpretation of this coefficient is straightforward. A high positive climate beta means that the firm's bond spread moves upward more when the climate index is higher, indicating that bond yields are more sensitive (riskier) to climate-related news. By comparison, a climate beta close to zero indicates little historical co-movement between the firm's spread and the index, while a negative beta indicates that the spread has tended to be lower when the index was higher.

Importantly, a high climate beta does not necessarily mean that the firm has high carbon emissions, poor environmental performance, or a permanently high bond spread. Instead, it indicates that the firm's borrowing-cost spread has been more sensitive to changes in market-wide climate attention or climate risk. This sensitivity may reflect the firm's business model, regulatory exposure, physical

[19] URL: https://sites.google.com/site/econrenatofaccini/home/research

assets, supply chain, or investors' assessment of its climate vulnerability. The beta itself does not identify which of these channels is responsible.

Because the regression is estimated using a rolling window, the climate beta is allowed to change over time as the firm's operations and investors' assessment of its exposure change. We merge these firm-level beta estimates with the bond-spread data, resulting in approximately 42,000 firm-month observations covering 568 U.S. firms from 2008 to 2021. In the empirical tests for month t, we use the climate beta estimated for month $t-1$. This one-month lag ensures that the exposure measure is based only on information available before the bond spread being examined.

The rolling-window design also determines the measurement horizon of climate beta. Because the beta is estimated using monthly observations from the previous 48 months, it captures the firm's recent historical sensitivity to climate-related attention. It does not measure the firm's total exposure to climate losses that may occur over future decades. The monthly updating frequency should also not be interpreted as a one-month pricing horizon; it only describes how frequently the exposure measure is re-estimated.

Table B1 in Appendix B presents summary statistics for the cross-section of bond spreads and climate beta, calculated across all available firm-month observations. The average annualized bond spread is 3.088%, while the pooled mean climate beta is approximately 0.030 (Attention to Climate News Index) and 0.031 (Faccini Climate Risk Index).

[Insert Table B1 here.]

Table B2 in Appendix B presents yearly cross-sectional summary statistics for corporate bond spreads. Average spreads exhibit a modest downward trend over the sample period. The number of observations increases from 1,244 in 2008 to 4,679 in 2021, reflecting a steady expansion in firm-bond coverage by Refinitiv. Bond spreads exhibit a pronounced decline following the Global Financial

Crisis, decreasing from a peak of 6.301% in 2009 to approximately 1.5–2.5% in the later years of the sample. This trend shows improving credit conditions and a prolonged low-interest-rate environment, with a temporary increase observed in 2020 during the COVID-19 pandemic.

[Insert Table B2 here.]

Other Variables: We also collect a range of firm-specific and bond-specific characteristics to serve as control variables in our subsequent estimations. Specifically, the variables include: net sales over total assets (Sales), operating cash flow over total assets (CF), leverage (Lev), cash holdings (Cash), net operating income scaled by net sales (Inc), return on assets (ROA), firm size (Size), the market-to-book ratio (MB), the bond's coupon rate (CPN), time to maturity (TTM), illiquidity (Illiq), distance to default (DD), and asset volatility (AV). Definitions and detailed descriptions of all variables are provided in Table B11 of the appendix. The DD and AV measures are derived using the KMV model, with further details provided in Appendix A, as in the first essay. For the month-t bond-spread tests, climate beta is measured at $t-1$, whereas all firm- and bond-level conditioning and control variables are measured at $t-12$. Aggregate factors used only in the time-series risk-adjustment regressions enter contemporaneously or at $t-1$, as specified separately.

3.4 Empirical Results

This section presents the empirical findings on the association between firm-level climate beta and corporate bond spreads. We begin with univariate portfolio sorts and then use Fama and MacBeth (1973) and panel regressions to account for observable firm- and bond-level characteristics. We subsequently examine whether the main association persists within characteristic-sorted portfolios and compare the results across different climate-risk dimensions.

3.4.1 Univariate Portfolio Sorts

We begin our analysis with univariate portfolio sorts based on firms' climate risk exposure, measured by β(Climate). Each month, we sort all available U.S. corporate bonds according to their most recent estimates of β(Climate). We then construct three portfolios based on the tertiles of the empirical distribution of β(Climate): a "Low" portfolio containing firms with the lowest climate risk exposure, a "High" portfolio containing firms with the highest exposure, and a "Medium" portfolio comprising the remaining firms. For each portfolio, we compute the equal-weighted average bond spread.

Accordingly, the High-$\beta(\mathrm{Climate})$ portfolio should be interpreted as a group of firms whose bond spreads have shown the strongest positive historical co-movement with the climate index. It is not a portfolio formed directly on firms' carbon emissions, environmental performance, or current spread levels. The High–Low comparison therefore examines whether firms with greater estimated sensitivity to market-wide climate conditions are associated with higher borrowing-cost spreads.

To mitigate potential forward-looking bias, we lag β(Climate) by one month. This sorting procedure generates portfolios of approximately equal size, with an average of around 83 firms per portfolio, ensuring adequate diversification.

Panel A of Table 3.1 reports the results of the baseline tertile sorts. Columns (1)–(3) present

the raw average bond spreads of the Low-, Medium-, and High-$\beta(\text{Climate})$ portfolios, respectively. Column (4) reports the raw High–Low spread differential, calculated as the average spread of the High-$\beta(\text{Climate})$ portfolio minus that of the Low-$\beta(\text{Climate})$ portfolio. Because the outcome is a yield spread rather than a bond return, the High–Low measure should be interpreted as a difference in annualized borrowing-cost spreads and not as the return on a tradable long–short portfolio.

The average bond spread is 3.235% for the Low-$\beta(\text{Climate})$ portfolio, 3.149% for the Medium portfolio, and 3.960% for the High portfolio. The spreads do not increase strictly monotonically because the Medium-portfolio spread is slightly lower than that of the Low portfolio. Nevertheless, the difference between the two extreme portfolios is economically and statistically meaningful. The raw High–Low spread differential is 0.725 percentage points, or 72.5 basis points, and is statistically significant at the 1% level (Newey–West t-statistic = 3.858). This result indicates that bonds issued by firms with high estimated climate-risk exposure have higher yield spreads, on average, than bonds issued by firms with low exposure.

Panel B reports the alternative quintile sorts. Columns (1)–(5) present the raw average bond spreads of the five portfolios, while Column (6) reports the raw High–Low spread differential. The High–Low differential is 0.948 percentage points, or 94.8 basis points, and remains statistically significant at the 1% level (Newey–West t-statistic = 4.318). Although the intermediate quintile spreads are not strictly monotonic, the positive difference between the High- and Low-exposure portfolios is consistent across both sorting specifications.

[Insert Table 3.1 about here]

To assess whether the raw High–Low spread differential is explained by exposure to systematic bond and market factors, Columns (5) and (6) of Panel A report intercepts from time-series regressions of the monthly High–Low spread differential on the four adjusted bond factors of Dickerson

et al. (2023) and four additional market and macroeconomic variables. The specification using contemporaneous factors is:

$$SPR_t^{High-Low} = \alpha_x^{BBWadj} + \beta_{MKT} MKT_t + \beta_{DRF} DRF_t + \beta_{CRF} CRF_t + \beta_{LRF} LRF_t + \beta_{SP500_Ret} SP500_Ret_t + \beta_{OilRet} OilRet_t + \beta_{defret} defret_t + \beta_{infl} infl_t + \epsilon_t, \tag{17}$$

where $SPR_t^{High-Low}$ is the monthly difference between the equal-weighted average bond spreads of the High- and Low-β(Climate) portfolios. The variables MKT, DRF, CRF, and LRF are the adjusted bond market, downside-risk, credit-risk, and liquidity-risk factors, respectively. The additional variables are the return on the S&P 500 index ($\mathrm{SP500Ret}$), the return on WTI crude oil (OilRet), the default-return spread (defret), and inflation (infl). Column (5) uses contemporaneous factors, while Column (6) replaces them with their one-month-lagged values.

The regression intercept, $\alpha_x^{\mathrm{BBWadj}}$, measures the average High–Low yield-spread differential that is not explained by the included factors. In this notation, $x = C$ denotes the contemporaneous-factor specification reported in Column (5) of Panel A, while $x = L$ denotes the lagged-factor specification reported in Column (6). Because the dependent variable is a yield-spread differential rather than a portfolio return, these intercepts should be interpreted as factor-adjusted spread differentials rather than conventional abnormal-return alphas.

The contemporaneous-factor intercept, $\alpha_C^{\mathrm{BBWadj}}$, is 0.720 percentage points, or 72.0 basis points, and is statistically significant at the 1% level (Newey–West t-statistic = 3.783). The lagged-factor intercept, $\alpha_L^{\mathrm{BBWadj}}$, is 0.772 percentage points, or 77.2 basis points, and is also statistically significant at the 1% level (Newey–West t-statistic = 3.754). Both estimates are close to the raw High–Low differential of 72.5 basis points, suggesting that the included factors explain little of the average spread difference between the High- and Low-exposure portfolios.

Columns (7) and (8) of Panel B report the corresponding factor-adjusted High–Low intercepts for the quintile sorts. The contemporaneous and lagged intercepts are 0.937 and 0.986 percentage points, respectively, compared with the raw High–Low differential of 0.948 percentage points. Both intercepts remain statistically significant at the 1% level. The similarity between the raw and factor-adjusted estimates across both panels indicates that the positive association between firm-level climate-risk exposure and corporate bond spreads is not fully accounted for by the included systematic factors.

Panel A also reports the factor loadings from the contemporaneous and lagged specifications. Among the contemporaneous factor loadings in Column (5), the coefficient on LRF is positive and statistically significant (Newey–West t-statistic = 3.478), while the coefficient on the S&P 500 return is negative and statistically significant (Newey–West t-statistic = -3.309). These estimates indicate that the High–Low spread differential covaries with bond-market liquidity conditions and tends to widen when equity-market performance is weaker. Nevertheless, the positive and significant intercepts show that these factor exposures do not fully explain the average spread differential associated with climate-risk exposure.

3.4.2 Fama–MacBeth & Panel Regressions

In the previous section, we examined the relationship between climate beta and bond spreads using univariate portfolio sorts. We next estimate Fama-MacBeth regressions of bond spreads on climate beta and various control variables:

$$SPR_{i,t} = \alpha_t + \beta_t \beta_{i,t-1}^{\text{climate}} + \sum_{j=1}^{N} \gamma_j Z_{i,j,t-12} + \epsilon_{i,t}, \tag{18}$$

where $SPR_{i,t}$ is the bond spread of firm i in month t, $\beta_{i,t-1}^{\text{climate}}$is the climate beta for firm i at the end of month $t-1$, and $Z_{i,j,t-12}$ denotes the month $t-12$ value of control variable j referring to firm i. The

set Z contains the following controls: Sales, Cash, Lev, CF, Inc, ROA, Size, MB, CPN, TTM, DD, AV, and Illiq, which are described in Section 3.3 and in Table B11 of the appendix.

[Insert Table 3.2 here.]

Table 3.2 reports the time-series average slope estimates and corresponding Newey and West (1987) (NW) t-statistics (in parentheses) of the Fama–MacBeth regressions. In Model (1), which does not include any control variables, the coefficient on the $\beta(Climate)$ variable is equal to 8.557 and statistically significant at the 1% level (NW t-stat. = 4.291), consistent with earlier evidence. Models (2)–(5) introduce $\beta(BondFactors)$, firm-specific and bond-specific control variables. The average slope estimate of $\beta(Climate)$ remains positive and statistically significant at the 1% level in the augmented model, albeit with a reduced magnitude. Thus, incorporating bond market factors and firm- and bond-specific characteristics into the models does not alter the positive association between climate beta and bond spreads, which remains significant at the 1% level.

The coefficients on $\beta(\mathrm{MKT})$, reported after being multiplied by 100, are -0.044, 0.036, and 0.036 in Models (2), (4), and (5), respectively. Their Newey–West t-statistics are -0.914, 1.010, and 0.821. Therefore, none of these coefficients is statistically significant. The change from a negative coefficient in Model (2) to positive coefficients in Models (4) and (5) also provides no evidence of a stable relation between market-factor exposure and bond spreads.

Here, $\beta(\mathrm{MKT})$ measures a firm's estimated exposure to the aggregate bond-market factor rather than the contemporaneous value of the market factor itself. Its coefficient tests whether differences in firms' market-factor exposure are associated with cross-sectional differences in bond spreads after accounting for the other variables in the model. The insignificant coefficients indicate that $\beta(\mathrm{MKT})$ does not provide a statistically reliable additional explanation for bond spreads in these specifications. This result does not mean that aggregate bond-market conditions are unimportant for the overall level of corporate bond spreads.

One possible explanation for the insignificant market-factor coefficient is the use of bond spreads rather than realised bond returns when constructing the betas. In this study, the bond-factor betas measure firms' historical spread sensitivity to return-based bond factors. Using these factors provides a practical way to account for common bond-market conditions, although the resulting exposures are spread sensitivities rather than conventional return betas. Noise in the bond-factor estimates and estimation error in the betas may also reduce coefficient precision in the subsequent Fama–MacBeth regressions.

The coefficient is already insignificant in Model (2), before the detailed firm- and bond-level controls are included, so these controls cannot be the sole explanation. Model (2) nevertheless includes climate beta and the other bond-factor exposures, whose explanatory information may overlap. These considerations provide possible explanations for the insignificant market-factor coefficient, although the present analysis does not identify their separate contributions. Climate beta remains positive and statistically significant across all five models, indicating that it contains information about bond spreads beyond that captured by the included bond-factor exposures.

Most control variables have significant slope estimates, and their signs are economically meaningful. For example, leverage is positively associated with bond spreads, indicating that firms with higher debt levels face higher borrowing costs due to greater default risk. In contrast, profitability measures such as ROA and income are negatively associated with bond spreads, suggesting that financially stronger firms are perceived as less risky by investors. Firm size also has a negative coefficient, suggesting that larger firms tend to have lower bond spreads, possibly due to better access to capital markets and greater financial stability. Similarly, the market-to-book ratio is negatively related to bond spreads, showing a more favorable growth outlook and lower perceived risk. Importantly, the distance-to-default (DD) variable has a negative coefficient, consistent with theory: firms farther from default risk have lower bond spreads. In contrast, asset volatility(AV) is positively re-

lated to bond spreads, indicating that greater uncertainty about firm value increases credit risk and prompts investors to demand higher yields. At the bond level, variables such as coupon rate and time to maturity are positively associated with spreads, consistent with higher compensation required for longer-term or higher-yield bonds. Illiquidity also has a strong positive effect, indicating that less-liquid bonds require higher yields to attract investors. Overall, these results are consistent with standard theories of credit risk and bond pricing, additionally supporting the validity of the empirical framework.

[Insert Table 3.3 here.]

For further robustness, we also estimate a panel regression specified as follows:

$$SPR_{i,t} = \alpha + \beta\beta_{i,t-1}^{\text{Climate}} + \sum_{j=1}^{N} \gamma_j Z_{i,j,t-12} + \eta_s + \tau_t + \mu_{i,t}, \tag{19}$$

where $SPR_{i,t}$ is the bond spread of firm i in month t, $\beta_{i,t-1}^{\text{Climate}}$ is the climate beta of firm i in month $t-1$, $Z_{i,j,t-12}$ is the month $t-12$ value of the control variable j. Depending on the specification, the regression includes month fixed effects (τ_t), industry fixed effects (η_s), or both. Standard errors are two-way clustered by firm and calendar year.

Table 3.3 presents the results of panel regressions. The slope estimate of the climate beta in Model (1) of Table 3.3, which excludes control variables, is uniformly positive and statistically significant at the 1% level. Model (3), which incorporates industry fixed effects, yields consistent results. In line with earlier evidence from the Fama and MacBeth (1973) regressions, the inclusion of control variables (Models (2) and (4)) reduces the magnitude of the climate beta coefficient. However, it remains statistically significant at the 5% level. Overall, the panel regression results closely mirror those obtained from the Fama-MacBeth approach, reinforcing the robustness of our findings.

3.4.3 Exploring Potential Drivers

Double Portfolio Sorts

The evidence thus far indicates a positive association between firm-level climate beta and corporate bond spreads. To examine whether this association persists within groups defined by observable firm and bond characteristics, we conduct double independent portfolio sorts on climate beta and each characteristic. At the end of each month, bonds are independently assigned to climate-beta tertiles and to tertiles based on the selected characteristic, producing nine portfolios. The conditioning variables are Sales, Cash, CF, Lev, Inc, ROA, Size, MB, DD, AV, CPN, TTM, and Illiq. Climate beta is lagged by one month, while each conditioning variable is lagged by 12 months.

For each characteristic tertile, the High–Low value is calculated as the average bond spread of the High-climate-beta portfolio minus that of the Low-climate-beta portfolio. A positive High–Low differential indicates that bonds issued by firms with greater estimated climate sensitivity have wider spreads within that characteristic group. If the differential becomes small or statistically insignificant after conditioning on a characteristic, this would indicate that the climate-beta association is attenuated within that subgroup. It would not, by itself, establish that the characteristic causally explains the relationship.

Table 3.4 shows that the High–Low spread differential generally remains positive and statistically significant across the characteristic-sorted portfolios. The results therefore indicate that the climate-beta–spread association is not fully absorbed by the observable characteristics considered in the double sorts. Nevertheless, the analysis remains descriptive and does not establish that climate exposure constitutes an independent causal source of credit risk.

[Insert Table 3.4 here.]

Firm-level climate-risk exposure and Firm Characteristics

While the double-sorting results provide strong evidence that the pricing of climate risk is not driven by standard firm and bond characteristics, it remains important to understand how these characteristics vary across climate-risk portfolios. Therefore, we next examine the underlying firm and bond attributes associated with different levels of climate risk. This helps us learn about the economic mechanisms underlying the observed pricing effect and further assess whether climate risk is linked to fundamental differences in firm quality and credit risk.

To better understand the underlying drivers of the credit spread differences observed across our $\beta(Climate)$—sorted portfolios, we next examine the characteristics associated with different levels of firm-level climate-risk exposure. Specifically, we construct tertile portfolios by sorting bonds according to their $\beta(Climate)$ scores, following the approach outlined in Section 3.4.1. For each of the three $\beta(Climate)$ tertile portfolios, we then compute the average value of a specific outcome variable. This analysis explores whether average bond-spread differentials across $\beta(Climate)$- sorted portfolios are associated with systematic differences in firm and bond characteristics.

[Insert Table 3.5 here.]

Table 3.5 reports the characteristics of portfolios sorted by climate beta. Several clear patterns emerge. First, firms with a higher climate beta tend to have weaker fundamentals. In particular, sales, cash flow, income, and ROA decline from the low to the high climate beta portfolios, with statistically significant differences. This suggests that firms with higher climate betas are generally less financially robust.

Second, credit risk increases with the climate risk beta. For example, distance-to-default (DD) shows a large and statistically significant negative High-Low difference, indicating that firms with high climate risk beta have a lower distance to default (i.e., have a higher default probability). At the same time, asset volatility (AV) increases across portfolios, further supporting the interpretation that climate risk beta is associated with greater asset volatility and a higher probability of default.

Third, bond characteristics also differ across portfolios. Bonds issued by high-climate-risk firms tend to have higher coupon rates and slightly longer maturities, consistent with investors requiring higher compensation to bear additional risk. Illiquidity is also higher for high-climate-risk bonds, suggesting they are more difficult to trade and require a liquidity premium.

In practical terms, Table 3.5 provides a descriptive picture of what a high-climate-beta firm looks like in our sample. Such firms tend to have weaker operating performance, lower cash flow and profitability, a lower distance to default, and higher asset volatility. Their bonds also tend to have higher coupon rates and greater illiquidity. However, these characteristics are not used to construct the climate beta. A firm is classified as having a high climate beta because its bond spread has historically shown stronger positive co-movement with the climate index, not because it satisfies any single firm or bond characteristic. The evidence in Table 3.5 therefore describes the characteristics associated with high climate sensitivity rather than providing a mechanical definition of the beta.

3.4.4 Dissecting the Impact of Climate Risk

Having established a positive association between climate beta and corporate bond spreads, we next compare the evidence across different dimensions of climate risk. H2 predicts a stronger association for transition-related exposure than for physical-risk exposure. We therefore conduct separate portfolio sorts and Fama–MacBeth regressions using the beta associated with each climate-risk dimension. These tests compare the relative strength and consistency of the associations; they do not identify the causal contribution of each dimension.

[Insert Figure 1 here.]

We first examine whether the pricing of climate risk differs across its underlying dimensions using portfolio sorts, following the approach outlined in Section 3.4.1. The results in Table 3.6 reveal substantial heterogeneity in the pricing effect.

[Insert Table 3.6 here.]

In Table 3.6, firms are sorted separately by their estimated beta with respect to each climate-attention sub-index. The Low and High portfolios therefore represent firms with low and high estimated exposure to the specified climate-risk dimension. The regulatory-attention sub-index, which captures the transition-risk dimension, produces the largest High–Low spread differential. In the tertile sorts based on this regulatory-attention beta, firms in the Low-exposure portfolio have an average bond spread of 3.146%, compared with 4.064% for firms in the High-exposure portfolio. The resulting difference is 0.918 percentage points, or 91.8 basis points. The High-exposure portfolio therefore has an average spread approximately 29.2% higher than that of the Low-exposure portfolio ($0.918/3.146 \times 100\% \approx 29.2\%$). The differential is also equivalent to approximately 29.7% of the full-sample mean spread of 3.088% reported in Table B1 ($0.918/3.088 \times 100\% \approx 29.7\%$).

The quintile sorts based on the same regulatory-attention beta produce an even larger High–Low differential of 1.174 percentage points, or 117.4 basis points. The average spread of the High-exposure portfolio is approximately 36.3% higher than that of the Low-exposure portfolio ($1.174/3.230 \times 100\% \approx 36.3\%$). The factor-adjusted spread differentials remain between 81.1 and 82.8 basis points in the tertile sorts and between 104.1 and 106.2 basis points in the quintile sorts. Thus, approximately 88.3%–90.5% of the raw transition-risk differential remains after factor adjustment (the lower and upper bounds are $0.811/0.918 \times 100\% \approx 88.3\%$ and $1.062/1.174 \times 100\% \approx 90.5\%$, respectively).

The other four dimensions generally produce smaller portfolio spread differences. In the tertile sorts based on the physical-risk-causes beta, the average bond spread is 3.503% for the Low-exposure portfolio and 3.777% for the High-exposure portfolio, with a High–Low differential of 27.4 basis points. For the physical-risk-results beta, the corresponding average spreads are 3.544% and 3.723%, with a differential of 17.9 basis points. For the opportunity-attention beta, the average spread increases from 3.240% in the Low-exposure portfolio to 3.921% in the High-exposure portfolio, with a

differential of 68.1 basis points. For the broad-climate-attention beta, labelled "Broad cognitive level" in Table 3.6, the corresponding average spreads are 3.336% and 3.885%, with a differential of 54.9 basis points.

The quintile sorts based on the corresponding sub-index betas produce High–Low differentials of 48.2 basis points for physical-risk causes, 25.0 basis points for physical-risk results, 87.3 basis points for opportunity attention, and 71.8 basis points for broad climate attention. The intermediate portfolios do not always follow a strictly monotonic pattern. Moreover, the significant results for physical-risk causes show that physical risk cannot be described as entirely unimportant. The portfolio evidence therefore indicates that regulatory-attention (transition-risk) exposure produces the largest and most consistent extreme-portfolio differences, rather than being the only climate-risk dimension associated with bond spreads.

[Insert Table 3.7 here.]

Because the five beta measures have different scales, the coefficients in Table 3.7 cannot be compared directly based only on their reported magnitudes. For economic interpretation, each coefficient is multiplied by the standard deviation of the relevant beta in the corresponding regression sample. The standard deviations and quartiles used below are calculated from the underlying data and are not separately reported in Table 3.7. Multiplying the coefficient by the standard deviation gives the spread change in percentage points; multiplying this result by 100 expresses it in basis points.

