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# Empirical Essays on Carbon Risk Management, Bond Short Selling and their Respective Impact on CDS Spread

by

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A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

In the field of Applied Finance
Macquarie University
Rozetta Institute

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08 April 2024

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# Declaration of Originality

I, Saurabh Trivedi, declare that this thesis, titled "Empirical Essays on Carbon Risk Management, Bond Short Selling and their Respective Impact on CDS Spread", is submitted in fulfilment of the requirements for the award of the degree of Doctor of Philosophy in the Macquarie Business School at the Macquarie University, Sydney.

I also certify that the thesis has been written by me and that any help that I have received in preparing this thesis and all sources used have been acknowledged in this thesis.

Signature of Candidate

Saurabh Trivedi

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# Preface

Chapters 2-4 in this thesis have been developed into individual co-authored working papers. The working paper version of Chapter 3 is currently being submitted to a top-tier finance journal. All chapters have been selected for presentation at various academic conferences and seminars. The list of working papers and conference presentations is as follows:

1. Duong, H.N., Kalev, P.S., Kalimipalli, M. and Trivedi, S., 2022. Do firms benefit from carbon risk management? Evidence from the credit default swaps market (Chapter 3)
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    b. The Midwest Finance Association, 11 March 2022
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    h. Research workshop at the EMLyon Business School, Research Seminar, Lyon, 31 May 2023

i. 29th Multinational Finance Society (MFS) Annual Conference, Paphos, Cypress 2-5 July 2023

j. Research workshop at the Finance Research Seminar at the University of Bamberg, 7 June 2023

2. Duong, H.N., Kalev, P.S., Kalimipalli, M. and Trivedi, S., 2023. Bond Short Selling and CDS Spread (Chapter 4)

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# Table of Contents


**Copyright** ..... i

**Declaration of Originality** ..... ii

**Acknowledgements** ..... iii

**Preface** ..... v

**Table of Contents** ..... vii

**List of Tables** ..... x

**List of Figures** ..... xii

**List of Abbreviations** ..... xiii

**Abstract** ..... xiv

**Chapter 1: Introduction and Overview** ..... 1

1.1 Introduction ..... 1

1.2 Motivation ..... 7

1.2.1 Essay 1: Firm-Level Carbon Risk Management ..... 7

1.2.2 Essay 2: Do Firms Benefit from Carbon Risk Management? Evidence from the Credit Default Swaps Market ..... 8

1.2.3 Essay 3: Bond Short Selling and CDS Spreads ..... 10

1.3 Contribution of Thesis ..... 11

1.4 Organisation of the Thesis ..... 14

**Chapter 2: Firm Level Carbon Risk Management** ..... 15

2.1 Introduction ..... 15

2.2 Data ..... 20

2.2.1 Carbon Risk Management Score ..... 20

2.2.2 Firm-Level Financial Variables ..... 23

2.2.3 Data on Firm-Level Climate Change Risk ..... 23

2.2.4 Data on Public Attention to Climate Change ..... 25

2.2.5 Sample Size and Descriptive Statistics ..... 28

2.3 Characteristics of the CRMS Measure ..... 28

2.3.1 Industry Variation of Carbon Risk Management Score ..... 28

2.3.2 Time Series Variation in Carbon Risk Management Score ..... 32

2.3.3 Variance Decomposition of Carbon Risk Management Score ..... 33

2.3.4 Carbon Risk Management and Firm Characteristics ... 34
2.3.5 Carbon Risk Management Score and Other ESG Risk Management Variables ... 37
2.3.6 Effectiveness of CRMS ... 39
2.3.7 Carbon Risk Management and Public Attention to Climate Change ... 40
2.3.8 Carbon Risk Management and Alternative Firm-Level Climate Change Risk Measures 43
2.3.8.1 Univariate Tests ... 44
2.3.8.2 Regression Tests ... 45
2.4 Conclusion ... 51
Appendix 2.A. Measurement of Carbon Risk Management Performance ... 53
Appendix 2.B. Variable Descriptions ... 54
Appendix 2.C. Summary of other Climate Risk Measures used in Prior Literature ... 56
**Chapter 3: Do Firms Benefit from Carbon Risk Management? Evidence from the Credit Default Swaps Market ... 57**
3.1 Introduction ... 57
3.2 Data ... 65
3.2.1 Carbon Risk Management Score ... 65
3.2.2 Credit Risk Measure ... 65
3.2.3 Control Variables ... 66
3.2.4 Sample Construction ... 67
3.2.5 Descriptive Statistics ... 68
3.3 Baseline Regression Results ... 70
3.4 Endogeneity Test: The Impact of the Paris Agreement ... 74
3.4.1 Test for Change in CDS Spread Around the Paris Agreement ... 78
3.4.2 Placebo Test for Paris Agreement ... 79
3.5 Endogeneity Test: Firms Headquartered in States with State Climate Adaptation Plans ... 82
3.6 Economic Channels, Alternative Explanations and Robustness Checks ... 87
3.6.1 Evaluating the CRMS Measure ... 87
3.6.2 Impact of Governance, Social and other Environmental Risk Management Factors ... 93
3.6.3 Impact of Carbon Risk Management on CDS of Different Maturities ... 95
3.6.4 Evaluating Alternative Channels for the Relationship Between CRMS and CDS Spreads ... 96
3.7 Signaling Effect of Carbon Risk Management ... 99
3.8 Conclusion ... 101
Appendix 3.A. Variable Description ... 104
Appendix 3.B. State Climate Adaptation Plans by US States ... 106
Appendix 3.C. Additional Regression Results ... 107

**Chapter 4: Bond Short Selling and CDS Spread** ..... **111**
4.1 Introduction..... 111
4.2 Data and Sample ..... 119
4.3 The relationship between bond short interest and CDS spread..... 124
4.4 Robustness Tests..... 127
4.4.1 Alternative Measures of CDS Spread and Bond Short Interest..... 127
4.4.2 The Role of Equity Short Selling and Option Markets..... 129
4.4.3 Persistence in CDS Spread ..... 132
4.4.4 Bond and Stock Risk and Return Variables ..... 132
4.5 Endogeneity Tests..... 135
4.6 Time-Series and Cross-Sectional Variations ..... 138
4.6.1 Impact of Natural Disasters on the CDS Spread and Bond Short Interest Relation ..... 138
4.6.2 Impact of Bond Short Selling Fee on the CDS Spread-Bond Short Selling Relation .... 142
4.6.3 Impact of CDS Liquidity..... 145
4.7 Bond Short Selling, Future Firm Performance, and Financing Costs ..... 148
4.7.1 Firm Performance..... 148
4.7.2 Financing Costs ..... 149
4.8 Conclusion..... 154
Appendix 4.A. Variable Description ..... 156
Appendix 4.B. Natural Disasters ..... 159
**Chapter 5: Conclusion** ..... **160**
5.1 Does a firm's carbon risk management contain information not captured by various climate change risk indicators?..... 160
5.2 Does the proactive carbon risk management of firms get rewarded in the credit derivative markets? ...... 161
5.3 How do changes in climate change regulations or investor awareness impact the relationship between a firm's carbon risk management score and its CDS spread?..... 162
5.4 Could CDS investors obtain value-relevant information from short selling in the bond market? ..... 163
5.5 Future Research Directions..... 164
**References** ..... **167**

# List of Tables


Table 2-1: Descriptive Statistics ........ 29

Table 2-2: Industry Distribution of Carbon Risk Management Score ........ 31

Table 2-3: Variance Decomposition of Carbon Risk Management Score ........ 34

Table 2-4: Carbon Risk Management Score and Firm Characteristics ........ 36

Table 2-5: Correlation Matrix for CRMS and Different ESG Components ........ 38

Table 2-6: Effect of CRMS on Total Carbon Emission of the Firm ........ 40

Table 2-7: Carbon Risk Management and Climate Change Media Attention ........ 42

Table 2-8: Correlation Matrix for CRMS and Different Firm–level Exposure Variables ........ 45

Table 2-9: Univariate Sorting Based on CRMS and Climate Change Exposure Measures of Sautner et al. (2023) ........ 47

Table 2-10: The Relationship Between CRMS and Firm–level Climate Change Exposure constructed by Sautner et al. (2023) ........ 49

Table 2-11: The Relationship Between CRMS and Other Climate Risk Measures ........ 50

Table 3-1: Descriptive Statistics ........ 69

Table 3-2: Correlation Matrix ........ 70

Table 3-3: The Relationship between CRMS and 5-Year CDS Spread ........ 73

Table 3-4: The Impact of the Paris Agreement on the CRMS–CDS spread Relation ........ 77

Table 3-5: Placebo Test for the Paris Agreement and Effect of Events indicating potential US withdrawal from Paris Agreement on CRMS–CDS Spread relation ........ 81

Table 3-7: CRMS and the Firm-level Climate Change Exposure Measures Constructed by Sautner et al. (2023) ........ 90

Table 3-8: Impact of Orthogonalised Measure of CRMS on CDS Spread ........ 91

Table 3-9: CRMS-CDS Relationship for subsamples based on Top and Bottom Quartiles of Firm Level Climate Change Exposure Measures constructed by Sautner et al. (2023) ........ 92