In the univariate specifications, a one-standard-deviation increase in exposure is associated with spread increases of 47.8 basis points for physical-risk causes ($8.606 \times 0.0555884 \times 100 \approx 47.8$), 21.6 basis points for physical-risk results ($2.776 \times 0.0778707 \times 100 \approx 21.6$), 60.1 basis points for regulatory or transition risk ($6.238 \times 0.0964042 \times 100 \approx 60.1$), 35.4 basis points for opportunities ($5.205 \times 0.0679444 \times 100 \approx 35.4$), and 37.1 basis points for broad climate attention ($11.214 \times 0.0330648 \times 100 \approx 37.1$).

After firm-, bond-, and factor-level controls are included, the corresponding calculations are $3.693 \times 0.0531322 = 0.1962$ percentage points, or 19.6 basis points, for physical-risk-causes exposure; $0.780 \times 0.0748932 = 0.0584$ percentage points, or 5.8 basis points, for physical-risk-results exposure; $1.954 \times 0.0920356 = 0.1798$ percentage points, or 18.0 basis points, for regulatory-attention (transition-risk) exposure; $1.068 \times 0.0580348 = 0.0620$ percentage points, or 6.2 basis points, for opportunity-attention exposure; and $4.008 \times 0.0300648 = 0.1205$ percentage points, or 12.0 basis points, for broad-climate-attention exposure. The controlled transition-risk effect represents approximately 5.8% of the full-sample mean spread reported in Table B1 ($18.0/308.8 \times 100\% \approx 5.8\%$). A movement from the 25th to the 75th percentile of transition-risk exposure is associated with an increase of approximately 15.1 basis points ($1.954 \times [0.061442 - (-0.015832)] \times 100 \approx 15.1$).

The smaller controlled regression effect does not conflict with the larger High–Low portfolio differential. The portfolio analysis compares firms in the extreme exposure groups without firm- and bond-level controls, whereas the regression estimate measures a conditional marginal association for a one-standard-deviation change. Overall, transition-risk exposure produces the largest portfolio spread differentials and remains statistically and economically meaningful after controls. However, the physical-risk-causes result is also significant and economically meaningful. The evidence therefore supports a particularly strong role for transition risk, but not an exclusive role. These estimates should be interpreted as associations rather than causal effects.

Several mechanisms may explain why transition-related exposure produces larger and more consistent portfolio spread differences. Regulatory changes can affect firms through carbon costs, compliance expenditure, required investment, and the loss of value of carbon-intensive assets. These effects may appear relatively quickly in cash flows, debt-servicing capacity, default probability, and recovery value. They are therefore directly relevant to bondholders. Policy announcements are also public and may affect many firms at the same time, making transition risk easier for investors to observe and

incorporate into bond spreads.

By comparison, physical climate risk is often more difficult to translate into an immediate change in expected credit losses. Its effect depends on the locations of a firm's assets and suppliers, the timing and severity of physical events, and the firm's insurance and adaptation capacity. Some physical damages may also occur beyond the remaining maturity of the bonds in the sample. In addition, a market-wide news index may measure geographically specific physical exposure less precisely than it measures common policy-related news. These factors may weaken the estimated relationship between physical-risk exposure and current bond spreads.

These mechanisms are plausible interpretations rather than directly tested channels. Table 3.6 shows that transition-risk exposure produces the largest portfolio spread differentials. However, in the fully controlled regressions in Table 3.7, the one-standard-deviation effect of physical-risk causes is approximately 19.6 basis points ($3.693 \times 0.0531322 \times 100 \approx 19.6$), compared with 18.0 basis points for transition risk ($1.954 \times 0.0920356 \times 100 \approx 18.0$). The coefficients are reported in Table 3.7, while the standard deviations of 0.0531322 and 0.0920356 are calculated from the corresponding fully controlled regression samples. Multiplication by 100 converts the estimated spread changes from percentage points to basis points. The evidence therefore does not show that transition risk dominates physical risk in every specification. Instead, it shows that transition-related exposure has the largest and most consistent association with bond spreads across the portfolio analyses, while some physical-risk information is also economically meaningful. The weaker results for other physical-risk measures may reflect a longer pricing horizon, firm adaptation, measurement limitations, or a slower incorporation of physical risk into bond spreads. The present analysis cannot distinguish among these explanations.

These results do not allow us to determine whether climate risks are fully or correctly priced. A positive relationship between climate-risk exposure and bond spreads indicates that investors require

some additional compensation for this exposure, but it does not show whether that compensation is sufficient relative to the associated expected default and recovery losses. Similarly, the generally weaker evidence for physical risk is consistent with, but does not establish, the underpricing of long-term physical consequences. It may also reflect differences in bond maturity, the timing of expected losses, adaptation and insurance, or measurement precision, as discussed in Section 3.6. Establishing underpricing would require an external benchmark for expected climate-related losses or evidence that current spreads systematically underreact and predict subsequent losses or excess returns. The present analysis provides no such benchmark. The results are therefore interpreted as evidence of differences in how climate-risk dimensions are incorporated into current bond spreads, rather than as proof of either market efficiency or mispricing.

3.5 Additional Results

The main analysis uses the Attention to Climate News Index. To examine whether the findings depend on this particular measure, we repeat the analyses using the Faccini Climate Risk Index. Tables B3–B9 report the results from portfolio sorts, Fama–MacBeth regressions, panel regressions, double sorts, portfolio characteristics, and dimension-level analyses. Overall, the alternative index produces broadly similar evidence, although the strength of the association differs across specifications and climate-risk dimensions.

Table B3 shows that the average spread of the High-exposure portfolio exceeds that of the Low-exposure portfolio by 60.8 basis points in the tertile sorts and 75.1 basis points in the quintile sorts. Both differences are statistically significant. The corresponding factor-adjusted spread differentials range from 65.3 to 65.9 basis points for the tertile portfolios and from 78.7 to 79.3 basis points for the quintile portfolios. Although the spreads of the intermediate portfolios do not increase strictly monotonically, the positive difference between the two extreme portfolios remains economically meaning-

ful.

The regression results provide a conditional interpretation of this relationship. Based on the univariate coefficient of 1.008 in Table B4 and the standard deviation of 0.336 reported in Table B1, a one-standard-deviation increase in the overall Faccini climate beta is associated with a 33.9-basis-point increase in the annualized bond spread ($1.008 \times 0.336 \times 100 \approx 33.9$). After including the full set of controls, the Fama–MacBeth coefficient is 0.351 in Table B4, while the fully controlled panel coefficient is 0.344 in Table B5. Both coefficients remain positive and are smaller than their respective univariate estimates.

Tables B8 and B9 examine the four dimensions of the Faccini Climate Risk Index. The strongest and most consistent evidence is found for U.S. policy exposure. In Table B8, moving from the Low- to the High-exposure portfolio is associated with an increase in the average bond spread of 80.7 basis points in the tertile sorts and 99.5 basis points in the quintile sorts. The High portfolio therefore has an average spread approximately 25.2% higher than the Low portfolio in the tertile sorts ($0.807/3.202 \times 100\% \approx 25.2\%$) and 29.6% higher in the quintile sorts ($0.995/3.359 \times 100\% \approx 29.6\%$). After controlling for systematic factors, the spread differentials remain 69.9 basis points in the tertile sorts and between 85.9 and 86.1 basis points in the quintile sorts. In the fully controlled Fama–MacBeth regression in Table B9, a one-standard-deviation increase in U.S. policy exposure is associated with an 18.2-basis-point increase in the annualized bond spread ($0.198 \times 0.9175 \times 100 \approx 18.2$), where 0.9175 is the standard deviation calculated from the corresponding regression sample. This is approximately 5.9% of the full-sample mean spread reported in Table B1 ($18.2/308.8 \times 100\% \approx 5.9\%$).

The results for the other dimensions are weaker. International-summit exposure produces raw High–Low differences of 37.7 and 45.1 basis points in Table B8. However, its coefficient becomes small and statistically insignificant after the controls are included in Table B9; the controlled one-standard-deviation effect is approximately 1.1 basis points ($0.015 \times 0.755302 \times 100 \approx 1.1$). The

High–Low differences for global-warming and natural-disaster exposure are below 10 basis points and statistically insignificant. Their controlled one-standard-deviation point estimates are 9.4 and 7.8 basis points, respectively ($0.059 \times 1.592447 \times 100 \approx 9.4$ and $0.056 \times 1.390579 \times 100 \approx 7.8$), but neither coefficient is statistically significant. These calculations use the climate-beta coefficients reported in Columns (4), (6), and (8) of Table B9, respectively. The corresponding beta standard deviations of 0.755302, 1.592447, and 1.390579 are calculated from the respective fully controlled regression samples. Therefore, the evidence from the Faccini index is strongest for U.S. climate-policy exposure rather than for every policy-related or physical-risk dimension.

Overall, these additional results show that the positive association between firm-level climate-risk exposure and corporate bond spreads is not limited to the Attention to Climate News Index. However, the results are neither strictly monotonic nor equally strong across all dimensions. The most robust evidence from the Faccini index concerns U.S. policy exposure, while the evidence for international summits, global warming, and natural disasters becomes weaker after the inclusion of controls. These findings represent associations rather than causal effects.

3.6 Conclusion

This essay examines the association between firm-level climate beta and corporate bond spreads using U.S. data from 2008 to 2021. Across portfolio sorts, Fama–MacBeth regressions, panel regressions, and double sorts, firms with higher estimated climate sensitivity tend to have wider bond spreads. The association remains after the inclusion of the observable firm, bond, and factor-exposure controls considered in the analysis.

Transition- or policy-related exposure produces the largest and most consistent portfolio spread differentials. Physical-risk causes also remain statistically and economically meaningful in some controlled regressions. The results therefore indicate a particularly strong role for transition-related exposure, but they do not show that transition risk dominates physical risk in every specification.

Similar patterns are obtained using both the attention-based index and the Faccini Climate Risk Index, although the magnitude and significance of the estimates vary across dimensions and specifications. The evidence is therefore not dependent on a single climate index, but it should still be interpreted as an association rather than as causal evidence or proof that climate risk is fully priced.

A key contribution of this essay is the direct comparison of transition and physical climate risk in corporate bond spreads. Transition-risk exposure produces larger and more consistent portfolio spread differentials, although physical-risk causes also remain statistically and economically meaningful in the controlled regressions. This evidence complements the finding of Faccini et al. (2023) that U.S. equity investors respond particularly strongly to climate-policy risk and the finding of Seltzer et al. (2022) that regulatory risk affects corporate credit ratings and bond spreads. The present study extends this literature by comparing several risk dimensions using the same firm-level exposure framework and two different climate indices. The distinction is especially relevant to creditors because transition risk may affect compliance costs, capital expenditure, stranded assets, and future cash flows, while physical risk may damage assets and interrupt business operations. Both channels can affect default

probability and recovery value, even though their relative importance differs across the empirical specifications.

We further show that our results are robust to alternative measures of climate risk, including both attention-based and news-based indices. This suggests that the pricing of climate risk is not driven by a single proxy but rather shows a stable, economically meaningful relationship.

Despite these findings, several limitations should be noted. First, the sample covers U.S. corporate bonds from 2008 to 2021. Climate policies, disclosure requirements, energy structures, insurance markets, and bond-market institutions differ across countries. The relationship between climate exposure and bond spreads may therefore be different in other developed markets or emerging economies. In addition, the rolling-beta estimation requires firms to have sufficient bond-spread observations. Issuers with short or irregular bond histories may consequently be under-represented. The findings should therefore be interpreted mainly in relation to U.S. firms with publicly traded bonds and sufficient historical data.

Second, the empirical analysis identifies associations rather than causal effects. Climate beta is estimated from the historical co-movement between a firm's bond spread and a market-wide climate index. It may therefore capture both climate-related sensitivity and other firm characteristics associated with credit risk. The Fama–MacBeth regressions, panel models, double sorts, and firm- and bond-level controls reduce several observable concerns, but they cannot remove all unobserved differences across firms. Lagging climate beta by one month ensures that the exposure measure is estimated before the current spread observation, but this timing choice does not by itself solve endogeneity. The results therefore cannot establish that greater climate exposure directly causes wider bond spreads or identify one specific economic mechanism.

Third, the analysis involves measurement limitations and a potential mismatch between the long horizon of climate risk and the remaining maturity of the bonds in the sample. The Attention to Cli-

mate News Index and the Faccini Climate Risk Index measure climate-related attention and news coverage rather than the expected monetary value of future climate losses. Climate beta is also estimated using a rolling 48-month window and therefore captures recent historical sensitivity to these indices. It does not measure a firm's total exposure to climate damage over future decades. At the same time, the monthly frequency of the data should not be interpreted as a one-month pricing horizon. A bond spread observed today reflects investors' current assessment of expected default losses and recovery value over the bond's remaining maturity. Climate risk can therefore affect current spreads when it is expected to influence cash flows, asset values, refinancing conditions, default probability, or recovery value within that period (Giglio et al., 2021).

This horizon distinction is particularly important for interpreting the physical-risk results. Transition-related events may create visible financial effects within a relatively short period, whereas some physical damages may occur after the maturity of the bonds currently outstanding. Distant physical losses may therefore receive less weight in current spreads. However, the weaker results for some physical-risk measures do not show that long-term physical risk is unimportant or fully reflected in bond prices. They may result from rational discounting, expected adaptation or insurance, measurement error, or a slower market response to complex long-term risks. The present analysis cannot distinguish among these explanations. Accordingly, the findings describe the association between recent climate-news sensitivity and current bond spreads rather than the complete pricing of climate damage over future decades.

These limitations suggest several directions for future research. First, the analysis could be extended to international bond markets, particularly emerging economies with different climate exposure, regulatory systems, and financial institutions. Second, future studies could use changes in climate regulation or specific physical events as external shocks to obtain stronger causal evidence. Third, more detailed information on the locations of firms' assets and suppliers, insurance coverage,

adaptation investment, and expected physical losses could improve the measurement of firm-level physical risk. Finally, comparing short- and long-maturity bonds would help determine whether climate exposure is priced differently across the term structure of corporate debt. Such evidence would provide a clearer understanding of how the horizon of climate risk interacts with the maturity of financial claims.

Overall, our findings show that current corporate bond spreads contain information related to firms' climate-risk exposure, particularly transition-related exposure. However, the analysis does not establish whether climate risks are fully or correctly priced. In particular, the weaker average evidence for some physical-risk measures should not be interpreted as proof either that investors ignore physical risk or that physical risk is economically unimportant. Determining whether climate risks are underpriced would require comparing observed spreads with an external measure of expected climate-related default and recovery losses, or examining whether current spreads systematically predict subsequent climate-related losses or excess returns. These questions remain important directions for future research.

Table 3.1: Portfolio Sorts on Firm-Level Climate-Risk Exposure

This table reports monthly portfolio sorts based on firms' climate-risk exposure, measured by $\beta(\text{Climate})$ and lagged by one month. Panel A forms three equal-weighted portfolios using tertile breakpoints, while Panel B forms five equal-weighted portfolios using quintile breakpoints. The columns under "Raw Portfolio Spreads" report the annualized average bond yield spread for each portfolio. "Raw High–Low" is calculated as the average spread of the High-$\beta(\text{Climate})$ portfolio minus that of the Low-$\beta(\text{Climate})$ portfolio. The final two columns report intercepts from time-series regressions of the monthly High–Low spread differential on the four adjusted bond factors of Dickerson et al. (2023) and four additional market and macroeconomic variables. Panel A also reports the corresponding factor loadings. The subscripts C and L denote specifications using contemporaneous and one-month-lagged factors, respectively. Because the dependent variable is a yield-spread differential rather than a portfolio return, these intercepts represent factor-adjusted spread differentials and should not be interpreted as abnormal investment returns. Portfolio means and intercept estimates are annualized and expressed in percentage points. Newey and West (1987) t-statistics based on four lags are reported in parentheses. The sample spans January 2008 to December 2021.

Panel A: Tertile Sorts (Baseline)

	Raw Portfolio Spreads			Raw High–Low	Factor-Adjusted High–Low	
	Low (1)	Medium (2)	High (3)	High–Low (4)	α_C^{BBWadj} (5)	α_L^{BBWadj} (6)
Mean spread / α	3.235 (21.372)	3.149 (13.617)	3.960 (13.897)	0.725 (3.858)	0.720 (3.783)	0.772 (3.754)
MKT_t	–	–	–	–	12.749 (1.193)	–
DRF_t	–	–	–	–	-5.749 (-0.731)	–
CRF_t	–	–	–	–	11.810 (1.764)	–
LRF_t	–	–	–	–	30.063 (3.478)	–
SP500_Ret_t	–	–	–	–	-9.252 (-3.309)	–
OilRet_t	–	–	–	–	0.886 (1.195)	–
defret_t	–	–	–	–	-4.059 (-0.538)	–
infl_t	–	–	–	–	-64.390 (-1.672)	–
MKT_{t-1}	–	–	–	–	–	8.992 (0.819)
DRF_{t-1}	–	–	–	–	–	-2.804 (-0.343)
CRF_{t-1}	–	–	–	–	–	11.537 (2.056)
LRF_{t-1}	–	–	–	–	–	25.398 (2.582)
SP500_Ret_{t-1}	–	–	–	–	–	-9.530 (-2.596)
OilRet_{t-1}	–	–	–	–	–	0.432 (0.499)
defret_{t-1}	–	–	–	–	–	-6.750 (-1.024)
infl_{t-1}	–	–	–	–	–	-79.637 (-1.919)
R^2	–	–	–	–	0.270	0.237
# Months	168	168	168	168	168	167

Panel B: Quintile Sorts (Alternative)

	Raw Portfolio Spreads					Raw High–Low	Factor-Adjusted High–Low	
	Q1 (Low) (1)	Q2 (2)	Q3 (3)	Q4 (4)	Q5 (High) (5)	High–Low (6)	α_C^{BBWadj} (7)	α_L^{BBWadj} (8)
Mean spread / α	3.345 (23.049)	3.075 (17.115)	3.145 (13.406)	3.409 (12.142)	4.293 (14.725)	0.948 (4.318)	0.937 (4.314)	0.986 (4.244)

Table 3.2: Fama-MacBeth Regression Results

This table reports the results from monthly Fama and MacBeth (1973) regressions in which current bond spreads are regressed on firm-level climate-risk exposure, lagged by 1 month, estimated exposures to four adjusted bond factors, and firm- and bond-level control variables, lagged by 12 months. Column (1) reports the univariate regression using $\beta(\text{Climate})$ as the sole explanatory variable. Column (2) adds $\beta(\text{MKT})$, $\beta(\text{DRF})$, $\beta(\text{CRF})$, and $\beta(\text{LRF})$. Column (3) adds the bond-level controls. Column (4) includes both the bond-factor exposures and bond-level controls, while Column (5) additionally includes firm-level controls. The four bond-factor variables represent firm-level estimated exposures rather than contemporaneous factor realizations. For ease of presentation, the reported coefficients on these four bond-factor exposures have been multiplied by 100. This rescaling does not affect the corresponding t-statistics or statistical significance. The third-to-last row reports the average R^2 across the monthly regressions. The second-to-last row reports the average number of firms per month, while the final row reports the number of monthly regressions. Newey and West (1987) t-statistics based on four lags are reported in parentheses. The sample spans January 2008 to December 2021.

	(1)	(2)	(3)	(4)	(5)
β(Climate)	8.557	8.090	5.233	5.150	2.837
	(4.291)	(4.293)	(4.897)	(4.762)	(4.145)
β(MKT) (coef. × 100)		-0.044		0.036	0.036
		(-0.914)		(1.010)	(0.821)
β(DRF) (coef. × 100)		-0.115		0.078	0.086
		(-1.203)		(1.156)	(0.990)
β(CRF) (coef. × 100)		-0.337		-0.109	-0.157
		(-3.071)		(-1.243)	(-1.775)
β(LRF) (coef. × 100)		0.011		0.045	0.062
		(0.276)		(1.335)	(1.728)
Sales					-0.121
					(-4.012)
Cash					-0.119
					(-0.526)
CF					-1.089
					(-3.002)
Lev					0.811
					(8.677)
Inc					-0.520
					(-1.953)
ROA					-2.832
					(-5.737)
Size					-0.272
					(-17.152)
MB					-0.022
					(-4.414)
DD					-0.028
					(-6.177)
AV					0.807
					(5.926)
CPN			0.599	0.595	0.395
			(21.316)	(21.329)	(15.475)
TTM			0.047	0.049	0.081
			(6.186)	(7.067)	(11.723)
Illiq			84.106	79.435	44.106
			(11.964)	(11.780)	(8.282)
Constant	3.269	3.236	-0.736	-0.735	7.018
	(16.123)	(16.528)	(-5.366)	(-5.508)	(12.817)
Mean of R^2	0.087	0.147	0.538	0.568	0.726
Mean Obs/Mth	250	249	249	248	184
# Months	168	168	168	168	168

Table 3.3: Panel Regression Results

This table reports panel regressions of corporate bond spreads on firms' 1-month-lagged climate betas and 12-month-lagged firm- and bond-level controls, as specified in Equation (19). Columns (1)–(2) include month fixed effects, while Columns (3)–(4) include both month and industry fixed effects. Columns (1) and (3) exclude the control variables, whereas Columns (2) and (4) include the full set of controls. t-statistics based on standard errors two-way clustered by firm and calendar year are reported in parentheses. The sample spans January 2008 to December 2021.

	(1)	(2)	(3)	(4)
β(Climate)	4.862	1.858	4.406	1.826
	(3.016)	(2.361)	(2.887)	(2.305)
Sales		-0.099		-0.084
		(-1.681)		(-1.308)
Cash		-0.318		-0.234
		(-0.776)		(-0.629)
CF		0.275		-0.509
		(0.234)		(-0.634)
Lev		0.837		0.999
		(3.027)		(3.102)
Inc		0.285		0.617
		(0.673)		(1.230)
ROA		-5.536		-5.609
		(-3.768)		(-3.613)
Size		-0.276		-0.299
		(-9.004)		(-8.650)
MB		-0.015		-0.014
		(-1.154)		(-1.083)
DD		-0.023		-0.021
		(-5.014)		(-4.793)
AV		0.599		0.452
		(2.064)		(1.661)
CPN		0.375		0.363
		(8.453)		(8.439)
TTM		0.069		0.069
		(4.689)		(4.432)
Illiq		52.556		52.362
		(2.694)		(2.673)
Intercept	2.941	7.005	2.955	7.562
	(44.057)	(9.112)	(47.910)	(9.162)
Observations	41,989	31,098	41,989	31,098
R^2	0.361	0.695	0.414	0.700
Time FE	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes

Table 3.4: Bivariate Portfolio Sorts

This table reports monthly double independent portfolio sorts based on one-month-lagged firm-level climate beta and the 12-month-lagged characteristic specified in each panel. At the end of each month, bonds are independently assigned to three climate-beta portfolios and three portfolios based on the conditioning variable, producing nine portfolios. The procedure generates a monthly time series of average bond yield spreads for each portfolio. Within each conditioning-variable tertile, the final column reports the High–Low spread differential, calculated as the average spread of the High-climate-beta portfolio minus that of the Low-climate-beta portfolio. Because the reported outcome is a bond yield spread rather than a portfolio return, the High–Low value should not be interpreted as a tradable long–short return. Newey and West (1987) t-statistics based on four lags are reported in parentheses. The sample spans January 2008 to December 2021.

		β(Climate)			
		Low	Med	High	High-Low
Sales	Low	3.366	3.194	4.082	0.716
		(17.764)	(13.184)	(13.093)	(3.348)
	Med	3.232	3.098	3.861	0.629
		(21.626)	(13.372)	(12.828)	(3.040)
	High	3.102	3.132	3.823	0.721
		(22.638)	(14.247)	(16.709)	(5.028)

		β(Climate)			
		Low	Med	High	High-Low
Lev	Low	3.132	3.049	3.610	0.478
		(18.719)	(13.562)	(17.216)	(3.945)
	Med	3.099	3.153	3.737	0.638
		(21.438)	(13.910)	(13.793)	(3.424)
	High	3.420	3.234	4.342	0.923
		(25.072)	(13.836)	(13.833)	(3.891)

		β(Climate)			
		Low	Med	High	High-Low
Size	Low	3.772	3.624	4.391	0.619
		(21.272)	(16.444)	(16.219)	(3.367)
	Med	3.110	3.132	3.638	0.528
		(21.242)	(13.243)	(14.237)	(3.337)
	High	2.711	2.862	3.650	0.938
		(18.230)	(12.437)	(11.056)	(4.219)

		β(Climate)			
		Low	Med	High	High-Low
AV	Low	3.053	2.927	3.887	0.834
		(21.079)	(13.085)	(13.503)	(3.720)
	Med	2.887	2.985	3.097	0.210
		(19.094)	(12.680)	(12.274)	(1.724)
	High	3.974	3.661	4.520	0.546
		(18.092)	(15.886)	(14.955)	(3.430)

		β(Climate)			
		Low	Med	High	High-Low
Illiq	Low	2.758	2.858	3.295	0.537
		(18.676)	(12.154)	(11.813)	(3.364)
	Med	3.031	2.994	3.500	0.469
		(20.113)	(13.376)	(13.407)	(3.114)
	High	3.932	3.692	4.746	0.814
		(21.077)	(16.093)	(15.914)	(4.297)

		β(Climate)			
		Low	Med	High	High-Low
Cash	Low	3.376	3.167	4.094	0.718
		(19.346)	(14.344)	(14.552)	(3.642)
	Med	3.095	3.042	3.909	0.814
		(24.717)	(14.018)	(15.024)	(4.349)
	High	3.291	3.245	3.862	0.571
		(18.454)	(12.120)	(12.725)	(3.215)

		β(Climate)			
		Low	Med	High	High-Low
Inc	Low	3.903	3.625	4.679	0.775
		(21.487)	(15.346)	(14.857)	(3.616)
	Med	2.939	3.010	3.435	0.496
		(20.931)	(13.518)	(13.969)	(3.394)
	High	2.874	2.906	3.468	0.594
		(19.905)	(12.051)	(12.442)	(3.517)

		β(Climate)			
		Low	Med	High	High-Low
MB	Low	3.826	3.496	4.478	0.652
		(16.151)	(15.331)	(14.697)	(3.529)
	Med	3.173	3.129	3.563	0.390
		(18.862)	(13.229)	(13.193)	(2.625)
	High	2.796	2.865	3.296	0.501
		(19.960)	(12.865)	(13.844)	(3.667)

		β(Climate)			
		Low	Med	High	High-Low
CPN	Low	2.385	2.473	2.892	0.507
		(16.121)	(12.241)	(10.335)	(3.254)
	Med	3.199	3.083	3.671	0.472
		(18.752)	(14.188)	(12.366)	(2.875)
	High	4.206	4.058	4.935	0.729
		(22.177)	(17.339)	(16.957)	(3.319)

		β(Climate)			
		Low	Med	High	High-Low
CF	Low	3.606	3.348	4.380	0.774
		(18.104)	(13.288)	(13.521)	(3.611)
	Med	3.285	3.194	3.826	0.541
		(19.691)	(14.508)	(14.236)	(3.361)
	High	2.907	2.908	3.439	0.532
		(22.253)	(13.110)	(15.572)	(3.745)

		β(Climate)			
		Low	Med	High	High-Low
ROA	Low	3.922	3.501	4.573	0.651
		(17.886)	(13.663)	(14.127)	(3.246)
	Med	3.211	3.147	3.583	0.372
		(20.574)	(14.605)	(14.442)	(2.597)
	High	2.735	2.861	3.275	0.540
		(21.306)	(12.499)	(15.022)	(4.530)

		β(Climate)			
		Low	Med	High	High-Low
DD	Low	4.299	3.716	4.841	0.541
		(17.325)	(15.974)	(15.479)	(2.817)
	Med	3.221	3.247	3.425	0.204
		(19.526)	(13.263)	(12.599)	(1.438)
	High	2.610	2.698	2.775	0.164
		(19.131)	(12.794)	(15.616)	(2.358)

		β(Climate)			
		Low	Med	High	High-Low
TTM	Low	2.836	2.648	3.885	1.049
		(20.108)	(11.825)	(11.630)	(4.296)
	Med	3.358	3.224	4.025	0.667
		(21.268)	(13.513)	(14.424)	(3.634)
	High	3.568	3.460	3.979	0.412
		(20.973)	(14.699)	(15.159)	(3.015)

Table 3.5: Characteristics of Climate Risk Effect-Sorted Portfolios

This table presents results from univariate portfolio sorts, with the climate risk effect as the sorting variable and the row-specific variables as outcomes. For instance, the "Sales" row reports the average firm sales across portfolios sorted by climate risk effect. At the end of each month, all available bonds are sorted by their most recent climate risk effect, and three portfolios are formed based on the empirical distribution of the climate risk effect. The "Low" ("High") portfolio includes bonds with a climate risk effect below (above) the bottom (top) tertile, while the "Med" portfolio contains the remaining bonds. The final column reports the average high-minus-low ("High-Low") difference in the outcome variable between the "High" and "Low" portfolios. Newey and West (1987) t-statistics with four-month lags are reported in parentheses. The sample period spans January 2008 to December 2021.

	(1) Low	(2) Med	(3) High	(4) H–L
Sales	0.739	0.704	0.658	-0.080
	(37.942)	(46.384)	(66.082)	(-3.997)
Cash	0.070	0.064	0.072	0.002
	(42.527)	(47.006)	(50.813)	(1.266)
CF	0.091	0.090	0.083	-0.008
	(42.229)	(101.328)	(50.843)	(-2.272)
Lev	0.513	0.508	0.523	0.010
	(110.027)	(118.065)	(138.489)	(1.852)
Inc	0.091	0.096	0.064	-0.027
	(34.083)	(27.772)	(7.415)	(-3.140)
ROA	0.048	0.047	0.032	-0.016
	(38.143)	(31.588)	(9.380)	(-4.200)
Size	23.701	24.078	23.680	-0.020
	(689.017)	(818.093)	(691.024)	(-0.498)
MB	3.088	3.245	2.881	-0.206
	(28.313)	(25.236)	(27.040)	(-1.476)
DD	23.384	24.612	19.143	-4.241
	(28.652)	(20.053)	(14.889)	(-4.477)
AV	0.281	0.288	0.328	0.047
	(17.512)	(14.921)	(14.023)	(4.920)
CPN	5.037	4.952	5.237	0.199
	(50.165)	(30.784)	(41.301)	(2.825)
TTM	10.495	11.264	10.691	0.196
	(53.683)	(88.039)	(69.475)	(0.764)
Illiq	0.006	0.006	0.008	0.002
	(9.961)	(7.808)	(6.618)	(2.590)

Table 3.6: Portfolio Sorting on Climate Risk Effect across Different Dimensions

This table reports portfolio sorting results based on different dimensions of climate risk effect. Portfolios are formed as described in Table 3.1. The table reports average bond spreads. Newey and West (1987) t-statistics are reported in parentheses. The sample period spans January 2008 to December 2021.

Physical risk causes attention							
Panel A: 3 Portfolios							
Low		Med		High	H-L	α_C^{BWadj}	α_L^{BWadj}
3.503		3.070		3.777	0.274	0.203	0.234
(14.450)		(14.370)		(17.800)	(2.007)	(1.582)	(1.729)
Panel B: 5 Portfolios							
Low	LMed	Med	HMed	High	H-L	α_C^{BWadj}	α_L^{BWadj}
3.660	3.203	3.046	3.215	4.142	0.482	0.389	0.431
(14.177)	(14.508)	(14.113)	(15.794)	(17.982)	(2.624)	(2.236)	(2.342)
Physical risk results attention							
Panel A: 3 Portfolios							
Low		Med		High	H-L	α_C^{BWadj}	α_L^{BWadj}
3.544		3.086		3.723	0.179	0.076	0.122
(14.477)		(14.325)		(17.526)	(1.228)	(0.556)	(0.829)
Panel B: 5 Portfolios							
Low	LMed	Med	HMed	High	H-L	α_C^{BWadj}	α_L^{BWadj}
3.789	3.133	3.071	3.236	4.039	0.250	0.129	0.178
(14.240)	(14.632)	(14.283)	(14.751)	(17.854)	(1.284)	(0.676)	(0.881)
Regulatory attention category							
Panel A: 3 Portfolios							
Low		Med		High	H-L	α_C^{BWadj}	α_L^{BWadj}
3.146		3.132		4.064	0.918	0.811	0.828
(19.290)		(13.903)		(14.315)	(4.803)	(4.661)	(4.605)
Panel B: 5 Portfolios							
Low	LMed	Med	HMed	High	H-L	α_C^{BWadj}	α_L^{BWadj}
3.230	3.014	3.124	3.496	4.404	1.174	1.041	1.062
(20.114)	(16.783)	(13.750)	(12.542)	(15.165)	(5.114)	(5.025)	(4.955)
Opportunity attention category							
Panel A: 3 Portfolios							
Low		Med		High	H-L	α_C^{BWadj}	α_L^{BWadj}
3.240		3.185		3.921	0.681	0.546	0.575
(24.942)		(14.057)		(12.539)	(2.951)	(2.590)	(2.634)
Panel B: 5 Portfolios							
Low	LMed	Med	HMed	High	H-L	α_C^{BWadj}	α_L^{BWadj}
3.332	3.089	3.159	3.482	4.205	0.873	0.714	0.743
(26.407)	(19.171)	(14.000)	(11.949)	(12.863)	(3.281)	(2.896)	(2.948)
Broad cognitive level							
Panel A: 3 Portfolios							
Low		Med		High	H-L	α_C^{BWadj}	α_L^{BWadj}
3.336		3.126		3.885	0.549	0.412	0.451
(21.144)		(13.855)		(13.924)	(3.282)	(3.192)	(3.204)
Panel B: 5 Portfolios							
Low	LMed	Med	HMed	High	H-L	α_C^{BWadj}	α_L^{BWadj}
3.473	3.116	3.106	3.383	4.190	0.718	0.566	0.599
(22.796)	(17.255)	(13.739)	(12.178)	(14.741)	(3.716)	(3.734)	(3.677)

Table 3.7: Fama-MacBeth Regression Results across Different Dimensions

This table presents the results from monthly Fama and MacBeth (1973) regressions, where bond spreads are regressed on climate risk effect, lagged by 1 month, and a set of 12-month-lagged control variables. Columns (1), (3), (5), (7), and (9) report estimates from univariate regressions in which climate beta is the sole explanatory variable. The remaining columns add the bond-factor exposures and firm- and bond-level controls. For ease of presentation, the reported coefficients on $\beta(\mathrm{MKT})$, $\beta(\mathrm{DRF})$, $\beta(\mathrm{CRF})$, and $\beta(\mathrm{LRF})$ have been multiplied by 100. This rescaling does not affect the corresponding t-statistics or statistical significance. The third-to-last row (Mean R^2) reports the average R^2 coefficient across regressions. The second-to-last row (Mean Obs/Month) reports the average number of firms per month, while the final row (# Months) indicates the total number of months in the sample. Newey and West (1987) t-statistics (with four lags) are reported in parentheses. The sample period spans January 2008 to December 2021.

	Physical risk causes attention		Physical risk results attention		Regulatory attention category		Opportunity attention category		Broad cognitive level	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
β(Climate)	8.606	3.693	2.776	0.780	6.238	1.954	5.205	1.068	11.214	4.008
	(3.533)	(3.898)	(2.188)	(1.772)	(5.194)	(3.830)	(3.121)	(1.638)	(4.184)	(3.532)
β(MKT) (coef. × 100)		0.058		0.022		0.044		0.015		0.036
		(1.258)		(0.516)		(1.201)		(0.356)		(0.812)
β(DRF) (coef. × 100)		0.104		0.050		0.089		0.035		0.086
		(1.236)		(0.657)		(1.188)		(0.405)		(1.012)
β(CRF) (coef. × 100)		-0.141		-0.149		-0.124		-0.180		-0.159
		(-1.649)		(-1.827)		(-1.454)		(-2.056)		(-1.825)
β(LRF) (coef. × 100)		0.055		0.048		0.064		0.039		0.060
		(1.649)		(1.686)		(1.790)		(1.198)		(1.798)
Sales		-0.118		-0.132		-0.115		-0.115		-0.128
		(-3.714)		(-3.950)		(-3.724)		(-4.018)		(-4.191)
Cash		-0.109		-0.157		-0.109		-0.101		-0.119
		(-0.504)		(-0.741)		(-0.478)		(-0.475)		(-0.555)
CF		-1.226		-1.174		-1.178		-1.027		-1.079
		(-3.189)		(-2.983)		(-3.342)		(-2.781)		(-2.874)
Lev		0.805		0.846		0.783		0.797		0.835
		(9.368)		(8.949)		(7.585)		(7.695)		(8.584)
Inc		-0.540		-0.584		-0.556		-0.473		-0.544
		(-1.898)		(-1.987)		(-2.063)		(-1.868)		(-1.986)
ROA		-2.719		-2.660		-2.696		-3.009		-2.753
		(-5.178)		(-5.320)		(-5.772)		(-6.378)		(-5.551)
Size		-0.272		-0.275		-0.273		-0.269		-0.276
		(-16.731)		(-16.354)		(-16.610)		(-18.305)		(-17.133)
MB		-0.019		-0.021		-0.020		-0.021		-0.023
		(-3.247)		(-3.342)		(-3.233)		(-3.777)		(-4.160)
DD		-0.028		-0.028		-0.028		-0.027		-0.028
		(-5.951)		(-6.068)		(-6.104)		(-6.641)		(-6.109)
AV		0.812		0.840		0.793		0.815		0.818
		(5.816)		(5.943)		(5.687)		(6.132)		(6.063)
CPN		0.399		0.398		0.388		0.392		0.397
		(15.106)		(15.622)		(15.345)		(15.829)		(15.681)
TTM		0.081		0.081		0.081		0.081		0.080
		(11.772)		(11.994)		(11.735)		(11.943)		(11.639)
Illiq		43.444		44.140		42.958		45.164		44.340
		(8.242)		(8.085)		(8.680)		(7.972)		(8.279)
Constant	3.296	6.970	3.317	7.077	3.305	7.115	3.309	6.963	3.334	7.117
	(14.471)	(12.634)	(15.052)	(12.400)	(17.002)	(12.769)	(18.500)	(13.647)	(16.753)	(12.731)
Mean of R^2	0.084	0.727	0.074	0.725	0.120	0.728	0.082	0.724	0.066	0.725
Mean Obs/Mth	250	184	250	184	250	184	250	184	250	184
# Months	168	168	168	168	168	168	168	168	168	168

Table B1: Descriptive Statistics for Bond Spreads and Climate Risk Effect

This table presents cross–sectional summary statistics for bond spreads and climate risk effect over the period 2008–2021. Reported statistics include the sample mean, 25th percentile, median (50th percentile), 75th percentile, standard deviation, skewness, and kurtosis. The final two rows report the number of unique firms and the total number of firm–month observations. All variables are winsorized at the 5% and 95% levels. ACNI represents Attention to Climate News Index and FCRI represents Faccini Climate Risk Index.

		Climate Risk Effect	
	Bond Spread (%)	ACNI	FCRI
Mean	3.088	0.030	0.031
25th Percentile	1.802	-0.002	-0.185
50th Percentile	2.663	0.012	0.008
75th Percentile	3.938	0.037	0.201
Maximum	13.058	0.805	1.981
Minimum	0.142	-0.110	-3.747
St. Dev.	1.883	0.074	0.336
Skewness	1.576	4.180	0.608
Kurtosis	6.823	28.023	6.486
# Firms	568	568	568
# Firm–month obs	42045	41989	42045

Table B2: Per Year Summary Statistics for Bond Spreads

This table reports the per-year summary statistics for the monthly cross-section of U.S. corporate bond spreads. The sample period is from January 2008 to December 2021. Descriptive statistics include the sample mean, standard deviation, skewness, and kurtosis for each year. The mean and standard deviation are annualized. Bond spreads are expressed in percentages. The last column reports the total number of firm–month observations per year.

Year	Mean	STD	Skewness	Kurtosis	NumObs
2008	5.040	2.479	0.998	3.273	1244
2009	6.301	2.793	0.947	3.257	1587
2010	4.382	1.603	0.263	2.155	1752
2011	4.065	1.625	0.503	2.532	2007
2012	3.277	1.569	0.722	2.755	2279
2013	3.253	1.280	0.403	2.446	2565
2014	3.145	1.161	0.499	2.741	2729
2015	3.483	1.410	0.990	3.563	2970
2016	3.415	1.634	1.216	3.970	3372
2017	2.630	1.087	0.880	3.117	3690
2018	2.461	0.982	1.003	3.399	4044
2019	1.576	1.240	1.431	4.603	4394
2020	2.899	2.458	1.765	5.546	4733
2021	2.387	1.082	1.189	4.088	4679

Table B3: Portfolio Sorts on Firm-Level Climate-Risk Exposure Using the Faccini Index

This table reports monthly portfolio sorts based on firms' climate-risk exposure, measured by $\beta(\text{Climate})$ constructed using the Faccini Climate Risk Index and lagged by one month. Panel A forms three equal-weighted portfolios using tertile breakpoints, while Panel B forms five equal-weighted portfolios using quintile breakpoints. The columns under "Raw Portfolio Spreads" report the annualized average bond yield spread for each portfolio. "Raw High-Low" is calculated as the average spread of the High-$\beta(\text{Climate})$ portfolio minus that of the Low-$\beta(\text{Climate})$ portfolio. The final two columns report intercepts from time-series regressions of the monthly High-Low spread differential on the four adjusted bond factors of Dickerson et al. (2023) and four additional market and macroeconomic variables. Panel A also reports the corresponding factor loadings. The subscripts C and L denote specifications using contemporaneous and one-month-lagged factors, respectively. Because the dependent variable is a yield-spread differential rather than a portfolio return, these intercepts represent factor-adjusted spread differentials and should not be interpreted as abnormal investment returns. All estimates are annualized and expressed in percentage points. Newey and West (1987) t-statistics based on four lags are reported in parentheses. The sample spans January 2008 to December 2021.

Panel A: Tertile Sorts (Baseline)

	Raw Portfolio Spreads			Raw High-Low	Factor-Adjusted High-Low	
	Low (1)	Medium (2)	High (3)	High-Low (4)	α_C^{BBWadj} (5)	α_L^{BBWadj} (6)
Mean spread / α	3.323 (17.655)	3.096 (14.792)	3.931 (14.455)	0.608 (3.731)	0.659 (4.213)	0.653 (3.818)
MKT_t	–	–	–	–	1.541 (0.184)	–
DRF_t	–	–	–	–	-3.006 (-0.385)	–
CRF_t	–	–	–	–	11.580 (2.236)	–
LRF_t	–	–	–	–	17.367 (1.412)	–
SP500_Ret_t	–	–	–	–	-8.280 (-3.923)	–
OilRet_t	–	–	–	–	-0.978 (-0.926)	–
defret_t	–	–	–	–	2.076 (0.321)	–
infl_t	–	–	–	–	-47.688 (-1.416)	–
MKT_{t-1}	–	–	–	–	–	4.016 (0.467)
DRF_{t-1}	–	–	–	–	–	-3.729 (-0.505)
CRF_{t-1}	–	–	–	–	–	10.757 (2.039)
LRF_{t-1}	–	–	–	–	–	16.086 (1.378)
SP500_Ret_{t-1}	–	–	–	–	–	-8.040 (-3.478)
OilRet_{t-1}	–	–	–	–	–	-0.463 (-0.465)
defret_{t-1}	–	–	–	–	–	2.906 (0.489)
infl_{t-1}	–	–	–	–	–	-46.784 (-1.313)
R^2	–	–	–	–	0.181	0.159
# Months	168	168	168	168	168	167

Panel B: Quintile Sorts (Alternative)

	Raw Portfolio Spreads					Raw High-Low	Factor-Adjusted High-Low	
	Q1 (Low) (1)	Q2 (2)	Q3 (3)	Q4 (4)	Q5 (High) (5)	High-Low (6)	α_C^{BBWadj} (7)	α_L^{BBWadj} (8)
Mean spread / α	3.555 (17.727)	2.961 (16.696)	3.115 (14.609)	3.336 (12.858)	4.307 (15.272)	0.751 (3.962)	0.793 (4.451)	0.787 (4.116)

Table B4: Fama-MacBeth Regression Results

This table presents the results from monthly Fama and MacBeth (1973) regressions, where bond spreads are regressed on the climate risk effect constructed using the Faccini Climate Risk Index and lagged by one month, and a set of 12-month-lagged control variables. Column (1) presents estimates from a univariate regression using climate risk effect as the sole explanatory variable. Columns (2)–(5) add bond market factors, firm-level, and bond-level controls. For ease of presentation, the reported coefficients on $\beta(\mathrm{MKT})$, $\beta(\mathrm{DRF})$, $\beta(\mathrm{CRF})$, and $\beta(\mathrm{LRF})$ have been multiplied by 100. This rescaling does not affect the corresponding t-statistics or statistical significance. The third-to-last row (Mean R^2) reports the average R^2 coefficient across regressions. The second-to-last row (Mean Obs/Month) reports the average number of firms per month, while the final row (# Months) indicates the total number of months in the sample. Newey and West (1987) t-statistics (with four lags) are reported in parentheses. The sample period spans January 2008 to December 2021.

	(1)	(2)	(3)	(4)	(5)
β(Climate)	1.008	0.993	0.712	0.703	0.351
	(4.125)	(3.771)	(4.723)	(4.132)	(2.380)
β(MKT) (coef. × 100)		-0.006		0.071	0.037
		(-0.103)		(1.453)	(0.654)
β(DRF) (coef. × 100)		0.002		0.173	0.106
		(0.016)		(1.836)	(0.923)
β(CRF) (coef. × 100)		-0.250		-0.051	-0.104
		(-2.257)		(-0.558)	(-1.116)
β(LRF) (coef. × 100)		0.070		0.086	0.072
		(1.428)		(2.063)	(1.686)
Sales					-0.111
					(-3.481)
Cash					-0.144
					(-0.685)
CF					-1.085
					(-3.159)
Lev					0.787
					(6.706)
Inc					-0.550
					(-1.976)
ROA					-2.745
					(-5.882)
Size					-0.278
					(-16.949)
MB					-0.020
					(-2.637)
DD					-0.029
					(-6.072)
AV					0.805
					(5.838)
CPN			0.600	0.595	0.389
			(21.112)	(20.643)	(15.459)
TTM			0.044	0.047	0.080
			(5.896)	(6.707)	(11.627)
Illiq			82.917	79.140	41.592
			(13.577)	(13.460)	(9.014)
Constant	3.460	3.411	-0.602	-0.622	7.294
	(17.234)	(17.415)	(-4.451)	(-4.419)	(12.907)
Mean of R^2	0.090	0.150	0.537	0.570	0.731
Mean Obs/Mth	250	249	249	248	184
# Months	168	168	168	168	168

Table B5: Panel Regression Results

This table reports panel regressions of corporate bond spreads on firms' climate betas constructed using the Faccini Climate Risk Index and lagged by one month, and 12-month-lagged firm- and bond-level controls, as specified in Equation (19). Columns (1)–(2) include month fixed effects, while Columns (3)–(4) include both month and industry fixed effects. Columns (1) and (3) exclude the control variables, whereas Columns (2) and (4) include the full set of controls. t-statistics based on standard errors two-way clustered by firm and calendar year are reported in parentheses. The sample spans January 2008 to December 2021.