Table 3-10: The Relationship between CRMS and 5-Year CDS Spread, Controlling for Governance, Social and other Environmental Risk Management Scores ........ 95

Table 3-11: Robustness Checks using CDS Spreads of Different Maturities ........ 97

Table 3-12: Exploring Alternative Channels for CRMS and CDS Spread Relation ........ 98

Table 3-13: CRMS-CDS Relationship for subsamples based on Firm-level total Carbon Emissions 101

Appendix Table 3-1: Cross-Sectional Regression and Baseline Regression with Industry × Quarter Fixed Effects ........ 107

Appendix Table 3-2: The Impact of the Paris Agreement on the CRMS–CDS Spreads (1-, 5-, 10-, 30-year maturity) Relation ........ 108

Appendix Table 3-3: Baseline Regression with Lagged CRMS, CDS Liquidity, and VIX ........ 109

Appendix Table 3-4: Implication of Distressed Firms on CRMS–CDS spread Relation .................. 110
Table 4-1: Descriptive Statistics .................................................................................... 123
Table 4-2: The Relationship between Bond Short Interest and 5–Year CDS Spread ........................ 126
Table 4-3: Robustness Checks .................................................................................... 133
Table 4-4: Heteroskedasticity-based instrumental variable (IV) analysis and Matched Sample Analysis .................................................................................... 137
Table 4-5: Bond Short Interest and CDS Spread: Natural Disaster vs. Non-Natural Disaster Periods .................................................................................... 141
Table 4-6: Impact of Relative Borrowing Cost of Bond Shorting on CDS–Bond Short Selling........ 144
Table 4-7: Impact of CDS Liquidity on the CDS Spread–Bond Short Selling Relation .................... 147
Table 4-8: Financial Channels Inducing the relationship between Bond Short Sell and CDS spreads .................................................................................... 149
Table 4-9: Bond Short Selling and the Cost of New Loan and Bond Issuance ................................. 153

# List of Figures

Figure 2-1: Time Series Variation in CRMS ........................................................................... 32
Figure 3-1: CDS Spread Around the Paris Climate Agreement ........................................................... 80

# List of Abbreviations

| | |
|---|---|
| BERT | Bidirectional Encoder Representations from Transformers |
| CCV | Climate Change Vocabulary |
| CDS | Credit Default Swap |
| CH | Crimson Hexagon Index |
| CO2 | Carbon Dioxide |
| COP | Conference of Parties |
| CPU | Climate Policy Uncertainty Index |
| CRMS | Carbon Risk Management Score |
| DCBS | Daily Cost of Borrowing Score |
| DiD | Difference-in-Differences |
| ESG | Environmental, Social, and Governance |
| FISD | Fixed Income Securities Database |
| GHG | Greenhouse Gas |
| IPCC | Intergovernmental Panel on Climate Change |
| IVOL | Idiosyncratic Volatility |
| MCCC | Media Climate Change Concerns |
| NLP | Natural Language Processing |
| OTC | Over the Counter |
| PCA | Principal Component Analysis |
| PSM | Propensity Score Matching |
| SBTi | Science Based Targets Initiative |
| SCAP | State Climate Adaptation Plans |
| TCFD | Task Force on Climate-related Financial Disclosures |
| TRACE | Trade Reporting and Compliance Engine |
| UN-PRI | United Nations Principles for Responsible Investments |
| US | United States of America |
| WSJ | Wall Street Journal |

# Abstract

This dissertation empirically examines two novel research issues: firm-level carbon risk management and corporate bond short selling.

The first essay (Chapter 2) develops a firm-level carbon risk management score (*CRMS*) to evaluate corporate practices around carbon risk mitigation. The indicators for CRMS are extracted from a wider set of environmental risk management indicators and capture preparedness through carbon risk mitigation policies and systems, as well as performance metrics like historical carbon emission relative to its industry peers. Regression analyses show CRMS conveys additional information beyond existing climate exposure measures, suggesting it provides a novel assessment of corporate transition risk management. The chapter thus presents a novel metric focusing on carbon risk management indicators, helping investors identify firms proactively transitioning their existing carbon-intensive business models to a low-carbon business model.

The second essay (Chapter 3) investigates how firms' carbon risk management practices (studied in Chapter 2) influence market assessment of their credit risk. While the effects of carbon emission risks on firm performance are understood, there is little evidence of the benefits of firms' proactive management of carbon emission risk. Using two quasi-exogenous events involving the 2015 Paris Climate Agreement and the staggered implementation of US state climate adaptation plans, we find that stronger carbon risk management is associated with significantly lower credit default swap (*CDS*) spreads. Our results are not driven by firm-level climate exposures, leverage, and social, governance, or distress risks. Firms with better carbon risk management also exhibit lower subsequent carbon

emissions. Overall, this essay highlights the importance of carbon risk management in mitigating credit risk.

The third essay examines the information flows from short sellers in the corporate bond markets to the credit default swap markets by examining the relationship between short-selling activity in the bond market and subsequent CDS spreads. While extant literature provides evidence on the information role of the CDS market for price formation in corporate bonds, we show that firm-level bond short interest is positively related to the one-month ahead CDS spreads. This finding is robust to alternative measurements or estimation methods, controlling for the influence of equity short interest and put options trading volume. The relationship between bond short interest and CDS spread is present mainly in firms with higher short-selling fees or where firm-level CDS contracts are more liquid. Firms with higher bond short-selling activities have higher credit risk profiles, as indicated by higher leverage, higher idiosyncratic volatility, lower firm performance, and higher financing costs. Overall, this essay shows the significance of the information provided by bond short sellers for cross-market assets such as CDSs.

In summary, this thesis offers significant original insights that advance comprehension of climate finance, climate risk management, credit derivative markets, and the informational value of short sellers for cross-asset markets. These are crucial topics relevant to the academic community and industry professionals.

# Chapter 1: Introduction and Overview

## 1.1 Introduction

The thesis consists of three independent essays focusing on credit derivative markets, climate finance, and corporate bond short selling. The first essay (Chapter 2) extracts measures for carbon risk management from wider environmental, social and governance risk management (ESG) score, assesses its characteristics and analyses whether it provides incremental information distinct from several proxies for climate change exposure risk. The second essay (Chapter 3) utilises the firms' proactive carbon risk management assessed in Chapter 2 and examines its impact on firms' credit default swaps. The third essay (Chapter 4) analyses information flows from short sellers in corporate bond markets to credit default swap markets. These essays shed light on various dimensions of empirical finance, including the characteristics of carbon risk management measures, the relationship between carbon risk management and credit default swaps, and the informational value of bond short selling for credit derivative markets.

Climate finance, a topical area of research assessing the interactions between climate change-related risks and financial assets, has grown rapidly in recent years (Giglio, Kelly, and Stroebel, 2021; Hong, Karolyi, and Scheinkman, 2020). It examines how financial markets address climate risks and opportunities. Previous research analyses how valuation models incorporate climate risks, which include physical hazards and transition risks[1] from decarbonizing. Understanding how markets price climate risk exposures remains a key focus

[1] *Transition risks* relates to the risks associated to transitioning to a lower-carbon economy, which may entail extensive policy, legal, technology, and market changes to address mitigation and adaptation requirements related to climate change.

of research in the climate finance domain. Past studies have predominantly used metrics such as carbon emissions or carbon intensity to proxy for transition risk exposure when evaluating impacts on asset values or returns (Aswani, Raghunandan, and Rajgopal, 2023; Bolton and Kacperczyk, 2021, 2023b; Duan, Li, and Wen, 2021; Ilhan, Sautner, and Vilkov, 2020). While risks arising from emissions are generally understood, there is limited evidence on the benefits of actively managing transition challenges through robust internal policies and management practices. Hence, carbon risk management is the focus of the first two essays, i.e. Chapter 2 and Chapter 3.

Similarly, a large body of research examines short selling in equity markets (Asquith, Pathak, and Ritter, 2005; Boehmer, Jones, and Zhang, 2008; Boehmer and Wu, 2013; Reed, 2013). However, relatively little is known about short-selling activity in the corporate bond markets despite bonds representing a significantly larger asset class globally. As of late 2022, the total outstanding value of bonds exceeded $128 trillion compared to around $95 trillion for global stocks.[2] This lack of research into bond short selling is surprising given the bond market size and economic importance. Prior studies investigating informational aspects of bond short selling have produced mixed results. Focusing on 2004-2007, Asquith et al. (2013) found no evidence that bond short sellers possessed private information on average. However, examining the bond short interest data for an extended sample till 2011, Hendershott, Kozhan, and Raman (2020) present evidence that bond short interest forecasts bond returns, especially following the 2008 financial crisis. Given these mixed results and limited research in understanding the

[2] Source: Global stock market value rises to a record $95 trillion this week on vaccine hope, CNBC (November 2020). https://www.cnbc.com/2020/11/12/global-stock-market-value-rises-to-a-record-95-trillion-this-week-on-vaccine-hope.html

dynamics of bond short selling, chapter 4 provides some novel evidence on the informational content of short-selling activity in the corporate bond market.