	(1)	(2)	(3)	(4)
β(Climate)	1.196	0.381	1.011	0.344
	(4.552)	(2.415)	(4.288)	(2.221)
Sales		-0.091		-0.078
		(-1.559)		(-1.191)
Cash		-0.275		-0.223
		(-0.692)		(-0.649)
CF		0.239		-0.485
		(0.201)		(-0.593)
Lev		0.875		1.018
		(3.137)		(3.127)
Inc		0.282		0.577
		(0.739)		(1.219)
ROA		-5.393		-5.473
		(-3.793)		(-3.670)
Size		-0.274		-0.296
		(-8.783)		(-8.419)
MB		-0.016		-0.015
		(-1.238)		(-1.130)
DD		-0.023		-0.021
		(-5.059)		(-4.858)
AV		0.628		0.488
		(2.071)		(1.685)
CPN		0.370		0.359
		(8.194)		(8.194)
TTM		0.069		0.069
		(4.654)		(4.414)
Illiq		52.457		52.255
		(2.698)		(2.667)
Intercept	3.050	6.992	3.056	7.518
	(59.545)	(8.984)	(63.763)	(8.982)
Observations	42,045	31,131	42,045	31,131
R^2	0.365	0.694	0.414	0.699
Time FE	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes

Table B6: Bivariate Portfolio Sorts

This table reports monthly double independent portfolio sorts based on one-month-lagged firm-level climate beta and the 12-month-lagged characteristic specified in each panel, using the Faccini Climate Risk Index. At the end of each month, bonds are independently assigned to three climate-beta portfolios and three portfolios based on the conditioning variable, producing nine portfolios. The procedure generates a monthly time series of average bond yield spreads for each portfolio. Within each conditioning-variable tertile, the final column reports the High–Low spread differential, calculated as the average spread of the High-climate-beta portfolio minus that of the Low-climate-beta portfolio. Because the reported outcome is a bond yield spread rather than a portfolio return, the High–Low value should not be interpreted as a tradable long–short return. Newey and West (1987) t-statistics based on four lags are reported in parentheses. The sample spans January 2008 to December 2021.

		β(Climate)			
		Low	Med	High	High-Low
Sales	Low	3.449	3.207	4.036	0.586
		(16.343)	(14.049)	(12.876)	(3.231)
	Med	3.334	3.026	3.765	0.430
		(15.975)	(14.649)	(14.504)	(2.591)
	High	3.161	3.021	3.872	0.711
		(20.513)	(15.496)	(16.511)	(4.402)

		β(Climate)			
		Low	Med	High	High-Low
Lev	Low	3.189	3.008	3.549	0.360
		(16.385)	(14.013)	(17.322)	(2.761)
	Med	3.278	2.991	3.684	0.406
		(17.239)	(15.394)	(15.772)	(2.588)
	High	3.458	3.152	4.302	0.843
		(19.622)	(16.064)	(14.548)	(3.668)

		β(Climate)			
		Low	Med	High	High-Low
Size	Low	3.948	3.516	4.351	0.403
		(17.112)	(17.448)	(17.099)	(2.413)
	Med	3.142	3.070	3.660	0.518
		(17.474)	(15.112)	(15.030)	(3.888)
	High	2.851	2.827	3.605	0.755
		(16.160)	(12.760)	(10.593)	(3.301)

		β(Climate)			
		Low	Med	High	High-Low
AV	Low	3.124	2.837	3.805	0.681
		(18.636)	(14.617)	(14.723)	(3.435)
	Med	2.914	2.875	3.201	0.287
		(15.397)	(13.790)	(13.375)	(2.687)
	High	3.959	3.722	4.507	0.549
		(18.026)	(15.799)	(14.949)	(3.254)

		β(Climate)			
		Low	Med	High	High-Low
Illiq	Low	2.825	2.758	3.278	0.453
		(16.018)	(13.119)	(12.645)	(3.032)
	Med	3.069	2.940	3.520	0.451
		(16.354)	(14.572)	(14.181)	(3.784)
	High	4.055	3.700	4.702	0.646
		(18.475)	(16.994)	(15.632)	(3.722)

		β(Climate)			
		Low	Med	High	High-Low
Cash	Low	3.427	3.117	4.017	0.590
		(18.791)	(15.024)	(15.334)	(3.196)
	Med	3.178	2.972	3.782	0.604
		(19.786)	(14.894)	(17.882)	(4.362)
	High	3.373	3.165	3.870	0.497
		(15.004)	(14.589)	(12.419)	(2.889)

		β(Climate)			
		Low	Med	High	High-Low
Inc	Low	3.997	3.582	4.599	0.602
		(18.211)	(16.670)	(15.784)	(3.234)
	Med	3.083	2.978	3.390	0.307
		(16.674)	(14.139)	(15.188)	(2.720)
	High	2.931	2.836	3.439	0.508
		(15.717)	(13.509)	(13.005)	(3.446)

		β(Climate)			
		Low	Med	High	High-Low
MB	Low	3.934	3.512	4.500	0.566
		(14.626)	(16.025)	(15.507)	(3.680)
	Med	3.184	3.017	3.601	0.417
		(16.232)	(13.718)	(13.644)	(2.730)
	High	2.827	2.806	3.289	0.462
		(18.002)	(14.360)	(13.902)	(3.383)

		β(Climate)			
		Low	Med	High	High-Low
CPN	Low	2.509	2.418	2.821	0.312
		(13.962)	(12.718)	(11.496)	(2.852)
	Med	3.221	3.074	3.673	0.453
		(16.086)	(15.005)	(12.940)	(3.556)
	High	4.283	4.055	4.865	0.582
		(20.275)	(19.237)	(16.598)	(2.653)

		β(Climate)			
		Low	Med	High	High-Low
CF	Low	3.718	3.397	4.310	0.592
		(16.337)	(14.072)	(13.778)	(3.375)
	Med	3.330	3.139	3.768	0.438
		(16.669)	(15.405)	(16.154)	(3.188)
	High	2.962	2.806	3.425	0.463
		(17.560)	(14.571)	(15.996)	(3.322)

		β(Climate)			
		Low	Med	High	High-Low
ROA	Low	3.933	3.572	4.500	0.566
		(16.454)	(14.366)	(14.357)	(3.065)
	Med	3.268	3.123	3.543	0.275
		(16.861)	(15.401)	(16.425)	(2.065)
	High	2.840	2.736	3.251	0.412
		(16.893)	(13.854)	(16.344)	(3.782)

		β(Climate)			
		Low	Med	High	High-Low
DD	Low	4.220	3.829	4.853	0.633
		(17.743)	(16.006)	(15.422)	(3.496)
	Med	3.272	3.191	3.458	0.186
		(15.731)	(13.903)	(13.940)	(1.838)
	High	2.641	2.608	2.777	0.136
		(16.255)	(14.106)	(17.280)	(1.577)

		β(Climate)			
		Low	Med	High	High-Low
TTM	Low	2.922	2.578	3.895	0.973
		(14.709)	(12.894)	(12.315)	(4.332)
	Med	3.420	3.138	4.042	0.622
		(19.005)	(14.572)	(15.691)	(4.331)
	High	3.627	3.423	4.003	0.376
		(18.137)	(15.657)	(15.614)	(3.878)

Table B7: Characteristics of Climate Risk Effect-Sorted Portfolios

This table presents results from univariate portfolio sorts, with the climate risk effect as the sorting variable and the row-specific variables as outcomes. For instance, the "Sales" row reports the average firm sales across portfolios sorted by climate risk effect. At the end of each month, all available bonds are sorted by their most recent climate risk effect, and three portfolios are formed based on the empirical distribution of the climate risk effect. The "Low" ("High") portfolio includes bonds with a climate risk effect below (above) the bottom (top) tertile, while the "Med" portfolio contains the remaining bonds. The final column reports the average high-minus-low ("High-Low") difference in the outcome variable between the "High" and "Low" portfolios. Newey and West (1987) t-statistics with four-month lags are reported in parentheses. The sample period spans January 2008 to December 2021.

	(1) Low	(2) Med	(3) High	(4) H–L
Sales	0.722	0.719	0.659	-0.063
	(51.568)	(47.000)	(55.524)	(-4.428)
Cash	0.071	0.067	0.068	-0.003
	(45.369)	(42.992)	(55.747)	(-2.131)
CF	0.089	0.094	0.082	-0.007
	(57.342)	(114.370)	(62.072)	(-2.722)
Lev	0.512	0.509	0.522	0.010
	(106.768)	(126.698)	(121.106)	(1.652)
Inc	0.088	0.097	0.066	-0.022
	(24.424)	(26.524)	(9.075)	(-3.205)
ROA	0.045	0.051	0.030	-0.015
	(29.607)	(40.883)	(10.113)	(-4.897)
Size	23.747	24.048	23.662	-0.085
	(714.604)	(1406.790)	(515.780)	(-1.460)
MB	3.016	3.446	2.753	-0.264
	(54.470)	(28.542)	(21.330)	(-2.492)
DD	22.910	25.006	19.170	-3.741
	(21.386)	(21.549)	(19.447)	(-6.818)
AV	0.290	0.288	0.318	0.028
	(16.277)	(14.964)	(14.796)	(4.021)
CPN	5.007	4.918	5.303	0.296
	(42.590)	(33.396)	(43.480)	(4.986)
TTM	10.596	11.385	10.475	-0.120
	(44.999)	(94.180)	(57.984)	(-0.364)
Illiq	0.006	0.006	0.007	0.001
	(9.069)	(8.163)	(6.884)	(2.430)

Table B8: Portfolio Sorting on Climate Risk Effect across Different Dimensions

This table reports portfolio sorting results based on different dimensions of climate risk effect. Portfolios are formed as described in Table 3.1. The table reports average bond spreads and the High–Low spread between portfolios with the highest and lowest exposure. Newey and West (1987) t-statistics are reported in parentheses. The sample period spans January 2008 to December 2021.

US Policy							
Panel A: 3 Portfolios							
Low		Med		High	H–L	α_C^{BWadj}	α_L^{BWadj}
3.202		3.138		4.008	0.807	0.699	0.699
(22.422)		(14.208)		(12.996)	(3.636)	(3.695)	(3.510)
Panel B: 5 Portfolios							
Low	LMed	Med	HMed	High	H–L	α_C^{BWadj}	α_L^{BWadj}
3.359	2.986	3.127	3.450	4.353	0.995	0.861	0.859
(22.853)	(18.029)	(14.310)	(11.783)	(13.586)	(3.801)	(3.917)	(3.734)
International Summits							
Panel A: 3 Portfolios							
Low		Med		High	H–L	α_C^{BWadj}	α_L^{BWadj}
3.461		3.054		3.838	0.377	0.294	0.303
(19.025)		(14.872)		(13.550)	(2.135)	(1.877)	(1.950)
Panel B: 5 Portfolios							
Low	LMed	Med	HMed	High	H–L	α_C^{BWadj}	α_L^{BWadj}
3.709	3.051	3.029	3.327	4.160	0.451	0.365	0.371
(18.575)	(17.318)	(15.039)	(13.057)	(13.740)	(2.061)	(1.868)	(1.938)
Global Warming							
Panel A: 3 Portfolios							
Low		Med		High	H–L	α_C^{BWadj}	α_L^{BWadj}
3.630		3.106		3.623	-0.007	0.113	0.104
(12.741)		(14.638)		(19.408)	(-0.037)	(0.663)	(0.613)
Panel B: 5 Portfolios							
Low	LMed	Med	HMed	High	H–L	α_C^{BWadj}	α_L^{BWadj}
3.855	3.250	3.070	3.149	3.950	0.095	0.221	0.202
(12.632)	(13.083)	(14.738)	(15.556)	(20.202)	(0.379)	(0.982)	(0.912)
Natural Disasters							
Panel A: 3 Portfolios							
Low		Med		High	H–L	α_C^{BWadj}	α_L^{BWadj}
3.620		3.096		3.642	0.022	0.106	0.106
(13.910)		(14.888)		(17.172)	(0.128)	(0.695)	(0.688)
Panel B: 5 Portfolios							
Low	LMed	Med	HMed	High	H–L	α_C^{BWadj}	α_L^{BWadj}
3.873	3.180	3.102	3.208	3.911	0.039	0.139	0.138
(13.718)	(13.954)	(14.767)	(14.774)	(18.519)	(0.189)	(0.756)	(0.736)

Table B9: Fama-MacBeth Regression Results across Different Dimensions

This table presents the results from monthly Fama and MacBeth (1973) regressions, where bond spreads are regressed on one-month-lagged climate risk effect and a set of 12-month-lagged control variables. Columns (1), (3), (5), and (7) report estimates from univariate regressions in which climate beta is the sole explanatory variable. The remaining columns add the bond-factor exposures and firm- and bond-level controls. For ease of presentation, the reported coefficients on $\beta(\mathrm{MKT})$, $\beta(\mathrm{DRF})$, $\beta(\mathrm{CRF})$, *and* $\beta(\mathrm{LRF})$ *have been multiplied by 100. This rescaling does not affect the corresponding* t*-statistics or statistical significance. The third-to-last row (Mean* R^2*) reports the average* R^2 *coefficient across regressions. The second-to-last row (Mean Obs/Month) reports the average number of firms per month, while the final row (# Months) indicates the total number of months in the sample. Newey and West (1987) t-statistics (with four lags) are reported in parentheses. The sample period spans January 2008 to December 2021.*

	US Policy		International Summits		Global Warming		Natural Disasters	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β(Climate)	0.352	0.198	0.260	0.015	0.147	0.059	0.171	0.056
	(3.129)	(3.186)	(2.503)	(0.268)	(1.964)	(1.514)	(1.832)	(1.244)
β(MKT) (coef. × 100)		-0.045		0.074		-0.001		-0.002
		(-1.126)		(1.659)		(-0.026)		(-0.039)
β(DRF) (coef. × 100)		-0.063		0.148		-0.018		-0.008
		(-0.805)		(1.643)		(-0.226)		(-0.088)
β(CRF) (coef. × 100)		-0.198		-0.123		-0.105		-0.191
		(-2.354)		(-1.383)		(-1.508)		(-2.120)
β(LRF) (coef. × 100)		0.000		0.082		-0.001		0.026
		(0.003)		(2.346)		(-0.051)		(0.768)
Sales		-0.111		-0.128		-0.103		-0.110
		(-3.774)		(-3.840)		(-3.476)		(-3.641)
Cash		-0.145		-0.147		-0.143		-0.171
		(-0.701)		(-0.712)		(-0.682)		(-0.831)
CF		-1.074		-1.047		-1.151		-1.197
		(-3.046)		(-2.618)		(-2.972)		(-3.233)
Lev		0.764		0.802		0.835		0.825
		(6.218)		(7.421)		(9.636)		(8.253)
Inc		-0.479		-0.639		-0.459		-0.537
		(-1.804)		(-2.163)		(-1.699)		(-1.892)
ROA		-2.794		-2.825		-2.795		-2.853
		(-5.686)		(-5.593)		(-5.809)		(-5.739)
Size		-0.275		-0.276		-0.278		-0.277
		(-16.859)		(-16.720)		(-16.679)		(-16.471)
MB		-0.020		-0.018		-0.022		-0.018
		(-3.138)		(-2.378)		(-3.837)		(-2.768)
DD		-0.028		-0.029		-0.028		-0.029
		(-6.800)		(-6.105)		(-6.083)		(-6.064)
AV		0.808		0.844		0.794		0.843
		(5.958)		(5.940)		(5.739)		(5.959)
CPN		0.392		0.390		0.397		0.392
		(16.576)		(15.373)		(15.033)		(15.410)
TTM		0.079		0.081		0.078		0.080
		(11.661)		(11.787)		(11.398)		(11.796)
Illiq		41.911		44.076		40.745		41.441
		(8.270)		(8.209)		(9.061)		(8.761)
Constant	3.434	7.236	3.402	7.174	3.477	7.239	3.555	7.256
	(18.955)	(12.873)	(15.296)	(12.592)	(15.904)	(13.041)	(16.548)	(12.676)
Mean of R^2	0.105	0.731	0.074	0.724	0.104	0.731	0.085	0.727
Mean Obs/Mth	250	184	250	184	250	184	250	184
# Months	168	168	168	168	168	168	168	168

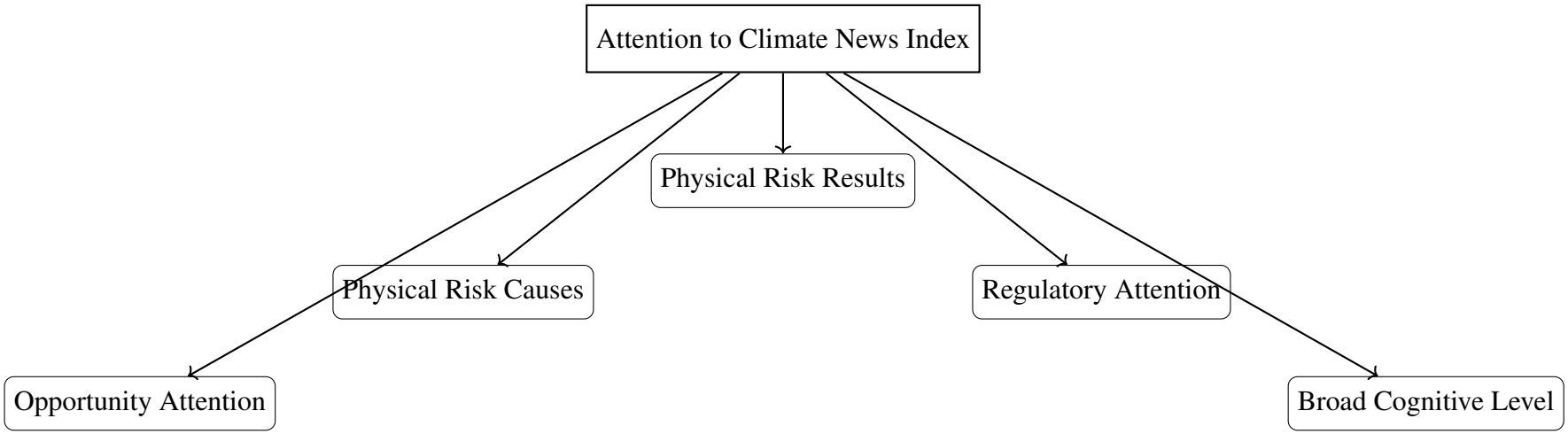
Table B10: Searching Topics about the Attention to Climate News Index

We group words into five different categories representing public climate attention and build a vocabulary for each aspect as follows.

Category	**Keywords**
Physical risk causes	Greenhouse gases, carbon dioxide, nitrogen oxides, sulfur oxides, carbon disulfide, methane, carbon monoxide, Freon, fossil fuel, smoke, exhaust gas, toxic gas, ozone, particle pollution
Physical risk results	Smog, air pollution, acid rain, ozone hole, water pollution, clean water, photochemical pollution, land desertification, extreme weather, abnormal temperature, cool summer, warm winter, extremely cold, extremely hot, heavy rain, blizzard thunderstorms, typhoons, polar vortexes, tropical cyclones, hail, earthquakes, wildfires, floods, droughts, volcanic eruptions, El Niño, global warming, sea level rise, melting glaciers
Regulatory attention	Emission reduction, carbon reduction, carbon tax, energy consumption regulation, environmental protection, carbon market, carbon price, carbon sink, carbon trading, energy independence, carbon neutrality, the Paris Agreement, Copenhagen Climate Change Conference, climate conference, the Kyoto protocol, United Nations climate conference
Opportunity attention	Clean energy, photovoltaic, solar energy, wind energy, tidal energy, biomass energy, green energy, geothermal energy, biofuel, hydrogen energy, nuclear energy, hydroelectric power, power generation, new energy vehicles, electric vehicles, smart grid, energy storage, green bonds, green insurance, green credit, green securities
Broad cognitive level	Climate, climate type, climate change, climate warming, climate zone

Table B11: Definition of Variables

Variable	Symbol	Definition
Sales	*Sales*	Firm's net sales scaled by total assets.
Cash	*Cash*	Firm's cash and cash equivalent items scaled by total assets.
Cash flow	*CF*	Firm's net operating cash flow scaled by total assets.
Leverage	*Lev*	Firm's sum of current liabilities and long-term debt scaled by total assets.
Income	*Inc*	Firm's income before extraordinary items scaled by net sales.
Return-on-assets	*ROA*	Operating income before depreciation as a fraction of average total assets.
Firm size	*Size*	Firm size measured by the logarithm of total assets.
Market-to-book ratio	*MB*	Market value of equity over the book value of equity.
Coupon rate	*CPN*	Bond's coupon rate.
Time to maturity	*TTM*	Bond's time to maturity.
Bond illiquidity	*Illiq*	Bond's illiquidity (Amihud).
Distance-to-default	*DD*	Distance to default computed using the KMV model.
Asset volatility	*AV*	Asset volatility estimated using the KMV model.



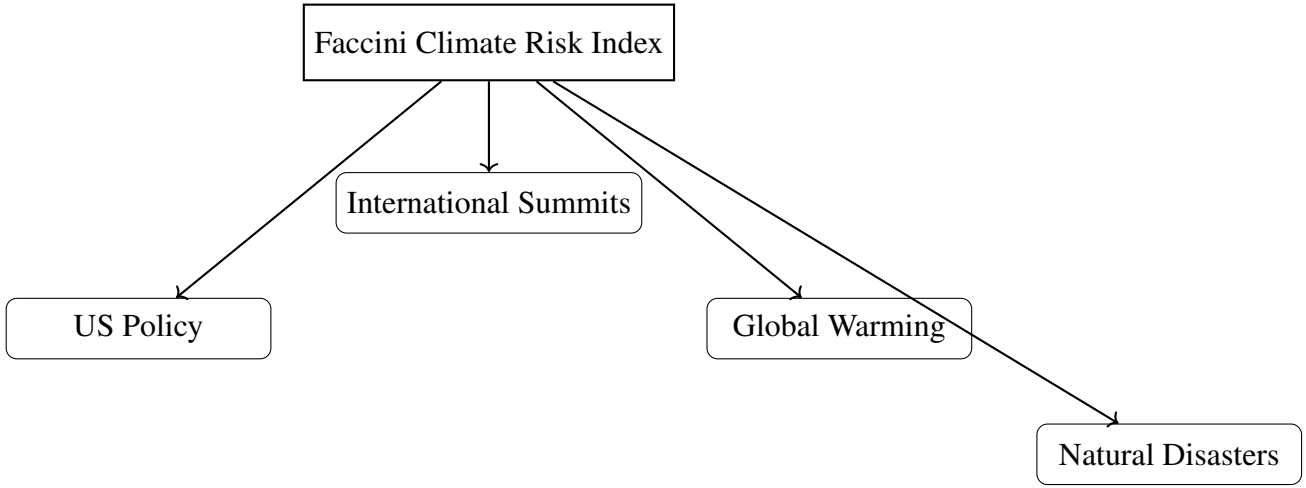


Figure 1: Dimensions of Climate Risk Indices

4 Essay 3: Climate Change Risk and the Cross-Section of Option Returns

4.1 Introduction

Climate risk in financial markets has been widely debated in recent years, as numerous media reports highlight how firm valuations and investment decisions are increasingly affected by severe climate change. Meanwhile, while much of the literature pays attention to the impact of climate-related risk on major financial products, such as corporate bonds or stocks, the impact on financial derivatives, which are important financial products used for risk management and price discovery, is relatively less studied.

This essay examines whether firms' historical option-return sensitivity to aggregate climate concerns is associated with subsequent equity option returns. The transmission mechanism differs across stocks, bonds, and options because these securities have different payoff structures. A stock is a direct claim on the residual value of a firm. Climate news therefore affects its price mainly by changing expected cash flows or the required rate of return, producing a directional increase or decrease in the stock price. A corporate bond promises fixed payments and offers limited upside. Climate risk becomes particularly important to bondholders when it increases the probability of default or reduces the expected recovery value, leading to a higher yield spread.

An option instead has a nonlinear and state-dependent payoff. Its value depends not only on the expected future stock price, but also on the dispersion and shape of possible stock-price outcomes. Climate news can increase this dispersion even when the expected direction of the stock-price response is unclear. For example, a new climate policy may create losses for some business activities but opportunities for others, thereby increasing the probability of extreme outcomes. Because both calls and puts have positive vega and convex payoffs, an increase in expected volatility or tail risk

can affect the values of both types of options. Option returns may also react strongly because the option premium is small relative to the exposure to the underlying stock. Option prices and returns may therefore reflect changes in expected volatility and tail risk in addition to directional changes in the underlying stock price.

To estimate firm-month climate exposure in options, we run a rolling version of regressions where individual firms' option returns are regressed on a media-based climate risk index by Ardia et al. (2023). This procedure is repeated for each firm-month. Then we use the regression coefficients on the climate risk index as a proxy for the option's sensitivity to climate-related news and sentiment over time. To test our argument, we examine whether the estimated climate beta can explain option returns in the next month.

Our sample includes U.S. equity option data from 2008 to 2021 obtained from OptionMetrics. The baseline analysis uses the 50% absolute-delta, 30-calendar-day point of the OptionMetrics volatility surface. This point provides a standardized at-the-money, constant-maturity measure across firms and months and corresponds to a relatively liquid and volatility-sensitive region of the option surface (Goyal and Saretto, 2009). A key challenge in constructing option returns is that theoretical and empirical asset pricing models are typically derived for European-style options, whereas the raw option prices reported in OptionMetrics are for American-style options. This distinction is important because early exercise features can bias return calculations, particularly for put options. While existing approaches attempt to recover European option prices from American prices, these adjustments are often imprecise and more difficult to implement for puts. To address this issue, we follow Martin and Wagner (2019) and compute option returns using prices implied from the OptionMetrics volatility surface. The volatility surface is constructed based on European-style pricing, which provides consistency with conceptual valuation frameworks and avoids biases associated with early exercise features.

We conduct several tests to analyze the association between the climate beta and the option returns. First, the portfolio sorting results show a monotonic relationship between climate beta and option returns. Options written on firms in the highest climate-beta group earn substantially higher returns than those on firms in the lowest group, with economically meaningful high-minus-low spreads. Second, these return differentials are statistically significant after adjusting for conventional risk factors, indicating that the return differential is not absorbed by the included Fama–French factors. Third, cross-sectional Fama-MacBeth regressions and panel regressions with time and industry fixed effects confirm that the positive association with lagged climate beta remains across the Fama–MacBeth and panel specifications, even after controlling for firm characteristics and equity option variables.

The common positive association for calls and puts is more consistent with a volatility-related channel than with a purely directional stock-price channel. However, the analysis does not separately identify volatility risk, tail risk, underpricing, or demand pressure.

This study contributes in several ways. First, our findings extend the current works of climate risk impact to equity option markets, which have received comparatively less attention. Second, we document climate-related exposure as a predictor of option returns. Third, it has practical implications for investors and risk managers, suggesting that climate sensitivity may be relevant to option valuation and risk monitoring, particularly volatility trading and tail-risk hedging.

The remainder of the essay is structured as follows: Section 4.2 is the literature review. Section 4.3 develops our hypotheses. Section 4.4 describes the data and variable construction. Section 4.5 presents the empirical results. Section 4.6 concludes.

4.2 Relevant Literature

4.2.1 Corporate Climate Risk

Climate risk commonly refers to the potential damage to human or ecological systems caused by climate change, and is divided into two broad categories: (i) Physical climate risk, which materializes in the form of financial losses or increased costs caused by the chronic and acute physical events and (ii) Transition risk, which arises from the economic adjustment towards a low-carbon economy and is typically prompted by changes in climate and/or environmental policy, technological advances, and/or movements in public preferences (Bua et al., 2024).

Physical climate risk reflects the direct damage caused by, for example, more frequent and severe floods or other extreme weather events. Research to date has documented severe economic consequences from increasingly severe climate threats. Cosemans et al. (2025) show that rising temperatures deepen investors' concern about the economic impact of climate change, thereby altering their long-horizon investment decisions. Ozturk et al. (2022) argue that climate uncertainty driven by climate policy and natural hazards is a significant driver of the dynamics of the prices of carbon emission allowances. Earlier studies focused more on climate physical risk, but recently, more attention has been on climate transition risk (Faccini et al., 2023).

Climate transition risk is the risk to businesses from the changes in environmental regulations, as firms may need to adapt to the new regulations, and the adaptation is usually a long-term adjustment to a low-carbon economy (Collender et al., 2023). In addition to direct impacts, recent studies find that firms are also significantly affected by the indirect impacts of the transition in climate policy. Bolton and Kacperczyk (2023) find that short-term transition risk is greater for firms located in countries with lower economic development, greater dependence upon fossil energy, and less open political systems. Importantly, they argue that climate transition risk is different from physical climate risk. Alessi and Battiston (2022) examine the relationship between greenness and transition risk of financial portfolios

and find that a green portfolio, i.e., a portfolio consisting of green assets, is not completely immune from transition risk. In fact, the authors point out that such a phenomenon happens perhaps due to the unequivocal approach to form a green portfolio under the green finance intention, while transition risk due to regulation change is more transparent. Therefore, green-finance investors are still advised to watch out for financial risks associated with the transition risk.

There are also several relevant studies on climate transition risk. Reboredo and Ugolini (2022) find that firms with low exposure to transition risk have better financial performance. They also find that the effect of transition risk is geographically heterogeneous: European firms are more sensitive to climate transition risks than U.S. firms. The findings in Reboredo and Ugolini (2022) are in line with Bolton and Kacperczyk (2023) in the sense that short-term transition risk is greater for firms located in the countries that rely more on fossil-fuel energy, while long-term transition risk is greater in countries with stricter domestic climate policies. Similarly, Dumrose and Höck (2023) analyze the relationship between corporate carbon risk and credit risk, and show that firms operating in more restrictive regulatory contexts tend to experience higher credit spreads, since stricter climate policies increase the perceived risk of investment. Better carbon-risk management is associated with lower credit spreads, as firms with strong sustainability practices can mitigate some financial risks associated with carbon exposure. Higher carbon-risk exposure, in turn, is associated with larger credit spreads, indicating the market's pricing of transition risks. Moreover, effective management has an important role in reducing these risks, as firms with strong governance and sustainability strategies are more resilient, thereby reducing credit risk. This strand of literature has grown rapidly recently, which we elaborate on in a later sub-section.

Climate Risk Measurement

There is growing academic interest in quantifying climate risk for financial risk measurement and

estimation. Research studies in this aspect sometimes provide novel climate risk indices to measure how financial markets price environmental uncertainty. Since these indices offer climate-related exposure, they are useful for risk premium estimation driven by climate risk.

Monasterolo and De Angelis (2020) provide one of the first systematic investigations on how global financial markets respond to climate policy shocks. They study the impact of the 2015 Paris Agreement and demonstrate that low-carbon indices exhibited a clear decline in systematic risk exposure after the agreement, whereas high-carbon indices maintained or increased their sensitivity to market risk. This result introduced the concept of a carbon risk premium, indicating that investors demand higher expected returns from carbon-intensive (brown) assets exposed to regulatory penalties and reputational costs. This premium reflects investors' gradual recognition of climate change as a priced risk factor, even when the market behaves heterogeneously.

Subsequent studies have expanded this perspective by analyzing the dynamic relationship between climate news and financial market volatility. Wang and Li (2023) examine the predictive power of climate risk indices in the Chinese market and find that combining such indices with ESG variables significantly improves volatility forecasting. Their evidence suggests that markets are increasingly incorporating environmental and sustainability factors into pricing models and risk assessments.

Researchers were also interested in derivative markets. Ford et al. (2022) show that firms in the highest ESG-rated portfolio receive significantly more optimistic sentiment than those in the lowest portfolio. They further document that the environmental score and ESG controversies score seem to be more influential. This evidence suggests that option traders also likely take a firm's environmental risks into trading consideration.

Interestingly, Monasterolo and De Angelis (2020) show that, while financial markets have started to reward low-carbon assets following the Paris Agreement, carbon-intensive assets are not penalized to the same extent. This asymmetric market reaction, in which climate transition risk is still only par-

tially incorporated into asset prices, implies the ongoing mispricing of "brown" assets and potentially underestimates stranded-asset risk.

To quantify climate risk exposure, researchers have developed several useful indices, using a quantitative or qualitative approach, as an alternative to the conventional ESG score. Faccini et al. (2023)'s Climate Risk Index is one of the text-based examples of climate risk indices, where the authors extract climate-related sentiment from media reports using natural language processing. Similarly, Ardia et al. (2023) construct the Media Climate Change Concerns Index by analyzing the attitude and frequency of climate coverage across prominent U.S. news sources.

Using online search data, Gong et al. (2023) incorporate search-engine data and develop the general public's Attention to Climate Risk Index using Google Trends terms. These aforementioned indices aim to give insights into, e.g., regulatory uncertainty and physical threats to changes in public attention.

4.2.2 Option Markets

Option markets are a central area of financial research in financial economics because options reflect not only market fundamentals but also investors' expectations, sentiment, and information asymmetry. Options are traded instruments that embody collective beliefs about volatility, skewness, and the probability distribution of future returns. Consistent with this view, Doran et al. (2013) show that option-implied volatility spreads contain both informational and mispricing components. While these spreads positively predict stock returns, they are negatively related to certain option returns, particularly for out-of-the-money calls. The authors attribute this pattern to heterogeneous investor demand, where less sophisticated investors contribute to option mispricing. This evidence shows that option returns are formed not only by risk fundamentals but also by investor demand and belief heterogeneity.

Early studies such as Bakshi et al. (2003) show that option-implied volatility carries predictive information beyond historical volatility. By incorporating implied-volatility measures into predictive models, they achieve greater accuracy in forecasting future stock returns and systemic risk. This evidence demonstrates that option prices contain forward-looking information about tail risk, which is often invisible in spot market data. Song and Xiu (2016) further expand this framework by demonstrating that option prices not only forecast future volatility but also uncover the state-dependent pricing of tail risk. By combining S&P 500 and VIX options, they show that volatility pricing kernels display clear nonlinearity and strong sensitivity to stress conditions, implying that systemic risk is largely reflected in derivatives markets rather than in spot returns.

Behavioral finance introduces another dimension to option markets. Zghal et al. (2020) demonstrate that option prices are influenced not only by fundamental risk factors but also by market mood and information asymmetry. Using S&P 500 index options, they show that incorporating trader sentiment and asymmetric information into the traditional Black-Scholes framework markedly improves option pricing accuracy. Their results suggest that deviations of option prices from theoretical values partly reflect investors' behavioral biases, implying that option markets embed both rational expectations and sentiment-driven distortions. Building on this behavioral perspective, subsequent studies show that option markets also reflect investors' concerns about non-financial risks. Ford et al. (2022) find that option traders' sentiment is closely related to a firm's ESG performance, especially environmental aspects. Using the put-call ratio as a measure of short-term sentiment, they show that firms with higher ESG ratings—particularly stronger environmental scores—are likely to attract more optimistic sentiment from option traders. In contrast, firms involved in ESG-related controversies exhibit a more pessimistic outlook in the options market. This evidence indicates that option prices incorporate not only risk and expectations about future returns, but also investors' behavioral responses to sustainability and climate-related risks.

Option Pricing

The study of option pricing has developed significantly since the Black-Scholes-Merton (BSM) model was first introduced. The BSM framework assumes continuous asset price movements and fully rational investors. However, later studies have shown that real markets display features such as volatility clustering, price jumps, and changing skewness that cannot be fully explained by the basic model. As a result, researchers have extended option pricing models to more successfully capture these market characteristics. More recently, behavioral factors and sustainability-related issues have also been incorporated, suggesting that option prices are influenced not only by fundamentals but also by investor psychology and environmental elements.

Option-implied measures, including volatility, skewness, and kurtosis, are widely used as forward-looking indicators of market risk. Empirical evidence (see, e.g., Bakshi et al., 2003; Song and Xiu, 2016) shows that these option-based indicators deliver better predictions of future market conditions than historical measures. In particular, option-implied volatility is often viewed as the market's expectation of future uncertainty. Changes in implied volatility tend to occur before changes in realized volatility, suggesting that option markets play an important role in aggregating information about risk. In addition to their informational role, recent studies document strong cross-sectional patterns in option returns that are difficult to reconcile with standard asset pricing models. For instance, Zhan et al. (2022) show that delta-hedged option returns are predictable using firm characteristics such as profitability and investment, and these patterns stay unexplained by traditional risk factors. This evidence suggests that standard models fail to capture important sources of risk within option markets.

At the firm level, Sheng (2022) finds that option pricing errors are larger for firms with higher information asymmetry. In such firms, the gap between implied and realized volatility reflects not only imperfect information but also speculative trading behavior. This implies that option prices are affected by both subjective beliefs and rational expectations. Consistent with this view, Zghal et al.

(2020) show that trader sentiment can further distort option prices, especially when information is unevenly distributed. Together, these results show that the interaction between sentiment and information asymmetry leads to non-linear effects in option pricing.

Coval and Shumway (2001) examine the behavior of expected option returns and find that call options generally earn higher returns than their underlying assets, while put options tend to achieve returns below the risk-free rate. Using index option data, they also show that these returns vary systematically with the option's strike price. Importantly, even market-neutral option strategies, such as zero-beta straddles, generate negative average returns. This finding implies that option markets price risks beyond usual market risk, such as volatility risk, and helps explain why observed option returns deviate from model-implied predictions.

Extending this line of work, Hu and Jacobs (2020) find that expected option returns are closely related to the volatility of the underlying stocks. Specifically, they show that call options on low-volatility stocks tend to earn higher average returns, while those on high-volatility stocks tend to earn lower returns. In contrast, the expected returns on put options increase with the underlying stock's volatility. These patterns are explained by the leverage embedded in options: options on low-volatility stocks are cheaper and therefore more leveraged, causing larger potential gains or losses. Their results suggest that volatility is a key factor in explaining cross-sectional differences in option returns.

Recent studies have begun to explore how environmental and ESG factors affect option markets. For example, Ford et al. (2022) and Wang and Li (2023) find that climate-related news has a strong impact on implied volatility, especially for firms and industries that are more exposed to environmental risks. These outcomes suggest that standard option-pricing models may underestimate risk in sectors sensitive to climate change. To improve pricing accuracy, researchers have proposed extending present models to include climate-related factors such as carbon emissions and uncertainty about climate policies. Both behavioral factors and sustainability concerns bring extra sources of risk

into option prices. As investor outlook can move market prices, uncertainty about ESG performance and climate policies can lead investors to demand higher compensation for bearing risk. Therefore, environmental uncertainty can be viewed as an additional component in option valuation.

Overall, understanding option pricing in practice requires going beyond traditional inputs such as volatility and interest rates. It is increasingly important to account for firm-specific risks, such as default risk, as well as exposure to climate and environmental elements.

Climate Risk and Option Markets

In fixed-income markets, Huynh and Xia (2021) show that climate news affects bond pricing, while Seltzer et al. (2022) report that firms with high carbon profiles face elevated borrowing costs, signaling elevated credit risk. Despite such progress, the options market—an essential instrument for managing tail risks and expressing directional bets—has received limited attention in this domain.

Bansal et al. (2017) demonstrate that climate change poses a long-run risk with important effects on asset prices. By including temperature dynamics into a long-run risks framework, they show that rising temperatures negatively affect economic growth and increase uncertainty, leading investors to demand a higher risk premium. Their data show that climate risk is priced in financial markets through its impact on future growth and tail risk. Although their analysis primarily focuses on equities, it provides a theoretical basis for understanding how climate risk may also alter option prices, particularly through changes in volatility and downside risk. Based on this literature, Faccini et al. (2023) show that not all types of climate risk are priced equally in U.S. financial markets. Using news-based measures, they find that risks related to climate policy and regulation play a more important role in asset pricing than physical risks such as natural disasters or rising temperatures. This implies that investors are more concerned about the economic impact of government action and transition policies than about the direct physical effects of climate change.

Options are unique financial instruments intended to hedge, speculate, or express views on future volatility. They are sensitive to downside risks and higher statistical parameters of return distributions (e.g., skewness and kurtosis), making them well suited to studying how markets respond to climate-related uncertainty. Ilhan et al. (2021) study how climate policy uncertainty affects option-implied tail risks and show that investors demand higher premiums to hedge against downside risks in firms with high carbon exposure, particularly during periods of intense climate-related media coverage. This suggests that option prices incorporate market expectations regarding climate risk, though a systematic examination of realized option returns in this context remains limited.

The intersection of option markets and climate risk has emerged as a growing area of research in modern finance. Because options capture expectations about future volatility and extreme events, they are naturally suited to reflect how investors perceive environmental uncertainty. Derivative prices can therefore serve as high-frequency indicators of changing attitudes toward climate risk.

Ilhan et al. (2021) show that climate policy uncertainty is clearly reflected in option prices. They find that options written on carbon-intensive firms are more expensive, especially those that provide protection against large downside risks. This means that investors are willing to pay more for insurance against extreme negative price movements for firms that are more exposed to climate regulation. Moreover, the cost of downside protection increases during periods when public attention to climate change is high, such as after major climate-related news or policy debates. These results suggest that option markets play an important role in pricing climate-related tail risk and provide evidence into how investors perceive regulatory and environmental uncertainty.

Relatedly, Cao et al. (2025) show that option markets also price environmental, social, and governance (ESG) risks. They find that options written on firms with lower ESG scores are more expensive, indicating that investors are willing to pay a premium to hedge against ESG-related uncertainty. In particular, this ESG premium is mainly caused by concerns about extreme downside events rather

than normal fluctuations in volatility. Their results suggest that option markets serve as an important channel through which investors manage and price sustainability-related risks, extending the evidence beyond carbon risk alone.

Overall, options provide a useful tool to understand how markets perceive climate risk. Existing studies suggest that climate risk is increasingly priced into financial markets through both policy-related channels and investor attention. Our study adds to this literature by focusing on realized option returns and firm-level climate exposure, extending the literature between climate finance and derivatives pricing.

4.3 Hypothesis Development

The expected relationship between climate beta and option returns involves two stages. First, news about physical damage, environmental regulation, technological change, or public climate concerns can change the market's assessment of the distribution of a firm's future cash flows. Investors may revise not only the expected level of these cash flows, but also their uncertainty, skewness, and probability of extreme outcomes. These revisions can affect implied volatility and tail-risk pricing in the option market.

Second, firms differ in how strongly their option returns respond to aggregate climate concerns. The rolling climate beta captures this historical sensitivity. An option with a high climate beta has previously responded more strongly when the MCCC index was elevated and therefore carries greater exposure to climate-attention shocks. If these shocks represent systematic risks that are difficult to diversify or hedge, investors may require compensation for holding options with greater exposure. This provides the economic motivation for expecting higher subsequent returns among high-climate-beta options.

Importantly, an increase in uncertainty may raise the current value of an option, but it does not mechanically guarantee a higher subsequent option return. A higher purchase price could offset the effect of a higher future payoff. The sign and significance of the relationship between lagged climate beta and next-month option returns must therefore be determined empirically. This leads to the first hypothesis:

H1: Climate risk is positively priced in the cross-section of option returns.

Note that option return is used in the main tests instead of option prices for two reasons. First of all, using the option return to test the impact of climate risk can have empirical results with better time-series stationarity. In addition, earlier studies suggest that option returns are more responsive to changes in volatility than the persistent drift term in prices (Coval and Shumway, 2001).

Climate risk is proxied by a climate index constructed by Ardia et al. (2023), and we run regressions to obtain firm-level estimates. The detailed discussion on variable construction is explained in the next section. Monthly option returns are constructed from the 50% absolute-delta, 30-calendar-day point of the OptionMetrics volatility surface. In fact, ATM options have the highest vega (i.e., option price sensitivity with respect to volatility) among options with different moneyness. In addition, short-maturity options are more liquid than other longer-maturity options; therefore, we can reduce potential concern due to illiquid contracts.

Calls and puts provide an additional way to distinguish the volatility channel from a simple directional stock-price channel. Calls and puts have opposite signs of delta: an increase in the underlying stock price generally benefits calls but reduces the value of puts, while a decrease has the opposite effect. However, both calls and puts have positive vega and can gain value when expected volatility increases. Therefore, a positive relationship between climate beta and both call and put returns would be more consistent with a common volatility and tail-risk channel than with a purely directional movement in the underlying stock price. This leads to the second hypothesis:

H2: Climate risk is positively associated with both call and put option returns.

To test the hypotheses listed above, we conduct portfolio sorting exercises by sorting option returns on their exposure to climate risk. We also test abnormal return, controlling for commonly known systematic factors in equity markets. We also test our hypotheses using firm-level observations by running Fama-MacBeth regressions, again controlling for known option-related variables and firm characteristics. All the technical details are provided alongside the empirical results.

In this study, the call option results are presented first and narrated as the main exhibition, while analyses on put options are tested analogously to the call option counterpart and presented as the auxiliary exhibition, for comparison.

4.4 Data and Variable Construction

4.4.1 Data Source

In this study, data are obtained from various sources. Option data are obtained from OptionMetrics, which provides option prices for U.S.-listed firms. Climate risk is proxied by the Media Climate Change Concerns (MCCC, hereafter) index constructed by Ardia et al. (2023), a multi-dimensional index capturing business impact, environmental impact, societal debate, and research activity.

Here, we briefly explain the index construction. The authors construct the MCCC index in three steps. First, each day, the authors scan climate-related news articles from ten major U.S. newspapers and two newswires using two sets of lexicons: one related to discussion of climate risk events and the other related to sentiment about increased climate risk. In the second step, they construct the "concern" score (i.e., the appearance of the lexicons scaled by the length of the article) for each article. In the final step, the authors standardize the scores to account for heterogeneity between sources and aggregate the scores over a time range (e.g., day, month, etc.).

The MCCC index is a positive time series. It, by its nature, captures the magnitude of attention on climate risk as well as the sentiment associated with the risks for a given time range. We use the main index to comprehensively depict the climate risk in general.[20] MCCC is available from the authors' supplementary materials or Sentometrics Research with an extended data period.

The matched sample period for the individual firm's option and MCCC index was initially from 2003 to 2021. However, the first five years of data are not available for the main analysis because the firm-level climate risk estimates are generated using the rolling 5-year data. Hence, the final sample used for the main portfolio and regression analysis is from 2008 to 2021, with a monthly frequency.

[20]The index can be split into four sub-indices: Business Impact, Environmental Impact, Societal Debate, and Research, and a further 30 sub-subject indices. Since a smaller subset may consist of scarce observations from the sources, it may generate higher estimation error when we generate firm-level estimates.

In addition to the main data source, firm characteristics are collected from COMPUSTAT and CRSP; U.S. equity market systematic factors are collected from Kenneth French's website.

4.4.2 Variable Construction

The main variable is the option return, defined as the annualized percentage change of the option prices (i.e., $12 \times (P_t/P_{t-1} - 1)$). In this study, we calculate the monthly return using the month-end option prices. Ideally, when testing on option return determinants, European-type options are used preferably to avoid the impact of option early exercise. Likewise, options with similar terms and a fixed length of maturity used for return calculation are also desired. However, option prices in OptionMetrics are American-type with fixed maturity dates, which impose challenges for empirical works. Prior studies (see, e.g., Carr and Wu, 2009; Hu and Jacobs, 2020) use American option data directly, while other studies (see, e.g., Aretz et al., 2023) use American calls written on zero-dividend single stocks to test the predictions, as Merton (1973) shows that it is never optimal to early exercise them, making them equivalent to European calls.