To separately analyse the implications of these two important phenomena on secondary credit markets, we select credit default swap as the primary asset class of interest in this dissertation. The market for CDS provides an ideal setting to study the effects of corporate carbon risk management and corporate bond short selling. The CDS market offers several advantages regarding carbon risk management's impact on credit risk. Sophisticated institutional investors actively trade CDS and should be better able to incorporate climate risks in their credit risk assessment in the underlying firms. The CDS spreads reflect credit risk changes more accurately than corporate bond yields. Unlike bonds, CDS spreads are free from issues specifying a benchmark yield curve. For bond short selling, we use CDS primarily because CDS specifically gauge credit risk, thus offering a more suitable context for examining the influence of bond short sellers on CDS spreads. This research direction naturally follows recent studies by Hendershott, Kozhan, and Raman (2020) and Duong, Kalev, and Tian (2023), which assess the effects of bond short selling on various market characteristics of corporate bonds.

In the remaining part of this section, we provide a brief overview of each of the three essays.

Chapter 2 aims to analyse the characteristics of corporate carbon risk management practices. It introduces the CRMS, derived from the Sustainalytics ESG rating data. It assesses two key dimensions - preparedness demonstrated by climate policies/systems and relative performance measured via carbon reduction and clean energy usage.

The chapter utilises data from various sources to analyze carbon risk management practices of firms. The main dataset i.e. CRMS is sourced from Sustainalytics, covering the period from 2009 to 2018. The CRMS is derived from Sustainalytics' ESG database, focusing specifically on carbon risk management indicators within the environmental dimension. These indicators evaluate firms' preparedness and performance in managing carbon risk across their operations. Additionally, firm-level financial variables are collected from the Compustat-North America database to analyze their relationship with carbon risk management practices.

Furthermore, firm-level climate change exposure is assessed using metrics developed by Sautner, Vilkov, Van Lent and Zhang (SVLZ hereafter), based on transcripts of quarterly earnings calls. SVLZ measures how frequently climate change is discussed during these calls, capturing different aspects such as climate-related opportunities, regulatory concerns, and physical shocks. The chapter also incorporates data on climate transition and physical risk scores constructed by Kölbel, Leippold, Rillaerts, Wang (KLRW, hereafter), obtained through analysis of regulatory disclosures in 10-K reports. Carbon emission data is sourced from the Refinitiv ESG database.

To gauge public attention to climate change, data is collected from various indices. These include climate change news indices from EGKLS, a climate policy uncertainty index constructed by Gavriilidis, and the Media Climate Change Concerns index developed by ABBI.

The final dataset comprises 405 unique firms with quarterly observations spanning from August 2009 to May 2018, totaling 9,407 firm-quarter observations. Descriptive statistics for the variables used in the chapter are presented in Table 2-1.

To assess the characteristics of CRMS, we first conduct a variance decomposition analysis, which shows that most of the variance within CRMS measures occurs at the firm level, not industry or over time, highlighting firm-specific heterogeneity. Next, the analysis shows that the larger firms, those with ample cash reserves, and those with high growth opportunities (proxied via TOBIN Q) tend to exhibit higher CRMS, underlying the influence of size and financial resources on carbon risk management practices. The chapter then examines if CRMS effectiveness can tangibly lower carbon emissions. Results indicate stronger risk management correlates with decreased emissions post-2015 Paris Agreement, suggesting credible signalling of transition commitments. Comparing the CRMS to existing measures of climate transition risk exposure constructed using textual analysis of earnings calls (Sautner et al., 2023) and regulatory filings (Kölbel et al., 2024), the results show little association between the CRMS and other climate change risk measures. Additional regression and principal components analysis indicate that the CRMS captures incremental information beyond other climate change exposure measures. The study also examines how public attention to climate change, measured through various indicators, may affect CRMS. The findings indicate that public attention to climate change risk does not substantially influence firms' carbon risk management practices, except during increased negative climate change news coverage. Overall, this chapter helps pinpoint the relevant dimensions of carbon risk management. By focusing on specific carbon risk management indicators, CRMS clarifies investment decisions, avoiding potential issues associated with aggregate ESG or climate risk scores.

Chapter 3 examines firms' CRMS impact on their CDS spread. The chapter explores whether firms actively managing their carbon risk receive favourable assessments in credit markets, specifically within the CDS market. The primary independent variable utilized is the CRMS, which is detailed in Section 2.2.1. Data on single-name Credit Default Swap (CDS) spreads, the key dependent variable, across various tenors are obtained from the IHS Markit database for US-based firms between August 2009 and May 2018. Additionally, a set of firm-specific and non-firm specific control variables are included to isolate the impact of CRMS on credit spreads, sourced from Compustat-North America and various other sources.

The sample construction process involves cleaning the CDS data and merging it with CRMS and control variables data. The final dataset consists of 405 unique firms with quarterly observations, yielding a total of 9,407 firm-quarter observations. Descriptive statistics of key variables used in the analysis are provided, showcasing a median 5-year CDS spread of 90.53 basis points and other relevant metrics such as asset size and leverage. Furthermore, correlations between CDS spreads and CRMS, along with other control variables, are examined and found to be statistically significant, indicating a negative relationship between CRMS and CDS spreads. Table 3-1 presents summary statistics of main variables used in Chapter 3.

The analysis in the chapter shows that firms with higher carbon risk management scores constructed by Sustainalytics exhibit significantly lower CDS spreads. We use two quasi-natural experiments - the 2015 Paris Climate Agreement and state-level climate adaptation plans to address potential endogeneity concerns. These events reinforce the positive impact of proactive carbon risk management on credit spreads. In summary, this chapter emphasises the importance of prudent carbon risk management on a firm's credit risk, using the CDS market as a robust empirical setting. The findings offer valuable insights for investors and policymakers in understanding the implications of carbon risk management practices on the credit risk of firms.

Chapter 4 analyses information flows from short sellers in the corporate bond markets to the CDS markets by examining the relationship between short-selling activity in the bond market and subsequent CDS spreads. We analyse the relationship using data from multiple sources. Corporate bond data are obtained from Trade Reporting and Compliance Engine (TRACE) and Fixed Income Securities Database (FISD), while firm-specific financial information comes from Compustat North America. Markit provides primary data for corporate bond lending and CDS spreads covering the period from February 2006 to December 2020.

The dataset undergoes cleaning procedures to ensure consistency. Explanatory variables, derived from various sources, include firm-specific fundamentals and macro-financial indicators. The merged dataset comprises 59,958 firm-month bond short interest observations for 648 unique single-name or firm-level CDS spreads. Summary statistics are presented in Table 4-1.

While previous research has highlighted the potential value of bond short sellers in predicting bond prices, this chapter extends the investigation to assess their impact on cross-market asset class, specifically focusing on CDS in this chapter. Results indicate a significant and positive relationship between bond short interest and future CDS spreads, even after controlling for several firm characteristics and macroeconomic factors. Additionally, the association is primarily present for firms with higher short-selling costs or where individual CDS contracts exhibit greater liquidity. Chapter 4 presents novel evidence that bond short sellers convey credit risk information impacting secondary CDS markets.

The three essays are individually presented in Chapters 2 to 4, each with a distinct set of research questions. Consequently, the literature relevant to the research questions pertaining to each chapter is discussed in those chapters. The remainder of Chapter 1 is organised as follows. Section 1.2 explains the motivation of each essay. Section 1.3 presents the contributions of the thesis. Section 1.4 provides the structure of the complete thesis.

## 1.2 Motivation

### *1.2.1 Essay 1: Firm-Level Carbon Risk Management*

> "More and more companies — and it will be a tsunami by Glasgow — will have net zero emissions plans."
>
> Mark Carney (2020)

As climate policies and low-carbon technologies accelerate the decarbonisation of the global economy, effectively managing transition risks will be vital for long-term corporate financial sustainability. However, existing research examining firm-level climate risks and exposures provides limited utility for investors seeking to evaluate corporate transition strategies and operationalise portfolio decarbonisation targets. Furthermore, aggregate ESG risk management metrics may obfuscate indicators most relevant to climate transition preparedness, while carbon emissions data alone fail to capture management efforts to adapt business models proactively. This limits the ability of investors to distinguish between a climate-risky firm and a climate-prudent firm.

This essay aims to fill this gap by assessing a specific metric of carbon risk management derived from a wider ESG risk management score. Such insights are valuable for investors seeking climate-aligned investment opportunities and portfolio strategies. Distinguishing risk exposures from risk management efforts provides a more comprehensive view of corporate climate strategies that conventional climate risk indicators alone cannot reveal. Therefore, the motivation is to advance understanding of this understudied dimension and equip stakeholders with tools to assess corporate climate readiness holistically.

### *1.2.2 Essay 2: Do Firms Benefit from Carbon Risk Management? Evidence from the Credit Default Swaps Market*

"A transition to net zero will affect how risk is measured and managed, and how assets are valued. This transition is creating the greatest commercial opportunity of our age."

– Mark Joseph Carney

"Seismic reallocation of capital' on the way towards climate friendly assets"

– Larry Fink (2020)

The above two quotes from the two industry leaders have been the main motivation for this chapter. Mark Carney, who was the Bank of England Governor and currently serving as the Head of Investments at Brookfield Asset Management, one of the largest clean energy investors globally and Larry Fink, CEO of Blackrock, both have alluded to the fact that investors are primed to invest in climate-friendly assets. These climate-friendly assets can be clean energy companies or firms that are future-ready in managing their carbon emission risk. However, no evidence exists that such firms are rewarded in the financial markets for adopting climate risk management practices. Hence, this chapter aims to empirically examine the relationship between firms' carbon risk management practices (assessed in Chapter 2) and how credit markets assess them.