To overcome the aforementioned challenges, we follow Martin and Wagner (2019)'s suggestion to use the option volatility surface reported by OptionMetrics. The pricing information in the OptionMetrics volatility surface is European type: OptionMetrics computes the option volatility for individual underlying firms by removing all the factors that account for the early exercise premium in the American option prices. Also, the daily volatility data are implied from the Black and Scholes (1973) model. OptionMetrics generates the volatility surface for individual options consisting of the BS-implied volatility by time to maturity (ranging from 10 days to 2 years) and by level of moneyness (ranging from 10% to 90% of option delta in absolute value), respectively. OptionMetrics also reports the BS-implied option premium and BS-implied option strike, along with the implied volatility.

In the main analysis, we use the 50% absolute-delta point to represent an at-the-money option

and the 30-calendar-day point to represent one-month maturity. For each firm and month, P(t) is the month-end Black–Scholes-implied call premium reported by OptionMetrics at this fixed point, while P(t-1) is the corresponding implied premium at the previous month end. The annualized call return is calculated as 12 times the percentage change from P(t-1) to P(t). Both prices therefore refer to the same firm, option type, delta, and constant maturity. This measure is not the holding-period return on one listed option contract, because the remaining maturity of such a contract would decline between the two month ends. Firm-month observations without the required implied premium at either month end cannot enter the return calculation.

The 50% absolute-delta point is used as the operational definition of an at-the-money option for three reasons. First, fixing delta provides a comparable measure of moneyness across firms and over time, even when the underlying stock price changes. Second, at-the-money options generally have the highest vega among options with different levels of moneyness. They are therefore well suited to testing whether climate concerns affect option premiums through changes in expected volatility. Third, this choice reduces measurement problems associated with more extreme options. Deep out-of-the-money options can have very small premiums, so a small price change may produce an extremely large percentage return. Deep in-the-money option premiums, in contrast, are more strongly affected by intrinsic value and directional movements in the underlying stock. The at-the-money region also tends to have more active trading and denser price information, which improves the reliability of the interpolated volatility surface.

The 30-calendar-day maturity is selected because it matches the monthly frequency of the empirical analysis. Both the current and previous month-end premiums are taken from the same 30-day point on the volatility surface. The comparison therefore keeps maturity constant instead of following one listed contract whose remaining maturity declines over the month. This design reduces the mechanical effect of changing time to expiration and makes the return series more comparable across

months. It also allows the option return to capture relatively prompt repricing following monthly changes in climate attention measured by the MCCC index. In addition, short-maturity at-the-money options are generally among the more actively traded parts of the equity option market, providing broader and more consistent coverage across firms.

The focus on short-maturity at-the-money options is consistent with established empirical studies of option returns (Goyal and Saretto, 2009; Cao and Han, 2013; Zhan et al., 2022). Taken together, these studies support this choice on the grounds of comparability across contracts, sensitivity to changes in underlying stock volatility, and relatively active trading with more reliable pricing information.

These choices improve measurement and comparability, but they also define the scope of the results. The baseline evidence concerns the short-horizon repricing of standardized at-the-money option premiums. It should not be interpreted as showing that climate risk has the same effect on deep out-of-the-money, deep in-the-money, or long-dated options. Moreover, using the more liquid part of the volatility surface reduces, but does not eliminate, option-liquidity concerns because no separate screens based on trading volume, open interest, or bid–ask spreads are imposed. Tables 4.6 and 4.7 address the maturity dimension by reconstructing the option returns and climate betas at the 60- and 91-calendar-day points. The moneyness definition remains fixed at 50% absolute delta, so the effect across alternative levels of moneyness remains a subject for future research.

Within each month, we winsorize the cross-section of annualized option returns at the 5th and 95th percentiles. Returns below the 5th percentile are replaced by the 5th-percentile value, while returns above the 95th percentile are replaced by the 95th-percentile value. These observations are not deleted. Winsorisation is completed before the rolling climate-beta estimation, and the resulting return series is used in the portfolio and regression analyses. The baseline climate-beta estimates are not winsorized. Table 4.8 separately examines results after the estimated climate betas are winsorized

within each month.

We do not impose additional screens based on option trading volume, open interest, or bid–ask spreads. This is because the implied premium is obtained from an interpolated volatility-surface point rather than from one individual traded contract. The main liquidity-related restriction is therefore the use of the ATM, 30-day part of the surface. We also require the relevant surface premiums to be available at consecutive month ends. These choices reduce, but do not eliminate, concerns about option-market liquidity. The regressions additionally control for the Amihud illiquidity of the firm's bonds, using the same measure as in Chapters 2 and 3. The two- and three-month analyses reported in Tables 4.6 and 4.7 provide additional evidence on whether the results depend on the baseline maturity choice.

Since the MCCC index is an aggregate rather than a firm-specific measure, we use a rolling beta to estimate how strongly each firm's option return has historically covaried with aggregate climate concerns. Each firm-month, we estimate the following time-series regression using the most recent 60 months of observations, subject to a minimum of 30 valid monthly observations:

$$\mathrm{CallRet}_{i,t} = \alpha_i + \beta_{i,t}^{\mathrm{Climate}} \mathrm{MCCC}_t + \varepsilon_{i,t}. \tag{20}$$

Here, $\mathrm{CallRet}_{i,t}$ is the return on the 50% absolute-delta, 30-calendar-day point of the OptionMetrics volatility surface for firm i, and MCCC_t is the level of the Media Climate Change Concerns index. The estimate $\beta_{i,t}^{\mathrm{Climate}}$ is the climate beta of firm i in month t. It converts the common MCCC index into a firm-level measure by capturing differences in how firms' option returns have historically moved with aggregate climate concerns.

A high positive climate beta means that the firm's option return has tended to be higher in months when the MCCC index was elevated. A beta close to zero indicates little historical co-movement, while a negative beta indicates movement in the opposite direction. Although all firms are matched

with the same MCCC index, their climate betas differ because their option returns have responded differently to climate-related concerns. Climate beta is therefore a market-based sensitivity measure rather than a direct measure of the firm's carbon emissions, environmental performance, or physical climate exposure.

The rolling regression is repeated each month, allowing the estimated climate beta to change over time as the firm's operations and market perceptions change. In the subsequent portfolio and regression analyses, the climate beta is lagged by one month. Thus, the climate beta used to explain the option return in month t is $\beta_{i,t-1}^{\text{Climate}}$, estimated using information available no later than month $t-1$. The option return in month t is therefore not used to construct its explanatory climate beta.

In intuitive terms, the analysis asks whether an option that responded more strongly to climate concerns during the preceding five years earns a different return in the following month. The rolling-window estimation allows the exposure measure to vary over time, while the one-month lag prevents the use of future or same-month return information. These choices mitigate look-ahead concerns, although they do not eliminate measurement error or establish a causal relationship.

Next, we merge firm-level climate beta estimates with call returns, ending up with a sample of 105,729 firm-month observations from 2008 to 2021, covering 1,276 U.S. firms. In the regression analysis, we lag our beta estimates by one month to avoid look-ahead bias.

Other Variables

Here we briefly outline the variable constructions for control variables. The first set of control variables is related to firm characteristics. We follow Lys et al. (2015) to include firm characteristics related to the firm's environmental and societal performance, listed below.

$Sales$: Firm's net sales scaled by total assets.

$Cash$: Firm's cash and cash equivalent items scaled by total assets.

$CashFlow$: Firm's net operating cash flow scaled by total assets.

$Leverage$: Firm's sum of current liabilities and long-term debt scaled by total assets.

$Income$: Firm's income before extraordinary items scaled by net sales.

ROA: Operating Income before depreciation as a fraction of average total assets based on the two most recent periods.

$Size$: Firm size measured by the logarithm of total assets.

MTB: Market value of equity over the book value of equity.

We also control for variables relating to option pricing. In particular, we include bond market illiquidity as well as higher moments in options.

$Illiq$: Amihud (2002) illiquidity of the firm's bonds, constructed as described in Chapter 2.

VS: Volatility spread measured by the difference in implied volatility between pairs of ATM call and put options.

$Skew$: Skewness of the risk-neutral option return distribution, following Bakshi et al. (2003).

$Kurt$: Kurtosis of the risk-neutral option return distribution, following Bakshi et al. (2003).[21]

For the month-t option-return tests, climate beta is measured at $t-1$, whereas all firm- and option-level control variables are measured at $t-12$.

Summary statistics

[21] We use the option prices on the volatility surface to calculate the option skewness and kurtosis by $Skew = M_3/V^{3/2}$ and $Kurt = M_4/V^2$,
where $V = 2e^{r\tau}\left(\int_0^F \frac{P(K)}{K^2}\,dK + \int_F^\infty \frac{C(K)}{K^2}\,dK\right)$, $M_3 = e^{r\tau}\left(\int_0^F \frac{6(F-K)}{K^3}P(K)\,dK - \int_F^\infty \frac{6(K-F)}{K^3}C(K)\,dK\right)$, and $M_4 = e^{r\tau}\left(\int_0^F \frac{12(F-K)^2}{K^4}P(K)\,dK + \int_F^\infty \frac{12(K-F)^2}{K^4}C(K)\,dK\right)$.
$C(K)$ or $P(K)$ stands for call or put price with strike price K.

Table 4.1 presents descriptive statistics for option returns and climate betas. The mean call return is 2.228%, with a standard deviation of 20.197%. The pooled mean and median climate beta are 0.943 and 1.132, respectively. The pooled mean assigns equal weight to each firm-month observation, but it does not assign equal weight to each calendar month. Months containing more firms therefore have a greater influence on the pooled mean.

To use an inference procedure consistent with the portfolio-sorting and Fama–MacBeth analyses, we first calculate an equal-weighted cross-sectional mean climate beta in each month. We then calculate the time-series average of these 168 monthly estimates, giving equal weight to every month. The resulting equal-month average is 0.740 ($124.293505/168 \approx 0.740$), where 124.293505 is the sum of the 168 monthly cross-sectional mean beta estimates. The Newey–West standard error of this average, calculated from the same monthly series using four lags, is approximately 0.511858. Using the average before rounding, the corresponding t-statistic is $0.739842/0.511858 \approx 1.445$. Therefore, although the average is positive, it is not statistically different from zero at conventional significance levels. This t-statistic relates to the equal-month average of 0.740 rather than to the pooled descriptive mean of 0.943. Accordingly, the positive pooled mean should not, by itself, be interpreted as evidence that the average option has positive exposure to climate concerns.

Climate beta also shows substantial cross-sectional dispersion. Its standard deviation is 7.343, which is much larger than its pooled mean. The 25th and 75th percentiles are -3.825 and 5.604, respectively, giving an interquartile range of 9.429 ($5.604 - (-3.825) = 9.429$). In addition, approximately 43.7% of the firm-month beta estimates are negative ($46{,}157/105{,}729 \times 100\% \approx 43.7\%$), while 56.3% are positive ($59{,}572/105{,}729 \times 100\% \approx 56.3\%$). Thus, the relatively small positive mean masks considerable differences in both the direction and magnitude of firms' sensitivities to climate concerns. This heterogeneity provides the basis for the subsequent portfolio-sorting and regression analyses. Sorting firms by their estimated climate beta does not require the unconditional

mean beta to be statistically different from zero. The substantial dispersion also raises the question of whether extreme beta estimates influence the regression results. The baseline analysis therefore retains the original beta estimates, while Table 4.8 examines the sensitivity of the results to winsorizing climate beta. Panel B reports the descriptive statistics for the control variables.

[Insert Table 4.1 here.]

Next, we report the summary statistics broken down by year in Table 4.2. We find that the number of observations increases over time, indicating increased inclusion by the data provider. The average call returns are positive across the years except in 2009, when the average return was -2.066%. The highest option return average was 5.486% in 2020.

[Insert Table 4.2 here.]

Table 4.2 further shows that climate beta varies substantially over time. The annual mean is negative from 2011 to 2014 but positive in the other sample years. Moreover, the number of firm observations increases over the sample period. Consequently, later months with mainly positive climate betas receive more weight in the pooled mean reported in Table 4.1. The positive pooled mean therefore does not imply that option returns have a consistently positive sensitivity to climate concerns throughout the sample period. Instead, both the sign and magnitude of climate beta change over time. This temporal variation also supports the use of rolling-window beta estimates.

4.5 Empirical Results

4.5.1 Call Option Portfolio Sorts on Climate Beta

We first examine the association between lagged climate beta and subsequent call returns using portfolio sorts. Each month, we sort the option returns written on U.S. firms into portfolios by their climate betas. Note that our climate betas are computed at monthly frequency using Eq. (20) with prior 5-year observations. Also note that we lag the betas by one month when forming the portfolios, and we use equal weights in portfolio construction.

Our baseline analysis forms three equal-weighted portfolios using monthly climate-beta tertiles. Each portfolio contains approximately 210 firms on average ($105,729 \div (168 \times 3) \approx 210$), providing a broad comparison across the climate-beta distribution. We also form five portfolios using quintile breakpoints as an alternative specification. Table 4.3 reports the time-series averages of the monthly portfolio returns together with Newey–West t-statistics based on four lags. Because the monthly option-price changes are multiplied by 12, all portfolio returns and return differentials are annualized and expressed in percentage points.

Panel A reports the baseline tertile results. Columns (1)–(3) present the average annualized returns of the Low-, Medium-, and High-climate-beta portfolios, respectively. The average return increases monotonically from 1.070% for the Low portfolio to 1.895% for the Medium portfolio and 2.891% for the High portfolio. The Low-portfolio mean has a t-statistic of 1.849, while the Medium- and High-portfolio means are statistically significant at the 1% level, with t-statistics of 3.309 and 4.292, respectively.

Column (4) reports the raw High–Low return differential, calculated as the average return of the High-climate-beta portfolio minus that of the Low-climate-beta portfolio. The differential is 1.822 annualized percentage points and is statistically significant at the 1% level, with a Newey–West t-statistic of 2.832. Thus, options written on firms in the High-climate-beta tertile earn an average

annualized return that is 1.822 percentage points higher than options written on firms in the Low tertile. The High-portfolio mean is approximately 2.7 times the Low-portfolio mean ($2.891/1.070 \approx 2.70$). For additional scale, the High–Low differential is approximately 81.8% of the full-sample mean call return of 2.228% reported in Table 4.1 ($1.822/2.228 \times 100\% \approx 81.8\%$). The magnitude is therefore economically meaningful as well as statistically significant.

The positive return levels of all three portfolios are not the main identifying comparison. These levels may reflect market-wide option-return conditions during the sample period. The High–Low differential is more informative because it compares firms with relatively high and low predetermined climate sensitivities within the same month.

[Insert Table 4.3 here.]

The raw High–Low return differential may partly reflect conventional equity-market risks rather than differences related specifically to climate beta. To examine this possibility, we regress the monthly High–Low return on the Fama–French five factors. We estimate one specification using contemporaneous factors and another using factors lagged by one month. The regression is specified as follows:

$$\begin{aligned} \text{CallRet}_t^{H-L} = \alpha + \beta_{MKT}\ \text{MKT}_t + \beta_{SMB}\ \text{SMB}_t + \beta_{HML}\ \text{HML}_t \\ + \beta_{RMW}\ \text{RMW}_t + \beta_{CMA}\ \text{CMA}_t + \epsilon_t \end{aligned} \tag{21}$$

In Equation (21), CallRet_t^{H-L} is the monthly return difference between the High- and Low-climate-beta portfolios. MKT, SMB, HML, RMW, and CMA are the Fama–French market, size, value, profitability, and investment factors, respectively. The intercept measures the average annualized High–Low return differential that is not captured by these conventional factors. It should there-

fore be interpreted as a factor-adjusted return differential rather than as an automatically identified causal climate-risk premium.

Both specifications use the monthly High–Low return series reported in Table 4.3. The first specification uses the contemporaneous monthly Fama–French factors, while the second uses the same factors lagged by one month. The factor data are obtained from Kenneth French's data library. Newey–West t-statistics based on four lags are used to account for heteroskedasticity and serial correlation in the monthly portfolio-return series. Because the dependent variable is annualized and expressed in percentage points, the regression intercept is also expressed in annualized percentage points. This adjustment controls only for linear exposure to the five included equity factors. It does not control for every option-specific source of risk, such as volatility risk, tail risk, option-market liquidity, or investor demand.

Column (5) of Panel A reports the regression using contemporaneous Fama–French factors. The factor-adjusted intercept is 2.074 annualized percentage points and is statistically significant at the 1% level, with a Newey–West t-statistic of 2.855. The contemporaneous factor loadings are not individually statistically significant, and the regression R-squared is 0.031. Thus, contemporaneous movements in the five factors explain only a limited part of the time-series variation in the High–Low portfolio return.

Column (6) uses the Fama–French factors lagged by one month. The factor-adjusted intercept remains positive at 2.021 annualized percentage points, with a Newey–West t-statistic of 3.313. Among the lagged factors, SMB and CMA have negative coefficients, while HML has a positive coefficient with weaker statistical significance. The regression R-squared increases from 0.031 to 0.053, suggesting that lagged factors provide slightly more explanatory power than contemporaneous factors. Nevertheless, the factor-adjusted intercept remains economically large and statistically significant.

The two factor-adjusted intercepts are similar in magnitude to, and slightly larger than, the raw

High–Low differential of 1.822 percentage points. Therefore, controlling for the Fama–French factors does not reduce the return difference between the High- and Low-climate-beta portfolios. This result indicates that the observed cross-sectional return differential is not absorbed by the conventional equity-market factors included in Equation (21).

Panel B reports the alternative quintile sorts. Columns (1)–(5) show a monotonic increase in average annualized call returns across the five portfolios. The average return rises from 0.828% in the Low portfolio to 1.545%, 1.930%, and 2.225% in the three intermediate portfolios, before reaching 3.274% in the High portfolio. The High-portfolio mean is statistically significant at the 1% level, with a Newey–West t-statistic of 4.470, whereas the Low-portfolio mean has a t-statistic of 1.334.

Column (6) reports a raw High–Low differential of 2.445 annualized percentage points, with a Newey–West t-statistic of 2.984. The average return of the High portfolio is therefore almost four times that of the Low portfolio ($3.274/0.828 \approx 3.95$). The return differential is also slightly larger than the full-sample mean call return of 2.228%, demonstrating the sizable economic separation between the two ends of the climate-beta distribution.

The final two columns report factor-adjusted intercepts of 2.806 percentage points using contemporaneous factors and 2.623 percentage points using one-month-lagged factors. Their Newey–West t-statistics are 3.019 and 3.324, respectively. Both estimates remain statistically significant at the 1% level. As in Panel A, adjustment for the Fama–French factors does not weaken the High–Low return differential.

The larger differential in Panel B is consistent with the wider separation between the extreme quintile portfolios. Nevertheless, the tertile and quintile results capture the same pattern: firms with higher predetermined climate betas are associated with higher subsequent call option returns. These portfolio comparisons do not establish that an increase in climate beta causes the same firm's option return to rise. Instead, they document an economically meaningful and statistically reliable cross-

sectional association between estimated climate sensitivity and subsequent option returns.

In economic terms, the higher measured call returns indicate greater subsequent percentage appreciation in standardized call premiums for firms with higher climate betas. For example, the tertile High–Low differential of 1.822 annualized percentage points corresponds to an average monthly difference of approximately 0.152 percentage points in premium growth ($1.822/12 \approx 0.152$). For investors, this means that climate sensitivity is relevant to changes in the premium required to obtain short-term upside exposure. The result concerns percentage changes relative to each firm's previous-month premium; it does not establish that high-climate-beta firms have higher absolute call prices. This interpretation relates to the fixed-delta, constant-maturity premium measure defined in Section 4.4.2.

4.5.2 Regression Analyses

FMB

We next use monthly Fama–MacBeth regressions to examine whether the positive association between lagged climate beta and subsequent call returns remains after the inclusion of firm- and option-level controls, expressed as follows:

$$\text{CallRet}_{i,t} = \alpha_t + \beta_t \beta_{i,t-1}^{\text{climate}} + \sum_{j=1}^{N} \gamma_j Z_{i,j,t-12} + \epsilon_{i,t} \tag{22}$$

Here, $\mathrm{CallRet}_{i,t}$ is the option return for firm i in month t, $\beta_{i,t-1}^{\mathrm{Climate}}$ is the firm's climate beta available at the end of month $t-1$, and $Z_{i,j,t-12}$ contains the firm- and option-level control variables measured at $t-12$. Consistent with the notation used in Chapter 3, $\beta_{i,t-1}^{\mathrm{Climate}}$ denotes the firm-level climate exposure estimated from the rolling regression, whereas β_t denotes the coefficient on that exposure in the month-t cross-sectional regression. The coefficient β_t therefore tests whether firms with different

predetermined climate sensitivities subsequently earn different option returns.

Equations (20) and (22) serve different purposes. Equation (20) uses each firm's historical time series to estimate its sensitivity to the MCCC index. Equation (22) then tests whether cross-sectional differences in these previously estimated sensitivities explain differences in option returns in the following month. The relationship is not mechanically generated because the month-t return used as the dependent variable in Equation (22) is excluded from the information used to estimate $\beta_{i,t-1}^{\text{Climate}}$. There is no mathematical requirement for β_t to be positive or statistically significant; it could be positive, negative, or zero. A significant coefficient therefore provides predictive evidence rather than an automatic consequence of the climate-beta construction procedure. Nevertheless, climate beta remains an estimated regressor, and the analysis does not eliminate measurement error, omitted variables, or alternative explanations such as investor demand.

Table 4.4 reports the Fama–MacBeth regression results. In Column (1), the coefficient on ClimateBeta is 0.127 and is statistically significant at the 1% level. Because the dependent variable is an annualized option return expressed in percentage points, this coefficient indicates that a one-unit increase in climate beta is associated with a 0.127-percentage-point increase in the annualized call return. Using the standard deviation of climate beta reported in Table 4.1, a one-standard-deviation increase of 7.343 units corresponds to an increase of approximately 0.933 percentage points in the annualized call return ($0.127 \times 7.343 \approx 0.933$).

The ClimateBeta coefficient remains positive and statistically significant when the control variables are introduced separately. In the complete specification reported in Column (14), the coefficient is 0.109, with a Newey–West t-statistic of 2.584. This estimate implies that a one-standard-deviation increase in climate beta is associated with an increase of approximately 0.800 percentage points in the annualized call return ($0.109 \times 7.343 \approx 0.800$). This amount is approximately 35.9% of the full-sample mean call return of 2.228% ($0.800/2.228 \times 100\% \approx 35.9\%$). Alternatively, moving from the

25th percentile of climate beta, -3.825, to the 75th percentile, 5.604, represents an increase of 9.429 units ($5.604 - (-3.825) = 9.429$) and implies an annualized return difference of approximately 1.028 percentage points ($0.109 \times 9.429 \approx 1.028$). These estimates show that the association is economically meaningful as well as statistically significant.

[Insert Table 4.4 here.]

Additionally, it is also interesting to see how firm characteristics and market conditions affect individual option returns. We find that although a few firm characteristics (e.g., Sales, Cash Flow, Size) occasionally explain option returns, option market conditions, e.g., option return skew, kurtosis, and volatility spread, are pretty strong in predicting individual option returns, alongside climate risk.

Panel Regressions

In the final set of main analyses, we use panel regressions with fixed effects to test whether the association between climate beta and option returns remains. The regression specification is as follows:

$$\text{CallRet}_{i,t} = \alpha + \beta\beta_{i,t-1}^{\text{Climate}} + \sum_{j=1}^{N} \gamma_j Z_{i,j,t-12} + \eta_s + \tau_t + \mu_{i,t}. \tag{23}$$

where η_s denotes industry fixed effects and τ_t denotes time fixed effects. The control variables are defined as in Equation (22). Depending on the specification, the model includes time fixed effects, industry fixed effects, or both. Standard errors are two-way clustered by firm and calendar year to account for dependence within firms over time and common shocks within calendar years.

Panel regression results with fixed effects and clustered standard errors are reported in Table 4.5. Columns (1), (3), and (5) are univariate regressions with different settings of fixed effects. In the univariate regression results, we find that the positive association remains. The magnitude of the coefficient and its corresponding statistical significance are similar to those in Fama-MacBeth regressions

when we consider one of the fixed effects or both. Again, the climate risk results are qualitatively the same when all the controls are included with fixed effects, reported in Columns (2), (4), and (6).