Second, there is increasing attention on corporate exposure to carbon and climate transition risks from investors and other stakeholders. A recent survey of institutional investors found that they are tilting their investments towards low carbon beta firms that are less risky regarding climate change. Investors also view risk management and engagement as better approaches than divestment to address climate risks (Krueger, Sautner, and Starks, 2020). As concerns about financial assets' exposures to climate risks grow, investors exert significant pressure on carbon-intensive firms to curb emissions. For example, Azar et al. (2021) show how the world's three largest asset managers (Blackrock, Vanguard and State Street Global Advisors) have been exerting pressure through engagement strategies on the corporate carbon emitters to reduce their emissions. Some investors may even divest from carbon-intensive firms altogether (Rohleder, Wilkens, and Zink, 2022). Concurrently, various climate initiatives encourage firms to invest in clean energy infrastructure and adopt practices avoiding costly carbon transition risks. These initiatives include prominent coalitions like the Climate Action 100+ and RE100 that push for emission reductions and renewable energy commitments.

However, it has not been clear whether firms that are prudent in managing their carbon risk, either proactively or due to investor pressure, are rewarded in the financial markets, specifically in the credit markets.

Third, while the implications of carbon emissions for various financial securities' performance are generally understood (Bolton and Kacperczyk, 2021; Duan, Li, and Wen, 2021; Ilhan, Sautner, and Vilkov, 2020), there is little evidence of benefits of proactively managing carbon and transition risks. Measuring corporate carbon risk management also poses challenges from varied reporting. This chapter aims to address these gaps. It evaluates whether firms with prudent carbon emissions management receive favourable credit assessments as reflected in credit default swap spreads.

By shedding light on these underexplored issues amid rising transition risk focus, this chapter aims to offer valuable insights for regulators, corporations, institutional investors and credit rating agencies.

### *1.2.3 Essay 3: Bond Short Selling and CDS Spreads*

'Short sellers double bets against China Evergrande's bonds'
Financial Times (August 4, 2020)[3]

Short selling a bond or a synthetic short through a CDS offers avenues for investors to profit from default risk or declining corporate bond valuations. It serves as a hedge against credit risk exposure. However, actively shorting bonds imposes higher costs than CDS, as Czech (2021) and Sambalaibat (2022) explain. Despite a higher cost, short sellers actively participate in bond markets, implying compelling reasons to opt for a short-selling strategy. Higher costs to short bonds than CDS suggest short sellers may actively access additional credit

[3] The article was published in August 2020 and five months later Evergrande defaulted.

information. CDS investors could then actively benefit from this information. This is the primary motivation of this essay.

This essay also delves into the significance of examining bond short sellers in the CDS market, where they signal a belief in the downside risk linked to the underlying firm. Given the relevance of CDS in assessing credit risk and default probabilities, they provide a fitting context for studying the impact of bond short sellers on CDS spreads. Therefore, this study is also motivated by a natural progression towards comprehending the impact of short selling on secondary credit markets.

Finally, the motivation also lies in enhancing our understanding of the relatively underexplored area of short selling in bond markets. Despite the vast size of the global bond market compared to stocks, there is limited research on this topic due to data scarcity, especially in the over-the-counter (OTC) bond market, which poses inherent challenges for studies related to bond short selling. This research question gains significance from the scale of the US corporate bond and CDS markets, the scarcity of existing research on corporate bond short selling, and the expectations of CDS counterparties and market dealers, given their sophistication, in understanding the role of bond short interest.

## 1.3 Contribution of Thesis

This thesis significantly contributes to multiple critical domains within empirical financial research. Overall, while the first two essays contribute to the emerging fields of climate finance, risk management and credit markets, the third essay contributes to the literature on bond short selling and credit derivative markets.

The first essay makes important contributions to the emerging field of climate finance research. Firstly, it provides a novel indicator for carbon risk management, i.e. CRMS. By isolating indicators of preparedness and performance from the wider ESG indicators, the CRMS avoids the issue of “zoo effects” in aggregated ESG scores. This provides a more granular assessment of transition risk management. Secondly, the essay shows that the CRMS conveys unique information beyond alternative climate exposure and risk measures. In particular, it is not subsumed by composite indicators of climate risk exposure. Thirdly, the findings suggest that stronger CRMS is associated with actual reductions in reported emissions, especially post-2015, when commitments to transition gained prominence. This lends credence to the CRMS as a measure of credible carbon risk management actions. Finally, this essay contributes to the literature on climate finance by validating the CRMS as a tool for investors looking to invest in firms that are at the forefront of capturing the opportunities arising due to climate change risk. Overall, by developing and using a metric focused on voluntary carbon risk management practices, the study makes an important empirical contribution to addressing information gaps faced by investors seeking to evaluate firms based on such management practices.

The second essay contributes to the emerging literature on climate finance (Giglio, Kelly, and Stroebel, 2021; Hong, Karolyi, and Scheinkman, 2020) by empirically examining the relationship between carbon risk management and corporate credit risk. The study contributes to the risk management literature (Bessembinder, 1991; Cornaggia, 2013; Ellul and Yerramilli, 2013; Froot, Scharfstein, and Stein, 1993; Gilje and Taillard, 2017; Graham and Rogers, 2002) by considering how prudent carbon risk management, via lower emissions and preparedness for transition risks, aligns with lower CDS spreads. This provides evidence that managing transition risks through climate policies follows theories of reduced distress costs. Moreover, comparing this to the closely related work of Seltzer, Starks, and Zhu (2022), the chapter shows carbon risk management plays a unique role above other ESG factors in influencing corporate credit assessments. The essay offers novel perspectives on the links between carbon risk management, firm-level financial implications, and a possible determinant of credit default swap spreads.

The third essay of the dissertation makes a distinctive and significant contribution by being the first to showcase the value of information possessed by bond short sellers beyond the confines of the bond market. Previous research, exemplified by Hendershott, Kozhan, and Raman (2020) and Duong, Kalev, and Tian (2023), predominantly concentrated on the role of bond short-selling within the bond market. Notably, Hendershott, Kozhan, and Raman (2020) asserted that bond short interest lacks relevance in cross-asset markets, particularly future stock returns. In contrast, this study extends their findings by emphasizing the significance of bond short interest in cross-market price discovery. Furthermore, while existing literature has extensively showcased the leading information content of CDS markets for corporate bonds, this research uniquely demonstrates the significant impact of information generated through bond short selling on subsequent CDS spreads. Our research presents empirical evidence that bond short sellers possess information that holds potential relevance for cross-market assets, particularly the CDS market. In summary, this essay pioneers in demonstrating the cross-market informational value of bond short sellers, establishing a robust association between bond short interest and the subsequent credit default swap spread.

Overall, this dissertation makes important novel contributions to furthering the understanding of climate finance, risk management, credit markets, and informational roles of short sellers - key topics with high academic and practitioner value.

### 1.4 Organisation of the Thesis

The subsequent sections of this thesis are structured as follows: Chapter 2 delves into an assessment of carbon risk management measures and their association with other climate risk measures. Chapter 3 provides an empirical analysis of the influence of carbon risk management of firms on their credit default swap spreads. Chapter 4 empirically scrutinises information flow from the short sellers in the corporate bond market to CDS investors. Finally, Chapter 5 offers concluding insights on the three empirical investigations.

# Chapter 2: Firm Level Carbon Risk Management

## 2.1 Introduction

The impacts of climate change, as outlined by the Intergovernmental Panel on Climate Change (IPCC), necessitate large-scale decarbonisation through energy system transformation, transport electrification, industrial process changes, and land use shifts. Achieving net-zero emissions by 2050 will require policy, technology and infrastructure adjustments (Bolton and Kacperczyk, 2023a). Financial risks arising from this transition are termed "climate transition risks." Existing research (Aswani, Raghunandan, and Rajgopal, 2023; Bolton and Kacperczyk, 2021; Duan, Li, and Wen, 2021) predominantly uses carbon emissions or carbon intensity metrics (carbon emission scaled by revenue or assets or market capitalisation) to proxy for transition risk exposure and its impact on pricing of financial assets or firm performance. Furthermore, forward-looking approaches now construct firm-level climate-change exposure indicators using earnings calls (Sautner et al., 2023) or regulatory disclosures in 10k fillings (Kölbel et al., 2024). As climate transition risks intensify, carbon risk management has also emerged as a key dimension of corporate practices but remains understudied, especially in financial markets. This study aims to understand the various characteristics of carbon risk management and how it relates to existing measures of climate risk exposure. The other objective is understanding whether carbon risk management conveys additional information not accounted for in the firm-level climate change risk variables.

Assessing corporate carbon risk management practices remains an important but challenging task due to data limitations and underlying heterogeneity in firms' transition risk exposures. This challenge is compounded by the voluntary nature of most disclosed indicators, which raises concerns regarding their credibility and potential for "greenwashing." As the construction of an indicator specifically for carbon risk management falls outside the scope of this chapter, we rely on Sustainalytics' proprietary ESG risk management score to capture firms' carbon risk management efforts.

We obtain the CRMS based on indicators from Sustainalytics that specifically focus on how firms manage carbon risk in their operations. Of the 59 indicators capturing environmental risk management, only 13 relate directly to carbon risk management. These include policies, programs and performance metrics that assess a firm's preparedness and ability to manage operational carbon emissions. Our CRMS measure sums the scores on the selected carbon risk indicators. Higher scores signify firms that are better prepared and performing to deal with transition risks. The CRMS disentangles carbon risk management from broader ESG factors by focusing only on climate-specific metrics. Sustainalytics assigns proprietary industry-adjusted weights on each indicator score to account for different exposure levels related to carbon risk. This allows consistent comparison of carbon risk management across diverse industries. The indicators broadly reflect two dimensions: preparedness based on carbon management systems/practices and performance measured by metrics like carbon intensity reductions and clean energy usage. Appendix 2.A provides further detail on the management practices and historical performance considered.

A few existing studies have employed alternative measures of firm-level carbon risk management to evaluate its influence on various characteristics at the firm level. Zhou et al. (2020) introduced a carbon risk management measure for firms in China called the carbon risk management index, which is based on the 2017 climate change questionnaire by the CDP. The index comprises 12 items that pertain to the pre-event, during-event, and post-event management of carbon risk. It represents a company's management proficiency in regulating carbon risk, encompassing three main components: measures to reduce carbon sources, carbon flow planning, and carbon trading. Similarly, the study conducted by Vozian and Costola (2023) for European firms constructed a metric to evaluate a firm's management of climate-related transition risk. To construct this metric, they utilised indicators related to internal policies, target establishment, emission trading, and internal carbon pricing. The data utilised in their study were drawn from diverse sources, including Refinitiv, Bloomberg, and the CDP. The major component of the carbon risk management measure in both studies is primarily the management of the impact of carbon pricing risk emanating from the carbon emissions trading regime in the respective geographies. However, as there is no country-level carbon pricing market in the US, our measure for carbon risk management is not driven by explicit carbon pricing risk. Instead, *CRMS* primarily reflects voluntary risk management practices and the historical performance of firms in terms of reduction in their carbon emission relative to their industry peers.

To understand the characteristics of the CRMS measures, firstly we conduct a variance decomposition analysis of the CRMS, which measures its magnitude of heterogeneity among the firms. The analysis shows that most variation in CRMS occurs at the firm level rather than at the industry or over time. We find that firm-fixed effects explain a substantial portion of the variation (84.1%), indicating the importance of firm-specific factors in determining carbon risk management practices.

Secondly, we analyse if any firm-level fundamental variables can explain a firm's carbon risk management performance. We find that larger firms tend to have higher CRMS, suggesting that size plays a role in a firm's ability to adopt carbon risk management practices. Cash reserves and TOBIN Q, which reflects efficiency and innovation, are also positively associated with CRMS. These findings imply that financial resources and market valuation are important factors driving carbon risk management efforts.

Thirdly, we examine the influence of public attention to climate change on *CRMS*. We use four public climate change attention proxies — two news indices, a policy uncertainty index, and a media concerns index. The first two proxies are based on residuals from autoregressive models using climate change innovation data as constructed in Engle et al. (2020) by Engle, Giglio, Kelly, Lee, and Stroebel (EGKLS hereafter). The first variable measures climate news coverage in The Wall Street Journal (WSJ), while the second variable utilises data from the Crimson Hexagon negative climate change news index. The third proxy is developed by Gavriilidis (2021) to measure Climate Policy Uncertainty (CPU). Lastly, the fourth proxy, the monthly average of the daily aggregate Media Climate Change Concerns (MCCC) index, is constructed by Ardia et al. (2022) to capture heightened attention to climate change. The results indicate that firms may be more inclined to improve their carbon risk management scores during heightened negative climate change news periods.

Fourthly, we conduct the regression analysis to assess the effectiveness of carbon risk management in reducing the carbon emissions of respective firms. We find that better carbon risk management is related to lower subsequent total carbon emission levels, and that effect is significant only after the post-Paris Climate Agreement of December 2015. This evidence is consistent with firms adopting stronger carbon risk management practices in the post-Paris Agreement period to signal their ability to reduce carbon emissions credibly.

Fifthly, we conduct univariate and regression analysis to evaluate the incremental information contained in CRMS measures over various firm-level climate change exposure measures created by SVLZ in Sautner et al. (2023). SVLZ leverages textual analytics of earnings calls to develop scores related to a firm's overall climate change exposure and specific risks from opportunities, physical impacts, and regulation. First, we conduct the univariate tests, which show that CRMS has low correlations with SVLZ's climate change exposure measures, indicating that CRMS captures unique information and does not simply mirror existing exposures. Firms with weak carbon risk management scores exhibit higher risks and poorer financial performance, while their climate change exposure scores are also low. This relationship is not observed when sorting firms based on SVLZ's exposure measures, suggesting that CRMS better captures heterogeneity across firms.

Next, we conduct a panel regression analysis to examine the relationship between CRMS and SVLZ's climate change exposure measures while controlling for other firm characteristics. The results indicate that CRMS is unrelated to any of Sautner's climate change exposure measures except for a weak association with a measure of opportunity exposure. We also conduct a principal component analysis (PCA) on three broad climate change exposure variables of SVLZ and find that only the first principal component has a weak association with the CRMS variable. Additionally, we analysed six sub-components of the climate change exposure variable constructed by SVLZ, but no meaningful relationship was found between these variables and CRMS.

Finally, we conduct robustness tests using alternative climate risk measures constructed by KLRW in Kölbel et al. (2024) and principal components combining SVLZ climate change exposure measure, KLRW measure and firm's total carbon emission continue to find no significant association with CRMS. These findings indicate that CRMS provides additional information beyond existing climate change exposure measures. Investors interested in assessing corporate transition strategies can benefit from these findings.

This study makes an important contribution to the climate finance literature by focusing specifically on components of carbon risk management rather than aggregate ESG scores, which can dilute meaningful indicators. ESG scores frequently incorporate various metrics, potentially leading to the "zoo effect", making it difficult to isolate those relevant to climate-related risks and opportunities. Thus, it minimises the issue of aggregate confusion (Berg, Kölbel, and Rigobon, 2022) and reduces the likelihood of measurement discrepancies among various rating providers. By examining a select set of key risk management indicators centred around carbon risk, this research provides insights for investors seeking to invest in the firms leading climate transition risk management.

Where past research has predominantly evaluated climate risks at the firm level, this does not provide a complete picture to investors regarding the decarbonisation of their portfolios. As transition risks and responsibilities associated with climate change span entire industries, firm-level perspectives may only identify high-risk companies without recognizing transition leaders. An analysis restricted to carbon exposures alone could generate an overly pessimistic "no-go" list without shining a light on firms proactively managing these challenges. This study aims to clarify this important variable and equip investors with a more holistic view of opportunities emanating from inevitable transition processes. Once the investors understand the carbon risk and its management, they will be in a better position to identify the winners amongst their target investments. Looking at carbon risk management provides critical information on which companies are serious about transitioning their business models into a low carbon business.

## 2.2 Data

### *2.2.1 Carbon Risk Management Score*

We use the Sustainalytics database on *ESG* to assess the carbon risk management practices adopted by firms from 2009 till 2018. The *ESG* scores developed by Sustainalytics measure how well companies manage *ESG* aspects of their operations and have been used in the extant literature (Engle et al., 2020; Görgen et al., 2020; Huynh and Xia, 2020). [4]

To study the characteristics of an individual firm's carbon risk management, we consider indicators that specifically focus on the firm's management of carbon risk related to its operations and exclude all other dimensions of *ESG* risk management. These carbon risk management scores are extracted from the environmental parameters within the overall *ESG* parameters included in the Sustainalytics database. The environmental dimension consists of about 59 indicators of environmental risk management practices, with 13 of them being relevant to carbon risk management, which is the primary focus of this chapter. Sustainalytics provides a firm-level score for each carbon risk management indicator, adjusted for industry effects using proprietary weights. The weights are assigned to a sub-industry depending on its exposure to an individual carbon risk indicator. Our *CRMS* measure is the sum of the individual scores for the selected indicators. A higher *CRMS* score means the firm is future-ready and well-prepared and future-ready to tackle the looming carbon transition risk. A higher value also indicates that the firm has performed better in managing carbon risk than others. The *CRMS* measure is exclusively centred on climate risk management and helps disentangle other aspects of ESG. By disaggregating the environment dimension and focusing solely on carbon risk, we achieve greater granularity and prevent information loss that can occur when aggregating multiple objectives (Berg, Kölbel, and Rigobon, 2022; Ehlers, Gao, and Packer, 2021).

[4] The Sustainalytics database evaluates firms' business models while assessing business impact due to inadequate management of *ESG* issues by collecting the required data and information via public disclosure, media, and non-governmental organisation reports. As a part of control and feedback process, Sustainalytics sends the draft *ESG* rating report to individual companies to gather further feedback on the accuracy of the information included in the draft report. Sustainalytics provides monthly *ESG* assessment of firms.