Table 4.5 shows that the positive association remains after controlling for time and industry fixed effects. In the fully controlled specification in Column (6), the ClimateBeta coefficient is 0.145, with a t-statistic of 2.690. A one-standard-deviation increase in climate beta therefore corresponds to an increase of approximately 1.065 percentage points in the annualized call return ($0.145 \times 7.343 \approx 1.065$). This represents approximately 47.8% of the full-sample mean call return ($1.065/2.228 \times 100\% \approx 47.8\%$). Similarly, moving from the 25th to the 75th percentile of climate beta implies an annualized return difference of approximately 1.367 percentage points ($0.145 \times [5.604 - (-3.825)] \approx 1.367$).

The economic magnitudes obtained from the panel regression are broadly consistent with those from the Fama–MacBeth analysis. Thus, the positive climate-beta coefficient remains both economically and statistically meaningful after accounting for observable controls and unobserved time and industry effects. These estimates represent conditional associations and should not be interpreted as causal effects.

[Insert Table 4.5 here.]

Economic Interpretation of Positive Option Returns

The positive option-return differential is consistent with the risk-compensation interpretation adopted in this essay. Options written on high-climate-beta firms are more sensitive to changes in aggregate climate concerns. If this sensitivity represents systematic repricing risk that cannot be easily diversified or hedged, investors may require a higher expected return for holding options with greater exposure. The positive factor-adjusted intercepts further show that the High–Low return differential is not absorbed by the conventional Fama–French factors. However, this evidence does not by itself

establish that the return difference is an equilibrium climate risk premium. The MCCC index is an attention-based measure rather than a traded risk factor, and a positive climate beta does not directly identify whether the option provides a hedge against, or bears losses during, economically adverse states.

A second possible explanation is initial underpricing. Because the effects of climate policy, physical events, and technological transition are difficult to evaluate, investors may initially underestimate their implications for the distribution of a firm's future value. Limited attention or gradual learning may therefore cause options on highly exposed firms to be priced too low relative to their subsequent values. When additional climate information is incorporated into option prices, these options may experience larger price increases and consequently higher measured returns. Under this interpretation, the return differential reflects delayed price adjustment or correction of mispricing rather than compensation for bearing risk.

A third explanation is climate-related hedging and trading pressure. Investors concerned about downside climate outcomes may increase their demand for put protection, while disagreement about transition winners and losers may also generate speculative demand for calls. Such demand can affect implied option premiums through order imbalances and the inventory constraints of option dealers. Strong demand may raise the initial option price and, other things being equal, reduce the subsequent return to a long-option position. However, if hedging demand continues to increase or the subsequent climate shock is stronger than initially expected, the standardized option premium may rise further and produce a positive return. The predicted sign of the demand effect is therefore not unambiguous.

The interpretation must also consider the construction of the dependent variable. The reported option return measures the percentage change in the premium at a fixed delta and constant-maturity point on the OptionMetrics volatility surface. It is not the holding-period profit from purchasing and selling the same listed option contract, and it does not include transaction costs or delta-hedging

gains and losses. A positive High–Low return therefore means that the standardized option premium increased more for high-climate-beta firms than for low-climate-beta firms on average. It should not be interpreted directly as an implementable arbitrage profit. The present portfolio and regression tests establish a robust predictive association, but they cannot fully distinguish risk compensation from underpricing or demand-based explanations.

Other Call Option Return Analyses

Our baseline analysis uses the 50% absolute-delta call option at the 30-calendar-day maturity point. To assess whether the results depend on this maturity choice, Tables 4.6 and 4.7 repeat the portfolio analysis using the 60- and 91-calendar-day points, respectively. The 50% absolute-delta definition of ATM remains unchanged.

For each alternative maturity, both the option-return series and the climate beta are reconstructed using implied premiums from the corresponding maturity point. Specifically, the two-month climate beta is estimated from the historical 60-day call-return series, while the three-month climate beta is estimated from the historical 91-day call-return series. In both cases, option returns are winsorized within each month at the 5th and 95th percentiles before climate beta is estimated. The rolling regression continues to use the preceding 60 months with a minimum of 30 valid observations, and the resulting climate beta is lagged by one month before portfolio formation. The portfolio construction, High–Low calculation, Fama–French factor adjustment, and Newey–West procedure are otherwise unchanged. Therefore, Tables 4.6 and 4.7 test the full procedure at alternative maturities rather than applying the baseline one-month climate beta to different option returns.

[Insert Tables 4.6 and 4.7 here.]

Tables 4.6 and 4.7 show that the positive climate-beta return differential is not limited to the baseline 30-day maturity. For the 60-day options reported in Table 4.6, the raw High–Low return

differential is 1.487 annualized percentage points in the tertile sorts and 1.901 annualized percentage points in the quintile sorts. The corresponding factor-adjusted intercepts range from 1.551 to 2.137 annualized percentage points. All these High–Low differentials and intercepts are statistically significant.

The results remain positive at the 91-day maturity reported in Table 4.7. The raw High–Low differential is 1.033 annualized percentage points in the tertile sorts and 1.439 annualized percentage points in the quintile sorts. The factor-adjusted intercepts range from 1.095 to 1.627 annualized percentage points and remain statistically significant. These results show that the main association is not produced only by the choice of the 30-day option.

The magnitude nevertheless decreases as maturity increases. Across the 30-, 60-, and 91-day specifications, the tertile High–Low differential declines from 1.822 to 1.487 and then to 1.033 annualized percentage points. The corresponding quintile differential declines from 2.445 to 1.901 and then to 1.439 annualized percentage points. This pattern is consistent with climate attention having a stronger effect on relatively near-term option repricing. However, the analysis does not formally test whether the estimates differ significantly across maturities. The declining magnitude should therefore be treated as descriptive evidence rather than as an estimated term structure of the climate effect. Overall, the alternative-maturity results support the use of the 50% absolute-delta, 30-calendar-day point of the OptionMetrics volatility surface as the baseline while showing that the conclusion remains valid at longer maturities.

Next, we examine whether the regression results are driven by extreme climate-beta estimates. The main analyses use the original climate beta without winsorisation. For the robustness test in Table 4.8, we winsorize the cross-section of climate beta separately within each month at the 5th and 95th percentiles. Values outside these limits are replaced by the relevant percentile values, while the observations remain in the sample. This treatment reduces the overall range of climate beta from

[-34.125, 44.535] to [-16.414, 19.576].

Only the treatment of climate beta is changed in this test. The option-return construction, the earlier within-month winsorisation of option returns, the control variables, the sample period, and the regression specifications remain the same as in the baseline analysis. The pooled standard deviation of climate beta decreases from 7.343 in Table 4.1 to 6.675 in Panel A of Table 4.8. The fully controlled Fama–MacBeth coefficient changes from 0.109 in Column (14) of Table 4.4 to 0.122 in Panel B of Table 4.8. Similarly, the panel coefficient with both time and industry fixed effects changes from 0.145 in Column (6) of Table 4.5 to 0.160 in Column (3) of Panel C of Table 4.8. Thus, the treatment of extreme beta values affects the estimated coefficient magnitudes. The coefficients remain positive and statistically significant, showing that the main positive association persists after winsorisation. However, winsorisation cannot remove all measurement error from an estimated beta.

[Insert Table 4.8 here.]

4.5.3 Put Option Analyses

In this section, we provide put option analysis. We repeat the previous specification of the portfolio analysis and regression analysis for the put option part. As a short remark, we generally find the results on put options are similar to those on call options. This implies that climate risk affects the implied volatility of both calls and puts. Put returns are constructed using the same procedure as call returns: the baseline uses the 50% absolute-delta and 30-calendar-day put point, returns are winsorized within each month at the 5th and 95th percentiles, and a separate put climate beta is estimated from the preceding 60 months of put returns before being lagged by one month.

Table 4.9 reports the summary statistics for firm-level put climate beta constructed from the 50% absolute-delta, 30-calendar-day put-premium surface point. For each underlying firm and each month, climate beta is the coefficient on the MCCC index estimated from a rolling regression of put option

returns using the preceding five years of data. The pooled mean and standard deviation of put climate beta are -1.579 and 8.511, respectively. The annual means vary substantially. They are positive in 2008, 2009, 2018, 2020, and 2021, but negative from 2010 to 2017 and in 2019.

[Insert Table 4.9 here.]

Table 4.10 reports the portfolio-sorting exercise for put options. Panel A presents the tertile sorts, while Panel B presents the quintile sorts. The raw High–Low return differential is 1.729 annualized percentage points in Panel A and 2.408 annualized percentage points in Panel B. The factor-adjusted intercepts range from 1.812 to 2.883 annualized percentage points, and all four estimates are statistically significant at the 5% level. These results show that the put-option return differential is not absorbed by the contemporaneous or lagged Fama–French five factors.

Nevertheless, the positive factor-adjusted intercepts should not be treated as direct proof of a climate risk premium. They are consistent with investors requiring compensation for climate-related option exposure, but they may also reflect initial underpricing of climate risk or changes in the demand for downside protection. In particular, climate-sensitive firms may attract greater put-hedging demand when climate concerns increase. Because the present analysis does not include direct measures of option order imbalance, dealer inventory, or climate-related hedging demand, it cannot separately identify these explanations.

[Insert Table 4.10 here.]

Next, we run the regression analyses. We use the original set of control variables for the put option analysis, as these control variables are not specific to call options. Table 4.11 reports the FMB (reported in Panel A) and panel regressions (reported in Panel B). We find that the coefficient on climate beta remains positive and statistically significant throughout all cases.

The results for calls and puts provide further intuition about the underlying mechanism. If climate risk affected options only by causing a directional change in the underlying stock price, calls and puts would generally be expected to respond in opposite directions because they have opposite signs of delta. The positive climate-beta coefficients observed for both option types are therefore difficult to explain only through a directional stock-return channel. Instead, the common positive association is more consistent with climate risk changing expected volatility and the probability of tail outcomes, since both calls and puts have positive vega and convex payoffs.

This mechanism also differs from the bond-market channel examined in the previous chapters. A bond is affected mainly when climate risk weakens the firm's ability to make its promised payments. An option can be repriced as soon as investors revise the range or shape of possible future stock-price outcomes, even before the firm's default probability changes materially. Nevertheless, the present analysis does not directly decompose option returns into delta, vega, gamma, and tail-risk components. The call and put evidence should therefore be interpreted as being consistent with the volatility and tail-risk mechanism, rather than as a definitive causal test of that mechanism.

[Insert Table 4.11 here.]

The call and put results show a similar portfolio pattern. In the tertile sorts, the raw High–Low return differential is 1.822 annualized percentage points for calls and 1.729 annualized percentage points for puts. In the quintile sorts, the corresponding differentials are 2.445 and 2.408 annualized percentage points. The factor-adjusted intercepts also remain positive and statistically significant for both option types. For calls, they range from 2.021 to 2.806 annualized percentage points, while the put estimates range from 1.812 to 2.883 annualized percentage points. The similarity across the two sorting specifications shows that the main result is not limited to call options.

The regression results provide a similar comparison. In the fully controlled Fama–MacBeth regressions, the climate-beta coefficient is 0.109 for calls and 0.083 for puts. These raw coefficients

should not be compared directly because call and put climate betas have different standard deviations. Using the full-sample standard deviations of 7.343 for calls and 8.511 for puts reported in Tables 4.1 and 4.9, respectively, a one-standard-deviation increase in climate beta is associated with an increase of approximately 0.800 percentage points in the annualized call return ($0.109 \times 7.343 \approx 0.800$) and 0.706 percentage points in the annualized put return ($0.083 \times 8.511 \approx 0.706$). In the fully controlled panel regressions with both time and industry fixed effects, the corresponding effects are approximately 1.065 percentage points for calls ($0.145 \times 7.343 \approx 1.065$) and 0.962 percentage points for puts ($0.113 \times 8.511 \approx 0.962$). The economic magnitudes are therefore broadly comparable. However, the analysis does not formally test whether the call and put coefficients are statistically equal, so the similarity should be interpreted as descriptive rather than as evidence of identical effects.

The payoff structures of calls and puts help explain the joint result. A call has positive delta and benefits from an increase in the underlying stock price, whereas a put has negative delta and benefits from a decrease in the stock price. If the result were caused only by a directional movement in the underlying stock, calls and puts would normally respond in opposite ways. In contrast, both calls and puts have positive vega, meaning that their premiums increase when expected volatility rises, holding other pricing inputs constant. The positive association found for both option types is therefore more consistent with a climate-related volatility or tail-risk channel than with a purely directional change in expected stock prices.

The two option types nevertheless capture different parts of the expected return distribution. Put options provide protection against adverse outcomes and are more directly related to downside climate risks, such as physical damage, stricter regulation, stranded assets, or unexpectedly high transition costs. Call options capture upside uncertainty as well. For example, disagreement about technological change, climate-policy support, or which firms will benefit from the transition may increase the value of calls. Evidence from both calls and puts therefore suggests that climate concerns may widen the

expected distribution of firm value, affecting both downside and upside tails rather than only shifting its expected level.

The call and put findings are not mechanically identical. Their return series are constructed separately, and each climate beta is estimated from the preceding 60 months of returns for the relevant option type before being lagged by one month. The call and put portfolios are then formed separately using their respective climate betas. Moreover, put–call parity does not require their percentage returns or climate-beta portfolio differentials to be equal, particularly because the analysis uses fixed-delta points on the volatility surface rather than matched positions in the same listed contracts. The comparable results from these separately constructed tests therefore provide additional evidence that the main association is robust across option payoff types.

4.6 Conclusion

This essay provides new evidence on the pricing of climate risk in derivative markets by examining its role in the cross-section of U.S. equity option returns. Using a firm-level measure of climate exposure estimated by regressing option returns on the MCCC index, we show that climate risk is positively and significantly associated with option returns.

The positive association is supported by several empirical tests. First, the portfolio-sorting results show a monotonic increase in option returns across climate-beta portfolios. The raw High–Low return difference is 1.822 annualized percentage points in the tertile sorts and 2.445 annualized percentage points in the quintile sorts. These return differences remain economically large and statistically significant after controlling for the Fama–French five factors.

Second, the regression estimates produce similar economic magnitudes. In the fully controlled Fama–MacBeth specification, a one-standard-deviation increase in climate beta is associated with an increase of approximately 0.800 percentage points in the annualized call return ($0.109 \times 7.343 \approx$

0.800). The corresponding effect in the fully controlled panel specification is approximately 1.065 percentage points ($0.145 \times 7.343 \approx 1.065$). These results indicate that the climate-beta association is not only statistically significant but also economically meaningful. The findings remain robust across different option maturities, alternative portfolio constructions, and additional robustness tests.

We also show that the positive climate-option association holds for both call and put options. The portfolio magnitudes are similar across the two option types. The raw High–Low differential is 1.822 annualized percentage points for calls and 1.729 annualized percentage points for puts in the tertile sorts. In the quintile sorts, the corresponding differentials are 2.445 and 2.408 annualized percentage points. The regression results also remain positive after controlling for firm characteristics, option-market conditions, and fixed effects. Although no formal test is conducted to determine whether the call and put effects are statistically equal, their similar signs and economic magnitudes show that the main result is not specific to one option payoff.

Calls and puts provide different directional exposures because calls have positive delta while puts have negative delta. However, both option types have positive vega and therefore benefit from an increase in expected volatility, holding other factors constant. The common positive result is consequently more consistent with a volatility and tail-risk channel than with a purely directional movement in the underlying stock price. Put options capture downside protection against adverse climate outcomes, whereas call options also capture upside uncertainty and disagreement about transition opportunities. Taken together, the evidence suggests that climate sensitivity is associated with outcomes consistent with changes in the width and tails of the expected firm-value distribution rather than only changing its expected direction.

Risk compensation is not, however, the only possible explanation. The positive return differential may also arise if investors initially underprice the effects of climate risk and option premiums subsequently adjust as additional information becomes available. Moreover, climate-related hedging

demand, speculative trading, and dealer inventory constraints may affect option premiums and subsequent returns. The factor-adjusted portfolio results and the controlled regressions show that the relationship is not explained by the included conventional factors and observable characteristics, but they do not separately identify these economic channels.

Future research could distinguish among these explanations more directly. Event studies around major climate-policy announcements could examine whether the return differential is concentrated around new information. Comparisons between implied and subsequently realized volatility could test whether high-climate-beta options systematically underestimate future volatility. Contract-level measures of trading volume, open interest, order imbalance, bid–ask spreads, and dealer inventory could also help identify whether hedging pressure or market-making constraints contribute to the results. These tests require information beyond the standardized volatility-surface data used in the present analysis.

Our work extends the climate-finance literature to equity options and provides new insights on how climate risk affects equity calls and puts. From a practical perspective, the findings show that investors and risk managers may account for climate exposure when designing option-based strategies, especially those related to volatility trading and tail-risk hedging.

Several paths for future research remain. First, it would be useful to distinguish between physical and transition climate risks. One possible approach is to use separate proxies for each type of risk. For example, physical risk can be measured using data on extreme weather events or temperature changes, while transition risk can be captured by climate policy uncertainty indices or carbon pricing measures. Prior studies, such as Faccini et al. (2023) and Bolton and Kacperczyk (2023), provide useful guidance on constructing and separating these risk measures. Second, future research can include more detailed option characteristics. Option characteristics matter because options respond differently to risk depending on their design. For instance, options with different moneyness or maturity have dif-

ferent sensitivity to volatility and tail risk. Therefore, including variables such as moneyness and maturity can help identify the channel through which climate risk affects option returns. This would provide a better understanding of whether the observed climate-related option-return differential is primarily associated with volatility risk or tail risk.

Tables and Figures

Table 4.1: Summary Statistics

This table reports pooled firm-month summary statistics for standardized call returns, climate beta, and the control variables. Call returns are constructed from monthly changes in the Black–Scholes-implied premium at the 50% absolute-delta, 30-calendar-day point of the OptionMetrics volatility surface, annualized by multiplying by 12, and expressed in percentage points. The sample contains 105,729 firm-month observations for 1,276 U.S. firms from January 2008 to December 2021. The pooled mean assigns equal weight to each firm-month observation, so months with more firms receive greater total weight. Section 4.4.2 separately reports the equal-weighted time-series mean of the monthly cross-sectional climate-beta averages.

	Mean	STD	Min	25%	50%	75%	Max
Panel A: Main Variables							
Call Return (%)	2.228	20.197	-41.131	-11.847	0.482	14.108	80.489
Climate Beta	0.943	7.343	-34.125	-3.825	1.132	5.604	44.535
Panel B: Control Variables							
Sales	0.750	0.581	0.033	0.291	0.630	1.067	2.593
Cash	0.093	0.087	0.002	0.023	0.065	0.138	0.373
CF	0.095	0.064	-0.086	0.051	0.090	0.135	0.271
LEV	0.459	0.168	0.112	0.340	0.452	0.568	0.849
Inc	0.083	0.129	-0.716	0.031	0.075	0.141	0.359
ROA	0.044	0.062	-0.229	0.011	0.042	0.080	0.194
Size	22.521	1.518	19.115	21.436	22.475	23.567	26.490
MB	3.124	2.543	0.516	1.410	2.273	3.863	15.237
VS	0.005	0.045	-0.278	-0.010	0.002	0.016	0.301
Illiq	0.037	0.066	0.001	0.005	0.013	0.037	0.677
Skewness	-0.025	0.126	-0.715	-0.079	-0.011	0.034	0.536
Kurtosis	0.274	0.090	0.220	0.235	0.241	0.263	0.982

Table 4.2: Summary Statistics for Call Returns and Climate Beta (By Year)

This table reports annual summary statistics for call returns and climate beta. Call returns are annualized and expressed in percentage points, whereas climate beta is reported in its original units. The final column reports the number of firm-month observations in each year.

	Call Return (%)		Climate Beta		
Year	Mean	STD	Mean	STD	#Obs
2008	1.410	16.817	2.863	4.026	2347
2009	-2.066	14.490	2.054	5.092	5115
2010	1.083	14.576	0.529	4.954	5825
2011	1.910	16.381	-0.368	5.718	6436
2012	0.821	17.110	-2.540	6.045	6890
2013	2.440	17.448	-5.332	6.592	7239
2014	3.377	20.895	-4.752	6.609	7424
2015	1.163	20.096	0.556	8.035	7520
2016	2.463	19.182	1.684	6.941	6631
2017	2.379	20.542	2.383	7.963	8639
2018	3.442	23.097	4.008	8.688	9689
2019	1.592	21.264	2.912	7.097	10131
2020	5.486	24.504	3.323	6.077	10611
2021	2.009	22.041	2.991	5.998	11232

Table 4.3: Call Portfolio Sorts on Firm's Climate Beta

This table reports the averaged call returns for the option portfolio sorted by firm's lagged climate beta. The sample period is from January 2008 to December 2021. Each month, option portfolios are rebalanced based on their climate beta: "Low" is the option portfolio with bottom climate betas while "High" is the option portfolio with top climate betas. The "H–L" portfolio is calculated as the monthly difference between the High and Low portfolios, reported in Column "H–L". The final two columns report the portfolio α after controlling for Fama–French five factors. Panel A reports the three-portfolio results and Panel B reports five-portfolio results. Call option returns are calculated from monthly option-price changes, annualized by multiplying by 12, and expressed in percentage points. Accordingly, the reported portfolio means, High–Low differences, and factor-adjusted intercepts are annualized percentage-point returns. The underlying call return is constructed from the 50% absolute-delta and 30-calendar-day point of the OptionMetrics volatility surface and is winsorized within each month at the 5th and 95th percentiles before climate beta is estimated. Of the final two columns, the first uses contemporaneous Fama–French five factors and the second uses the factors lagged by one month. Newey and West (1987) t-statistics with 4-month lags are used for statistical inference and reported in parentheses.