The indicators comprising our *CRMS* data broadly reflect two dimensions of carbon risk management within a company: *preparedness* and *performance*. *First*, the preparedness dimension consists of indicators related to a firm's policies, programs, and management system applicable to its operations across its value chain designed to manage the material impact of carbon risk. *Preparedness* assesses various practices adopted by a firm to identify, assess, disclose, and manage its own operational energy usage and carbon emissions, which include Scope 1 and Scope 2 emissions and parts of Scope 3 emissions. [5] Some other key practices assessed are transitioning to renewable energy, improving energy efficiency, and placing greater emphasis on developing "greener" products and services within their operations with disclosure on Scope 3 emissions. *Second*, the performance dimension comprises quantitative and qualitative indicators capturing a firm's ability to manage its carbon risk. These indicators include the firm's relative performance in reducing its carbon intensity vis-à-vis its peers, the percentage of energy use from clean energy sources, revenue from clean technology or climate-friendly products, and carbon intensity of the energy mix.

The risk management metrics are industry adjusted, enabling comparisons of firms across industries. As a result, a financial services company can be directly compared with an energy company or any other type of company. Appendix 2.A provides details on management practices and performance indicators that constitute our measure of a firm's carbon risk management. Sustainalytics reports the values of firm-level carbon risk management indicators at the end of each month.

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[5] Scope 1 emissions are direct emissions from company-owned and controlled resources. Scope 2 emissions are indirect emissions from the generation of purchased energy, from a utility provider. Scope 3 emissions are all indirect emissions — not included in Scope 2 — that occur in the value chain of the reporting company, including both upstream and downstream emissions.

While Sustainalytics is a primary source for ESG risk and management scores, supplementing with data from MSCI, S&P Trucost, and Bloomberg ESG would enhance analysis robustness. Additionally, the data is limited to September 2019 (till September 2018 when the analysis was being conducted) on Wharton Research Data Services (WRDS). Additionally, relying on the sample constructed (discussed in Section 2.2.5) in Chapter 3 by merging datasets (Markit, Compustat, Sustainalytics) resulted in a loss of many firm-level CRMS observations.

### *2.2.2 Firm-Level Financial Variables*

We select several firm-level financial variables that can drive the firm's carbon risk management practices. These variables include *SIZE* (natural logarithm of total assets), *LEVERAGE* (Total Debt/Assets), *CASH* (Cash/Assets), *CAPEX* (CAPEX/Assets), *IVOL* (Idiosyncratic volatility), *TURNOVER* (Total Revenue/Assets), *PPE* (Property, Plant and Equipment Value/Assets), *ROA* (Return on Assets) and *TOBIN Q* ((Total Assets - Book value of equity + Market value of equity)/Total Assets). The details of these variables are available in Appendix 2.B. We utilise the Compustat-North America database to extract the quarterly data for these firm fundamentals.

### *2.2.3 Data on Firm-Level Climate Change Risk*

In this chapter, we capture a firm's climate change exposure using a series of measures developed by SVLZ from transcripts of quarterly earnings calls. These calls enable market participants to hear from management, ask questions, and discuss important current and future matters. They also serve as a platform for addressing risks and opportunities related to climate change. The SVLZ measures specifically focus on the extent to which climate change is discussed during these earnings calls. To measure climate change exposure, SVLZ identifies the salient word combinations used in discussions about climate change between analysts and management. They do this by adapting the keyword discovery algorithm by King, Lam, and Roberts (2017) to produce bigrams unique to climate change discussions. These bigrams are then separated into three categories: climate-related opportunity, regulatory, and physical shocks. Based on these bigrams, SVLZ constructs four metrics to quantify a firm's exposure to climate change. These metrics capture how frequently a set of climate change bigrams appears in a transcript scaled by the length of the transcript. The overall measure is labelled as *CCExposure*, and the three topic-based measures as $CCExposure^{Opp}$, $CCExposure^{Reg}$, *and* $CCExposure^{Phy}$, respectively.[6] After merging the main dataset with the SVLZ climate risk measure, we can match 331 firms (using the GVKEY as the matching identifier) out of the 405 firms available in my main CRMS dataset sample. This led to a final sample size of 7,465 firm-quarter observations.

We use the firm-level climate change risk as an alternative proxy for the firm-level climate transition risk and physical risk scores constructed by KLRW. They devised a unique firm-specific metric of climate risk by analyzing regulatory disclosure information in 10-K reports. They utilised a powerful natural language processing (NLP) technique known as bidirectional encoder representations from transformers (BERT), which is an advanced deep neural network developed by Google researchers (Devlin et al., 2018). The authors trained BERT to differentiate between transition and physical climate risks based on the disclosures in 10-K reports, thereby generating a firm-specific measure for both transition and physical risks.[7] After merging the KLRW's climate transition and physical score data into the main

[6] The dataset is made publicly available by the authors (Sautner et al. (2023). "Data for 'Firm-level Climate Change Exposure" and can be downloaded from the Open Science Framework https://osf.io/fd6jq/
[7] The data can be downloaded from the Open Science Framework; https://osf.io/pk2u9

sample, the number of matched firms reduced to 272 from the earlier 405 firms, and the total number of firm-quarter observations reduced to 6,431.

Finally, we also collect firm-level total carbon emissions data from the Refinitiv ESG database, which provides data on Scope 1, Scope 2, and Scope 3 levels of carbon emissions and firm-level total carbon emissions. Because the Refinitiv ESG provides carbon emission data on an annual basis and the main sample considers a quarterly frequency, we use linear interpolation and the nearest value method to impute the carbon emission values and transform the annual frequency data to quarterly frequency data. The main measure for carbon emission is the natural logarithm of total carbon emissions.

We also list various other climate risk measures used in climate finance literature in Appendix 2.C.

#### *2.2.4 Data on Public Attention to Climate Change*

We borrow data on public or media attention to climate change from three sources. The first source is the climate change news indices constructed by EGKLS.[8] EGKLS's first news index is a market-wide index reflecting the climate change risk. The climate change news index measures the intensity of discussions about climate change in the WSJ. Specifically, this index is determined by measuring the correlation between WSJ texts and the climate change vocabulary (CCV), constructed by extensively searching authoritative reports published by various governmental and research organisations. To reasonably capture the overall negative sentiment among investors towards climate change risk at a particular moment, EGKLS conducted several validation tests on this index. Building upon their seminal study, this analysis

[8] The EGKLS's climate change news index data are available on both Stefano Giglio's website at https://sites.google.com/view/stefanogiglio and Johannes Stroebel's website at http://pages.stern.nyu.edu/~jstroebe

incorporates innovations in the climate change news index, represented by the residuals derived from a first-order autoregressive model. EGKLS also provide an alternative proxy for the climate change news index called Crimson Hexagon (CH) negative climate change news index. The CH index is sourced from the data analytics provider Crimson Hexagon and has been accessible since June 2008. Its calculation involves determining the proportion of news articles classified by Crimson Hexagon as having a negative sentiment among those discussing climate change. We use both these indices of EGKLS as proxies for heightened attention to climate change risk.

Next, we use the climate policy uncertainty index (*CPU_Index*) constructed by Gavriilidis (2021).[9] This index is constructed based on news from major US newspapers and captures the level of uncertainty related to climate policy. Gavriilidis (2021) follows the methodology outlined in "Measuring Economic Policy Uncertainty" by Baker, Bloom, and Davis (2016). Gavriilidis (2021) collected data from eight prominent US newspapers, including the Boston Globe, Chicago Tribune, Los Angeles Times, Miami Herald, New York Times, Tampa Bay Times, USA. Today, and the Wall Street Journal. He searched for articles published between January 2000 and March 2021 that contained specific terms related to climate policy uncertainty and key policy-related terms. The search terms included variations of terms such as "uncertainty," "carbon dioxide," "climate," "climate risk," and "greenhouse gas emissions," as well as terms like "regulation," "legislation," "White House," and others.

Gavriilidis (2021) then scaled the number of relevant articles per month for each newspaper, considering the total number of articles published in the same month. The scaled series were standardised to have a unit standard deviation and averaged across the eight

[9] The *CPU_Index* data can be accessed from Economic Policy Uncertainty database at https://www.policyuncertainty.com/climate_uncertainty.html

newspapers every month. Finally, the averaged series were normalised to have a mean value of 100 from January 2000 to March 2021. This methodology resulted in the Climate Policy Uncertainty (CPU) index, which provides a quantified measure of uncertainty related to climate policy based on the news coverage in the selected newspapers. The CPU index tends to spike around significant events such as the introduction of new emissions legislation, global strikes on climate change, and statements made by the President regarding climate policy. The study's findings suggest higher climate policy uncertainty strongly and negatively impacts CO2 emissions. The CPU index is available in monthly frequency. We merge the month-end value of the index with the last month of the quarter in the main sample.

Finally, we use the Media Climate Change Concerns index, i.e., the MCCC index recently developed in Ardia et al. (2022) by Ardia, Bluteau, Boudt and Inghelbrecht (ABBI, hereafter). ABBI constructed the daily index to capture unexpected increases in climate change concerns using news about climate change published by major US newspapers and newswires. Only articles categorised as discussing climate change are included in the analysis. Each selected article is assigned a "concerns score" that reflects the combined levels of negativity and risk discussed within the article. This score quantifies the extent of concerns expressed regarding climate change. The data are normalised separately for each news source to address the heterogeneity of news outlets in terms of coverage, themes, and the degree of concerns expressed. This normalisation process ensures that the scores are comparable across different sources. Finally, the daily climate change concerns scores from all sources are aggregated to create the MCCC.[10] The index provides a comprehensive measure of climate change concerns

[10] The MCCC index is available at https://sentometrics-research.com/. Examples of recent research using MCCC index are (Alekseev et al., 2022), (Ballinari and Mahmoud, 2021), (Campos-Martins and Hendry, 2023), and (Pástor, Stambaugh, and Taylor, 2022), among others.

captured by the US news media, considering the diversity of coverage, themes, and levels of concern across various outlets. As the sample is in quarterly frequency, we take the average of the daily MCCC score in each quarter and merge it with the main dataset.

### *2.2.5 Sample Size and Descriptive Statistics*

The final sample consists of 405 unique firms with a quarterly frequency from August 2009 to May 2018, providing 9,407 firm-quarter observations. While the data for CRMS are available monthly, the firm-level financial variables are reported quarterly. Hence, we use the quarterly frequency for our sample construction. As we utilise the same sample constructed in Chapter 3, the sample size is constrained by matching various datasets used in that chapter. Finally, all continuous variables are winsorised at the 1st and 99th percentile to mitigate the effect of either data errors or outliers. The descriptive statistics of CRMS, firm fundamentals, aggregate measures capturing climate change risk and firm-level climate change exposure measures created by SVLZ are presented in Table 2-1.

## 2.3 Characteristics of the CRMS Measure

### *2.3.1 Industry Variation of Carbon Risk Management Score*

In this section, we compute the average values of the carbon risk management score variable by industry sector (based on the industry classification provided by Sustainalytics) and present a ranking of these means in Table 2-2. As these scores are industry adjusted using proprietary weights by Sustainalytics, we can cross-compare these industry scores. The sectors with the highest carbon risk management score include semiconductors (mean CRMS of 8.23), followed by auto components mean (CRMS of 7.68) and automobiles (mean CRMS of 7.23). It is interesting to see these sectors at the top regarding managing their carbon emission. Given that these sectors are also among the high carbon emission sectors, their relative CRMS score suggests that these are also the ones that are putting in place better prudent practices to manage their carbon footprint. Almost all the major automobile companies across the globe have ventured into electric vehicle production. They are also forcing the upstream companies in the

**Table 2-1: Descriptive Statistics**

This table provides the summary statistics of the test variables for a sample of 405 US firms from August 2009 to May 2018. *CRMS* denotes the sum of the scores of each carbon risk management practice adopted by a firm. *LEVERAGE* is the ratio of total liabilities to total assets. *IVOL* is the idiosyncratic volatility of a firm; it is the standard deviation of daily excess returns, computed as the difference between a firm's stock return and the CRSP value-weighted return over the past 180 days. *Total Asset Value* is the firm's size measured by total assets. Our regression analysis uses the natural logarithm of *Total Asset Value* denoted as *SIZE*. *ROA* is the return on assets, *PPE* is the property, plant, and equipment scaled by the firm's total assets, and *CAPEX* is the capital expenditure scaled by total assets. *CASH* and *TURNOVER* are the cash & short-term investments and total revenue of the firm, respectively, both scaled by the total assets of the firm. *CCExposure* measures the relative frequency with which bigrams related to climate change occur in the transcripts of analyst conference calls and other sub–measures. $CCExposure^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of analyst conference calls. The details of these variables are provided in Appendix 2.B. All continuous variables except *CRMS* are winsorised at the 1st and 99th percentile.

| | Obs. | Mean | Median | min | p5 | p95 | max | Std. Dev. |
|---|---|---|---|---|---|---|---|---|
| | | | *Carbon Risk Management Score* | | | | | |
| CRMS | 9,407 | 3.71 | 3.40 | 0.00 | 0.000 | 8.76 | 16.00 | 2.73 |
| | | | *Firm Level Variables* | | | | | |
| LEVERAGE | 8,716 | 0.312 | 0.29 | 0.02 | 0.067 | 0.61 | 0.87 | 0.17 |
| IVOL (%) | 9,407 | 1.39 | 1.19 | 0.42 | 0.71 | 0.94 | 1.60 | 2.78 |
| Total Asset Value (in billion $) | 9,407 | 55.86 | 16.78 | 2.26 | 3.463 | 235.50 | 841.37 | 130.82 |
| ROA | 9,403 | 0.01 | 0.01 | –0.06 | –0.010 | 0.04 | 0.05 | 0.02 |
| CASH | 9,407 | 0.09 | 0.06 | 0.00 | 0.005 | 0.28 | 0.49 | 0.09 |
| TURNOVER | 9,359 | 0.19 | 0.15 | 0.01 | 0.025 | 0.54 | 0.92 | 0.17 |
| PPE | 8,625 | 0.31 | 0.22 | 0.00 | 0.009 | 0.81 | 0.88 | 0.26 |
| CAPEX | 9,397 | 0.03 | 0.01 | 0.00 | 0.000 | 0.09 | 0.17 | 0.03 |
| TOBIN Q | 9,406 | 1.68 | 1.47 | 0.80 | 0.96 | 3.13 | 4.74 | 0.74 |
| | | | *Sautner et al. (2023) Climate Exposure Measures* | | | | | |
| *CCExposure* | 7,465 | 1.2 | 0.31 | 0.00 | 0.00 | 6.20 | 44.05 | 3.16 |
| $CCExposure^{Opp}$ | 7,465 | 0.48 | 0.00 | 0.00 | 0.00 | 2.46 | 23.95 | 1.54 |
| $CCExposure^{Reg}$ | 7,465 | 0.08 | 0.00 | 0.00 | 0.00 | 0.43 | 8.79 | 0.39 |

value chain, i.e. auto components companies, to produce required components for electric vehicle manufacturing. These sectors are seeing an opportunity to gain a competitive advantage by reducing their carbon emissions. Electric vehicles are becoming increasingly popular, and these sectors are well-positioned to supply the components needed for production. By reducing their carbon emissions, these sectors can position themselves as leaders in the emerging electric vehicle market. This seems to be one of the driving factors leading to a higher average CRMS of these companies.

Let's compare the average CRMS of the two most carbon-intensive sectors, namely utilities (which primarily include power companies involved in thermal coal power generation) and oil and gas production companies. We find that the former has done relatively better than the latter. The utilities sector has a mean CRMS of 4.72, while the oil and gas production sector has a mean CRMS of 2.65.

There may be a few possible explanations for this difference. First, the utility sector has been considered relatively more technically feasible to adopt cleaner forms of energy generation. For example, utilities can switch to renewable energy sources, such as solar and wind power, or invest in storage solutions, such as batteries or pumped hydro storage. Second, utilities have been under the most regulatory pressure compared to other industries. Governments worldwide increasingly regulate greenhouse gas emissions, and utilities are often the target of these regulations. This regulatory pressure is likely to force utilities to adopt more sustainable practices. Third, utilities have relatively less market power than oil and gas companies, which are massive in terms of balance sheet. A recent study by Li, Trencher, and Asuka (2022) found that four of the world's largest oil and gas companies (Chevron, ExxonMobil, BP and Shell) failed to back their commitments and pledges on climate change. This means that power companies are less able to resist regulatory pressure or to pass on the costs of carbon emissions to consumers. As a result, they may be more likely to invest in carbon emission reduction measures to avoid regulatory penalties or to maintain their competitive position. The other sectors that have fared worst in managing their carbon risk are construction material and homebuilder companies. While the exact reason for a low *CRMS* is unclear, it may

**Table 2-2: Industry Distribution of Carbon Risk Management Score**

This table represents firm-level carbon risk management scores for all the industries in the sample. Statistics are reported at the firm–level across different industries based on the classification provided by Sustainalytics. The CRMS measure is the average monthly firm-level CRMS value during a quarter.