Panel A: Tertile Sorts (Baseline)

	Raw Portfolio Returns			Raw High–Low	Factor-Adjusted High–Low	
	Low (1)	Medium (2)	High (3)	High–Low (4)	α_C^{FF5} (5)	α_L^{FF5} (6)
Port. Mean / α	1.070 (1.849)	1.895 (3.309)	2.891 (4.292)	1.822 (2.832)	2.074 (2.855)	2.021 (3.313)
MKT_t	–	–	–	–	-0.154 (-0.924)	–
SMB_t	–	–	–	–	0.173 (0.602)	–
HML_t	–	–	–	–	0.123 (0.623)	–
RMW_t	–	–	–	–	-0.318 (-0.901)	–
CMA_t	–	–	–	–	0.421 (1.121)	–
MKT_{t-1}	–	–	–	–	–	0.029 (0.200)
SMB_{t-1}	–	–	–	–	–	-0.543 (-1.996)
HML_{t-1}	–	–	–	–	–	0.487 (1.822)
RMW_{t-1}	–	–	–	–	–	-0.155 (-0.458)
CMA_{t-1}	–	–	–	–	–	-0.974 (-2.489)
R^2	–	–	–	–	0.031	0.053
# Months	168	168	168	168	168	167

Panel B: Quintile Sorts (Alternative)

	Raw Portfolio Returns					Raw High–Low	Factor-Adjusted High–Low	
	Q1 (Low) (1)	Q2 (2)	Q3 (3)	Q4 (4)	Q5 (High) (5)	High–Low (6)	α_C^{FF5} (7)	α_L^{FF5} (8)
Port. Mean / α	0.828 (1.334)	1.545 (2.753)	1.930 (3.427)	2.225 (3.607)	3.274 (4.470)	2.445 (2.984)	2.806 (3.019)	2.623 (3.324)

Table 4.4: Fama-MacBeth Regression Results

This table reports the average intercept and slope estimates from Fama-MacBeth (1973) cross-sectional regressions using call option returns as the dependent variable. Column (1) reports the univariate regression. Columns (2)–(13) add one control variable at a time, and Column (14) reports the full specification. The sample period is from January 2008 to December 2021. Newey and West (1987) t-statistics (with 4 lags) are reported in parentheses. The bottom rows present the average R^2, the average number of observations used in the monthly cross-sectional regressions and the number of months. Call option returns are annualized and expressed in percentage points. The coefficient on ClimateBeta therefore measures the change in the annualized call option return, in percentage points, associated with a one-unit increase in climate beta.

	y = Call Option Return													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
ClimateBeta	0.127	0.130	0.124	0.129	0.132	0.125	0.128	0.127	0.124	0.118	0.126	0.111	0.127	0.109
	(2.726)	(2.794)	(2.686)	(2.782)	(2.782)	(2.723)	(2.787)	(2.744)	(2.698)	(2.659)	(2.704)	(2.596)	(2.706)	(2.584)
Sales		0.451												0.207
		(3.285)												(1.197)
Cash			1.418											-0.838
			(1.603)											(-0.826)
CF				2.534										1.061
				(2.240)										(0.628)
LEV					-0.102									0.171
					(-0.236)									(0.266)
Inc						-0.371								-0.380
						(-0.372)								(-0.309)
ROA							2.170							-0.372
							(1.242)							(-0.165)
Size								-0.256						0.118
								(-2.668)						(0.912)
MB									0.039					0.067
									(1.146)					(1.103)
Skew										-22.217				5.717
										(-12.321)				(2.255)
Kurt											-14.623			-11.933
											(-3.175)			(-2.856)
VS												137.217		152.754
												(17.948)		(16.635)
Illiq													12.578	6.490
													(2.414)	(1.142)
Intercept	1.747	1.410	1.655	1.504	1.828	1.789	1.634	7.520	1.657	1.883	5.310	1.390	1.521	1.809
	(3.168)	(2.361)	(2.882)	(2.651)	(3.409)	(3.413)	(3.021)	(3.972)	(3.094)	(3.388)	(4.452)	(2.565)	(2.542)	(0.609)
Mean R^2	0.041	0.047	0.045	0.046	0.047	0.051	0.050	0.058	0.047	0.065	0.055	0.100	0.050	0.173
Mean Obs	629	623	583	624	507	624	625	625	604	628	628	628	597	455
# Months	168	168	168	168	168	168	168	168	168	168	168	168	168	168

Table 4.5: Panel Regression Results

This table reports the panel regression results for call option returns on firm's climate beta. The sample period is from 2008 to 2021. Columns (1), (3), and (5) report the univariate regressions including firm's climate beta only, while Columns (2), (4), and (6) report the multivariate regressions. We also include time and/or industry fixed effects in the panel regressions. t-statistics based on standard errors two-way clustered by firm and calendar year are reported in parentheses. Call option returns are annualized and expressed in percentage points. The coefficient on ClimateBeta therefore measures the change in the annualized call option return, in percentage points, associated with a one-unit increase in climate beta.

	y = Call Option Return					
	(1)	(2)	(3)	(4)	(5)	(6)
ClimateBeta	0.157	0.146	0.176	0.166	0.155	0.145
	(2.763)	(2.714)	(3.465)	(3.417)	(2.718)	(2.690)
Sales		0.401		0.392		0.299
		(2.951)		(1.834)		(2.378)
Cash		-0.256		-1.935		-1.134
		(-0.315)		(-2.054)		(-1.673)
CF		1.994		-0.246		3.308
		(1.004)		(-0.097)		(1.590)
LEV		-0.056		-0.301		-0.258
		(-0.088)		(-0.322)		(-0.429)
Inc		1.298		3.986		1.130
		(3.227)		(2.612)		(2.144)
ROA		-3.897		-4.806		-4.680
		(-2.485)		(-0.944)		(-2.696)
Size		-0.001		-0.166		-0.001
		(-0.010)		(-1.132)		(-0.010)
MB		0.079		0.085		0.065
		(1.276)		(0.795)		(1.085)
Skew		7.505		7.498		7.681
		(1.288)		(1.616)		(1.307)
Kurt		-1.555		-3.637		-1.688
		(-0.450)		(-0.604)		(-0.455)
VS		112.930		109.847		113.348
		(4.313)		(3.694)		(4.300)
Illiq		-6.261		-8.561		-6.150
		(-4.552)		(-3.330)		(-4.423)
Intercept	2.081	1.896	2.062	6.560	2.083	2.149
	(35.569)	(0.595)	(4.460)	(2.448)	(36.531)	(0.687)
Obs	105,729	76,466	105,729	76,466	105,729	76,466
R^2	0.197	0.247	0.005	0.048	0.197	0.248
Time FE	Yes	Yes	No	No	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes	Yes

Table 4.6: Call Portfolio Return Analysis - 60-Calendar-Day Surface Point

This table reports the portfolio analysis using call returns constructed from the 50% absolute-delta, 60-calendar-day point of the OptionMetrics volatility surface. Returns are winsorized within each month at the 5th and 95th percentiles before the maturity-specific climate beta is estimated. The sample period is from January 2008 to December 2021. Each month, option portfolios are rebalanced based on their climate beta: "Low" is the option portfolio with bottom climate betas while "High" is the option portfolio with top climate betas. The "H–L" portfolio is calculated as the monthly difference between the High and Low portfolios, reported in Column "H–L". The final two columns report the portfolio α after controlling for Fama–French five factors. Panel A reports the three-portfolio results and Panel B reports five-portfolio results. All portfolio means and factor-adjusted intercepts are annualized and expressed in percentage points. Newey and West (1987) t-statistics with 4-month lags are used for statistical inference and reported in parentheses.

Panel A: Tertile Sorts

	Raw Portfolio Returns			Raw High–Low	Factor-Adjusted High–Low	
	Low (1)	Medium (2)	High (3)	High–Low (4)	α_C^{FF5} (5)	α_L^{FF5} (6)
Port. Mean / α	0.615 (1.147)	1.306 (2.718)	2.102 (3.804)	1.487 (2.793)	1.696 (2.900)	1.551 (3.012)
MKT_t	–	–	–	–	-0.135 (-0.987)	–
SMB_t	–	–	–	–	0.134 (0.984)	–
HML_t	–	–	–	–	0.181 (1.034)	–
RMW_t	–	–	–	–	-0.201 (-0.931)	–
CMA_t	–	–	–	–	0.056 (0.206)	–
MKT_{t-1}	–	–	–	–	–	0.077 (0.602)
SMB_{t-1}	–	–	–	–	–	-0.405 (-1.543)
HML_{t-1}	–	–	–	–	–	0.322 (1.429)
RMW_{t-1}	–	–	–	–	–	-0.086 (-0.288)
CMA_{t-1}	–	–	–	–	–	-0.656 (-2.070)
R^2	–	–	–	–	0.035	0.042
# Months	168	168	168	168	168	167

Panel B: Quintile Sorts

	Raw Portfolio Returns					Raw High–Low	Factor-Adjusted High–Low	
	Q1 (Low) (1)	Q2 (2)	Q3 (3)	Q4 (4)	Q5 (High) (5)	High–Low (6)	α_C^{FF5} (7)	α_L^{FF5} (8)
Port. Mean / α	0.437 (0.774)	0.966 (1.902)	1.321 (2.345)	1.678 (3.253)	2.338 (4.007)	1.901 (2.790)	2.137 (2.841)	1.996 (3.001)

Table 4.7: Call Portfolio Return Analysis - 91-Calendar-Day Surface Point

This table reports the portfolio analysis using call returns constructed from the 50% absolute-delta, 91-calendar-day point of the OptionMetrics volatility surface. Returns are winsorized within each month at the 5th and 95th percentiles before the maturity-specific climate beta is estimated. The sample period is from January 2008 to December 2021. Each month, option portfolios are rebalanced based on their climate beta: "Low" is the option portfolio with bottom climate betas while "High" is the option portfolio with top climate betas. The "H–L" portfolio is calculated as the monthly difference between the High and Low portfolios, reported in Column "H–L". The final two columns report the portfolio α after controlling for Fama–French five factors. Panel A reports the three-portfolio results and Panel B reports five-portfolio results. All portfolio means and factor-adjusted intercepts are annualized and expressed in percentage points. Newey and West (1987) t-statistics with 4-month lags are used for statistical inference and reported in parentheses.

Panel A: Tertile Sorts

	Raw Portfolio Returns			Raw High–Low	Factor-Adjusted High–Low	
	Low (1)	Medium (2)	High (3)	High–Low (4)	α_C^{FF5} (5)	α_L^{FF5} (6)
Port. Mean / α	0.326 (0.696)	0.897 (2.263)	1.359 (3.339)	1.033 (2.502)	1.160 (2.684)	1.095 (2.783)
MKT_t	–	–	–	–	-0.044 (-0.431)	–
SMB_t	–	–	–	–	0.832 (0.515)	–
HML_t	–	–	–	–	0.259 (1.830)	–
RMW_t	–	–	–	–	-0.074 (-0.201)	–
CMA_t	–	–	–	–	-0.177 (-0.713)	–
MKT_{t-1}	–	–	–	–	–	0.081 (0.991)
SMB_{t-1}	–	–	–	–	–	-0.379 (-1.378)
HML_{t-1}	–	–	–	–	–	0.311 (1.111)
RMW_{t-1}	–	–	–	–	–	-0.067 (-0.362)
CMA_{t-1}	–	–	–	–	–	-0.454 (-1.292)
R^2	–	–	–	–	0.037	0.062
# Months	168	168	168	168	168	167

Panel B: Quintile Sorts

	Raw Portfolio Returns					Raw High–Low	Factor-Adjusted High–Low	
	Q1 (Low) (1)	Q2 (2)	Q3 (3)	Q4 (4)	Q5 (High) (5)	High–Low (6)	α_C^{FF5} (7)	α_L^{FF5} (8)
Port. Mean / α	0.162 (0.315)	0.536 (1.588)	0.925 (2.451)	1.002 (3.797)	1.601 (4.134)	1.439 (2.644)	1.627 (2.921)	1.509 (3.004)

Table 4.8: Results for Winsorized Climate Beta

This table reports robustness tests using climate beta winsorized at the 5th and 95th percentiles within each monthly cross-section. Values outside these limits are replaced by the corresponding percentile values and are not deleted. The baseline option-return construction and return-winsorisation procedure remain unchanged. Panel A reports summary statistics for the winsorized climate beta, Panel B reports the Fama–MacBeth regression, and Panel C reports the panel regressions. For the Fama–MacBeth regressions, Newey and West (1987) t-statistics based on four lags are reported in parentheses. For the panel regressions, the reported t-statistics are based on standard errors two-way clustered by firm and calendar year.

Panel A: Summary Statistics for Winsorized Climate Beta

	Mean	STD	Min	25%	50%	75%	Max
Climate Beta	0.920	6.675	-16.414	-3.815	1.132	5.569	19.576

Panel B: FMB

y=CallRet	
	(1)
Winsorized ClimateBeta	0.122
	(2.616)
Sales	0.210
	(1.207)
Cash	-0.903
	(-0.894)
CF	1.002
	(0.598)
LEV	0.172
	(0.269)
Inc	-0.436
	(-0.351)
ROA	-0.343
	(-0.152)
Size	0.115
	(0.893)
MB	0.067
	(1.102)
SKEW	5.758
	(2.268)
KURT	-11.938
	(-2.850)
VS	153.286
	(16.621)
ILLIQ	6.296
	(1.117)
Intercept	1.880
	(0.636)
Mean R^2	0.171
Mean Obs	455
#Mth	168

Panel C: Panel Regression

y=CallRet			
	(1)	(2)	(3)
Winsorized ClimateBeta	0.161	0.182	0.160
	(2.684)	(3.383)	(2.662)
Sales	0.405	0.393	0.300
	(2.984)	(1.814)	(2.365)
Cash	-0.284	-1.924	-1.133
	(-0.353)	(-2.067)	(-1.695)
CF	1.965	-0.309	3.281
	(0.986)	(-0.121)	(1.572)
LEV	-0.041	-0.251	-0.224
	(-0.065)	(-0.266)	(-0.372)
Inc	1.344	4.045	1.199
	(3.294)	(2.678)	(2.329)
ROA	-3.956	-4.703	-4.758
	(-2.532)	(-0.924)	(-2.763)
Size	-0.006	-0.171	-0.009
	(-0.044)	(-1.162)	(-0.066)
MB	0.077	0.081	0.064
	(1.244)	(0.752)	(1.055)
SKEW	7.534	7.643	7.713
	(1.290)	(1.634)	(1.309)
KURT	-1.565	-3.651	-1.698
	(-0.451)	(-0.606)	(-0.456)
VS	113.036	110.113	113.468
	(4.303)	(3.689)	(4.290)
ILLIQ	-6.336	-8.801	-6.235
	(-4.588)	(-3.404)	(-4.480)
Intercept	2.004	6.650	2.313
	(0.635)	(2.499)	(0.750)
R^2	0.247	0.048	0.248
Obs	76,466	76,466	76,466
Time FE	Yes	No	Yes
Industry FE	No	Yes	Yes

Table 4.9: Summary Statistics for Climate Beta Using Put Options

This table reports summary statistics for firm-level put climate beta. Put returns are constructed from the 50% absolute-delta, 30-calendar-day point of the OptionMetrics volatility surface. Equation (20) is re-estimated using these put returns to obtain the firm-level put climate beta. Summary statistics include sample mean, STD, skewness, and kurtosis. The last column reports the number of observations. We first report statistics for all years, followed by a yearly breakdown.

Year	Mean	STD	Skewness	Kurtosis	#Obs
All	-1.579	8.511	-0.129	3.584	105,729
2008	2.655	4.141	-0.356	3.161	2,347
2009	0.855	5.313	-0.366	5.165	5,115
2010	-2.686	5.130	0.012	5.135	5,825
2011	-4.211	6.257	0.224	4.342	6,436
2012	-6.722	6.578	0.084	4.263	6,890
2013	-9.544	6.981	-0.038	4.548	7,239
2014	-8.094	6.925	0.065	4.328	7,424
2015	-2.099	8.854	0.089	4.316	7,520
2016	-1.005	7.836	0.063	4.091	6,631
2017	-0.631	8.867	-0.111	3.530	8,639
2018	0.638	9.949	-0.284	3.623	9,689
2019	-0.083	8.031	-0.341	4.162	10,131
2020	2.093	7.185	-0.497	4.123	10,611
2021	3.651	7.387	-0.822	5.531	11,232

Table 4.10: Put Portfolio Sorts on Climate Beta

This table reports monthly equal-weighted portfolio returns for put options sorted by firms' lagged put climate betas. Put returns are constructed from the 50% absolute-delta, 30-calendar-day point of the OptionMetrics volatility surface. The sample period is from January 2008 to December 2021. Each month, option portfolios are rebalanced based on their climate beta: "Low" is the option portfolio with bottom climate betas while "High" is the option portfolio with top climate betas. The "H–L" portfolio is calculated as the monthly difference between the High and Low portfolios, reported in Column "H–L". The final two columns report the portfolio α after controlling for Fama–French five factors. Panel A reports the three-portfolio results and Panel B reports five-portfolio results. All portfolio means and factor-adjusted intercepts are annualized and expressed in percentage points. Newey and West (1987) t-statistics with 4-month lags are used for statistical inference and reported in parentheses.

Panel A: Tertile Sorts (Baseline)

	Raw Portfolio Returns			Raw High–Low	Factor-Adjusted High–Low	
	Low (1)	Medium (2)	High (3)	High–Low (4)	α_C^{FF5} (5)	α_L^{FF5} (6)
Port. Mean / α	2.037 (2.643)	2.510 (3.651)	3.767 (4.746)	1.729 (2.196)	2.165 (2.542)	1.812 (2.363)
MKT_t	–	–	–	–	-0.208 (-0.992)	–
SMB_t	–	–	–	–	0.974 (0.241)	–
HML_t	–	–	–	–	0.443 (1.429)	–
RMW_t	–	–	–	–	-0.174 (-0.412)	–
CMA_t	–	–	–	–	-0.134 (-1.034)	–
MKT_{t-1}	–	–	–	–	–	0.132 (0.710)
SMB_{t-1}	–	–	–	–	–	-0.713 (-2.499)
HML_{t-1}	–	–	–	–	–	0.348 (0.967)
RMW_{t-1}	–	–	–	–	–	-0.203 (-0.506)
CMA_{t-1}	–	–	–	–	–	-0.767 (-1.715)
R^2	–	–	–	–	0.032	0.045
# Months	168	168	168	168	168	167

Panel B: Quintile Sorts (Alternative)

	Raw Portfolio Returns					Raw High–Low	Factor-Adjusted High–Low	
	Q1 (Low) (1)	Q2 (2)	Q3 (3)	Q4 (4)	Q5 (High) (5)	High–Low (6)	α_C^{FF5} (7)	α_L^{FF5} (8)
Port. Mean / α	1.999 (2.451)	2.211 (3.054)	2.424 (3.826)	2.841 (5.135)	4.407 (5.192)	2.408 (2.376)	2.883 (2.580)	2.434 (2.466)

Table 4.11: Regression Results for Puts

This table reports the Fama–MacBeth and panel regression results for put returns constructed from the 50% absolute-delta, 30-calendar-day point of the OptionMetrics volatility surface. The put returns are regressed on firms' lagged put climate betas. The sample period is from 2008 to 2021. Panel A reports the FMB results, and Panel B reports panel regression results. For the Fama–MacBeth regressions, Newey and West (1987) t-statistics based on four lags are reported in parentheses. For the panel regressions, the reported t-statistics are based on standard errors two-way clustered by firm and calendar year.

Panel A: FMB

y=PutRet	
	(1)
ClimateBeta	0.083
	(2.210)
Sales	0.357
	(1.486)
Cash	-0.061
	(-0.050)
CF	0.931
	(0.411)
LEV	-0.207
	(-0.298)
Inc	0.443
	(0.261)
ROA	2.546
	(0.647)
Size	-0.042
	(-0.283)
MB	0.034
	(0.597)
SKEW	14.872
	(6.565)
KURT	0.761
	(0.214)
VS	-122.718
	(-17.396)
ILLIQ	11.483
	(1.882)
Intercept	2.851
	(0.861)
Mean R^2	0.163
Mean Obs	455
#Months	168

Panel B: Panel Regression

y=PutRet			
	(1)	(2)	(3)
ClimateBeta	0.111	0.156	0.113
	(2.134)	(3.595)	(2.184)
Sales	0.278	0.173	0.233
	(1.508)	(0.729)	(1.292)
Cash	-0.764	-2.272	-1.700
	(-0.578)	(-1.480)	(-1.439)
CF	1.480	-3.369	3.505
	(0.637)	(-0.874)	(1.513)
LEV	-0.123	-0.955	-0.598
	(-0.221)	(-1.213)	(-0.967)
Inc	0.380	3.901	-0.355
	(0.652)	(1.896)	(-0.768)
ROA	2.690	-1.622	1.763
	(1.472)	(-0.443)	(0.996)
Size	-0.156	-0.528	-0.106
	(-1.080)	(-2.756)	(-0.732)
MB	-0.005	0.085	-0.024
	(-0.087)	(0.678)	(-0.430)
SKEW	25.367	21.387	25.740
	(8.266)	(7.613)	(8.211)
KURT	13.296	12.437	12.932
	(3.917)	(1.805)	(3.814)
VS	-67.723	-81.526	-67.217
	(-7.447)	(-6.903)	(-7.344)
ILLIQ	13.365	13.797	13.755
	(5.981)	(3.184)	(6.175)
Intercept	2.928	12.258	2.191
	(0.995)	(3.555)	(0.758)
R^2	0.299	0.059	0.300
Obs	76,466	76,466	76,466
Time FE	Yes	No	Yes
Industry FE	No	Yes	Yes

Table C1: Definition of Variables

Variable	Symbol	Definition
Sales	*Sales*	Firm's net sales scaled by total assets.
Cash	*Cash*	Firm's cash and cash equivalent items scaled by total assets.
Cash flow	*CF*	Firm's net operating cash flow scaled by total assets.
Leverage	*Lev*	Firm's sum of current liabilities and long-term debt scaled by total assets.
Income	*Inc*	Firm's income before extraordinary items scaled by net sales.
Return-on-assets	*ROA*	Operating income before depreciation as a fraction of average total assets.
Firm size	*Size*	Firm size measured by the logarithm of total assets.
Market-to-book ratio	*MB*	Market value of equity over the book value of equity.
Bond illiquidity	*Illiq*	Bond's illiquidity (Amihud).
Volatility spread	*VS*	Volatility spread measured by the difference in implied volatility between pairs of ATM call and put options.
Skewness	*Skew*	Skewness of the risk-neutral option return distribution, following Bakshi et al. (2003).
Kurtosis	*Kurt*	Kurtosis of the risk-neutral option return distribution, following Bakshi et al. (2003).

5 Conclusion

This thesis investigates how climate-related risks are priced in corporate bond and equity options markets. While the current literature has a primary interest in equity stocks, this thesis fills the gap by extending the analyses on fixed-income and derivative securities, shedding light on the climate risk impact on other assets.

The findings indicate that climate-related measures are significantly associated with pricing outcomes across the assets examined. In the bond essays, stronger environmental performance is associated with lower yield spreads, while greater sensitivity to aggregate climate news is associated with wider spreads; these patterns are consistent with credit-risk and cash-flow channels. In the option essay, higher lagged climate beta is associated with higher subsequent call and put returns, a pattern more consistent with volatility and tail-risk repricing than with a purely directional stock-price channel. The empirical designs do not identify these mechanisms causally, and risk compensation cannot be distinguished from underpricing or option-demand pressure.

In corporate bond markets, climate risk is primarily reflected through credit risk. In Essay 1, the results show that firms with stronger environmental performance benefit from decreased borrowing costs, while firms with greater exposure to climate risk face higher yield spreads. Deeper analysis shows that climate risk affects bond pricing by altering perceptions of default risk and future cash flow uncertainty.

Essay 2 further examines whether firms' sensitivity to climate-related information is associated with corporate bond spreads. Transition- or policy-related exposure produces the largest and most consistent portfolio spread differentials, while physical-risk causes also remain economically meaningful in some controlled specifications.

In contrast, in equity option markets, climate risk is priced through expectations of future uncertainty. As shown in Essay 3, options associated with higher climate-risk exposure have higher

returns. This finding is consistent with investors requiring compensation for climate-related volatility and tail risk, although underpricing and option-demand pressure cannot be excluded. This spotlights the forward-looking nature of derivative markets in incorporating climate-related uncertainty.

Taken together, the results show that climate risk is associated with asset prices in different ways across financial markets. This thesis contributes to the literature by showing that climate risk is multi-dimensional and systematically associated with pricing outcomes across several asset classes, although the underlying mechanisms are not identified causally. It provides new evidence that credit markets primarily capture the impact of climate risk on default risk and cash flows, while derivative markets reflect its impact on volatility and tail risk.

This thesis is subject to several limitations that also point to possible paths for future research. The proxies used to measure corporate greenness (e.g., in Essay 1) are based on ESG scores provided by data vendors; therefore, they may not fully capture all dimensions of climate risk. Having said that, there are different measures of robustness in the studies as an attempt to overcome this concern.

As for future research suggestions, one way is to explore the interaction between firm-level and aggregate climate risk. For example, subsequent studies could investigate how firm-specific environmental characteristics influence sensitivity to aggregate climate shocks, and whether this interaction varies across industries or over time. Additionally, further work could examine the cross-market transmission of climate risk. In particular, it would be valuable to study whether information about climate risk is first incorporated in forward-looking markets, such as options, and then transmitted to bond and equity markets. This would provide a greater understanding of the role of different financial markets in processing climate-related information. Finally, the analysis in this thesis focuses on the U.S. market due to the availability of data. Broadening the framework to international settings would help clarify how institutional environments, regulatory regimes, and market structures influence the pricing of climate risk. Cross-country comparisons may also help to identify whether the findings

documented in this thesis apply beyond the U.S. context.

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