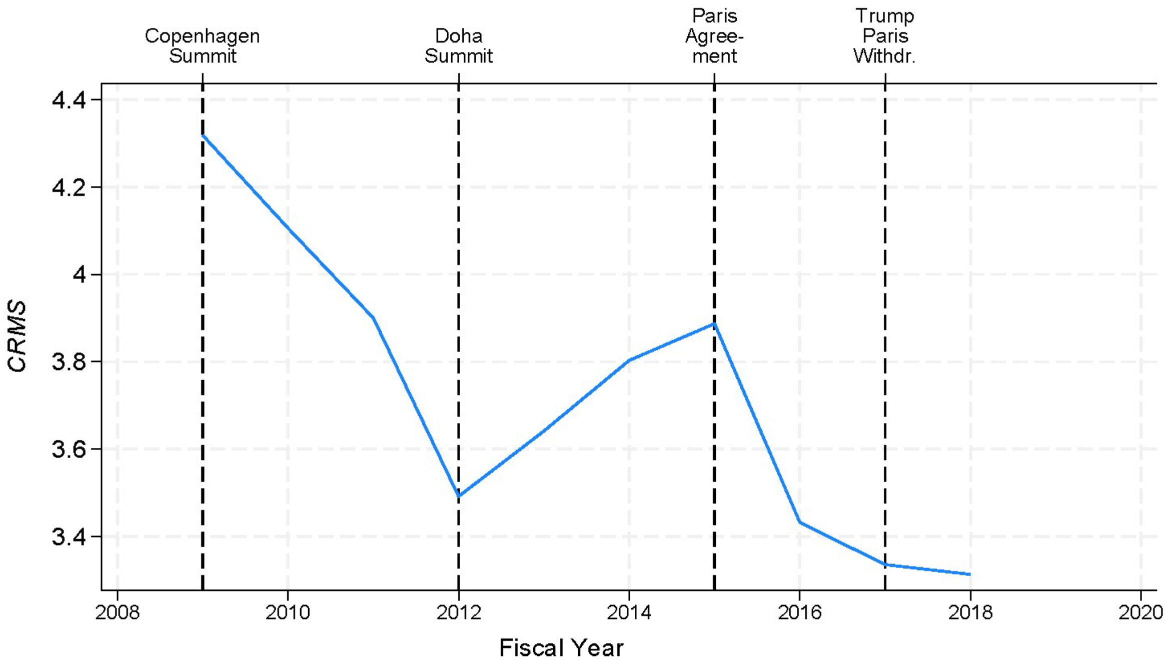
| Industry Classification | Mean | SD | Median | Observations |
|---|---|---|---|---|
| Semiconductors | 8.23 | 2.06 | 8.45 | 149 |
| Auto Components | 7.68 | 2.15 | 8.20 | 99 |
| Automobiles | 7.23 | 1.67 | 7.50 | 35 |
| Aerospace & Defense | 6.72 | 3.04 | 7.14 | 300 |
| Household Products | 6.05 | 1.16 | 5.92 | 173 |
| Technology Hardware | 5.93 | 2.80 | 5.73 | 229 |
| Industrial Conglomerate | 5.78 | 3.14 | 4.88 | 86 |
| Transportation | 5.07 | 1.68 | 5.01 | 274 |
| Machinery | 5.01 | 3.35 | 3.84 | 362 |
| Pharmaceuticals | 4.96 | 1.63 | 4.97 | 349 |
| Utilities | 4.72 | 2.83 | 4.00 | 682 |
| Software & Services | 4.68 | 3.00 | 4.25 | 277 |
| Containers & Packaging | 4.56 | 2.62 | 3.87 | 169 |
| Chemicals | 4.54 | 2.03 | 4.70 | 406 |
| Commercial Services | 4.51 | 2.31 | 4.82 | 142 |
| Precious Metals | 4.49 | 0.64 | 4.34 | 35 |
| Paper & Forestry | 4.44 | 1.00 | 4.53 | 54 |
| Energy Services | 4.43 | 2.77 | 4.26 | 126 |
| Building Product | 4.41 | 1.26 | 4.56 | 35 |
| Retailing | 4.26 | 2.88 | 4.25 | 506 |
| Diversified Metals | 4.17 | 0.88 | 3.68 | 60 |
| Textiles & apparels | 3.78 | 1.28 | 3.87 | 79 |
| Food Products | 3.72 | 1.63 | 3.65 | 404 |
| Electrical Equipment | 3.71 | 1.70 | 3.70 | 69 |
| Consumer Durable | 3.35 | 1.64 | 3.19 | 204 |
| Food Retailers | 3.22 | 1.55 | 3.30 | 191 |
| Healthcare | 3.20 | 2.71 | 2.93 | 481 |
| Steel | 3.13 | 2.30 | 1.87 | 149 |
| Banks | 2.84 | 1.25 | 2.85 | 55 |
| Oil & Gas Production | 2.65 | 1.31 | 2.68 | 508 |
| Diversified Financing Companies | 2.61 | 1.72 | 2.85 | 363 |
| Consumer Service | 2.27 | 1.77 | 2.25 | 273 |
| Construction & Equipment | 2.25 | 0.65 | 1.81 | 9 |
| Refiners & Pipeline | 2.13 | 1.35 | 1.52 | 101 |
| Media | 1.80 | 1.67 | 1.54 | 295 |
| Insurance | 1.71 | 1.70 | 1.50 | 619 |
| Real Estate | 1.44 | 1.46 | 1.03 | 607 |
| Telecommunication | 1.31 | 1.63 | 0.55 | 173 |
| Homebuilders | 0.74 | 1.15 | 0.20 | 200 |
| Construction Material | 0.73 | 1.15 | 0.26 | 34 |
| Traders & Distributors | 0.67 | 0.97 | – | 47 |

be attributed to the fact that these sectors are largely not under the radar of regulators or investors, which can force them to manage their carbon risk. Furthermore, these sectors are considered hard to decarbonise, implying that the requisite technologies for decarbonising their operations are either unavailable or economically unfeasible.

### *2.3.2 Time Series Variation in Carbon Risk Management Score*

Figure 2-1 shows the average carbon risk management score (CRMS) for firms over the sample period, highlighting several notable periods in climate policy. CRMS values were initially higher but trending downward from 2009 to 2012. We then observe an increase in average CRMS from 2013 to 2015. However, after the landmark Paris Agreement in December 2015, there is a steady decline in the average CRMS.

**Figure 2-1: Time Series Variation in CRMS**




One potential explanation for this trend is the heightened expectations for carbon risk management that followed the Paris Agreement. The accord significantly ramped up global climate ambitions, increasing transition risks and regulatory uncertainty facing firms. In this challenging post-Paris environment, companies may have found it more difficult to achieve high scores according to Sustainalytics' methodology, which assesses firms' ability to construct these risk management scores based on the corresponding risks and firms' ability to manage these risks.

The declining CRMS trend therefore provides useful insights. It suggests standards of carbon risk management may have to continually strengthen to keep pace with the rising climate risks and policy targets set through landmark agreements like the Paris Accord. Looking ahead, maintaining high CRMS will likely require firms to proactively decarbonize their business models and strategies at an accelerated rate. The graph offers a basis to further explore firm-level drivers of changes in risk management practices over time.

### *2.3.3 Variance Decomposition of Carbon Risk Management Score*

We conduct a variance decomposition analysis to examine the extent to which *CRMS* quantify firm-level variation in carbon risk management. Table 2-3 reports the explanatory power of conditioning the *CRMS* measure on fixed effects that plausibly drive the variation. Time-fixed effects (i.e., economy-wide changes in aggregate exposure) proxied as quarter-year fixed effects explain little variation, yielding an incremental $R^2$ below 6% (Column 1). In contrast, the *CRMS* has a sizeable industry component ($R^2$ of 37.1%), which might stem from regulation targeting specific industries or technological developments affecting entire sectors (Column 2). This suggests that around 50% of the measure is unexplained by these fixed effects. Indeed, the firm fixed effects explain most of the variation ($R^2$ of 84.1%) (Column 3). Finally, even after adding the interaction between industry and time-fixed effects along with firm-fixed effects, the incremental $R^2$ reaches 91.2% (Column 4).

**Table 2-3: Variance Decomposition of Carbon Risk Management Score**

This table provides a variance decomposition of the CRMS measure. Regressions are estimated at the firm-quarter level. The column results show the incremental $R^2$ from adding a specific fixed effect in each subsequent column. The CRMS measure is the average value of the monthly firm-level CRMS values during a quarter.

| | CRMS | CRMS | CRMS | CRMS |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Quarter–Year FE | Yes | No | No | No |
| Industry FE | No | Yes | No | No |
| Industry × Quarter–Year FE | No | No | No | Yes |
| Firm FE | No | No | Yes | Yes |
| Observations | 9,409 | 9,409 | 9,409 | 9,409 |
| Incremental $R^2$ | 0.052 | 0.371 | 0.841 | 0.912 |

We could not attribute the remaining variation of around 8% in the *CRMS* to any fixed effects. Overall, we find that the major variation in *CRMS* plays out at the firm level rather than by industry or over time.

### *2.3.4 Carbon Risk Management and Firm Characteristics*

Having documented meaningful variations of *CRMS* variables at the firm level, we next examine their correlations with a series of fundamental firm characteristics. We perform this analysis because within-sector heterogeneity in *CRMS* could arise from firms having different technology vintages, capital structures, or growth opportunities. The specification below isolates the firm-level variation in CRMS by including the industry and quarter-year fixed effects:

$$CRMS_{i,t+1} = \alpha + \beta^X X_{i,t} + \delta_j + \delta_t + \epsilon_{i,t+1}\,, \qquad (2.1)$$

where, $CRMS_{i,t+1}$ is the one quarter ahead monthly average of carbon risk management score in each quarter, and where the vector $X_{i,t}$ contains a set of firm characteristics that include *SIZE*, *LEVERAGE*, *CASH*, *CAPEX*, *IVOL*, *TURNOVER*, *PPE*, *ROA* and *TOBIN Q*. $\beta^X$ captures the effect of firm-level financial characteristics on its carbon risk management score. $\delta_j$ and $\delta_t$ are industry (based on the Sustainalytics industry classification) and quarter-year fixed effects, respectively. Carbon risk management practices could concentrate across firms and over time; therefore, we cluster standard errors at the firm and the quarter-year level to account for cross-sectional and serial correlation in the error terms.

Table 2-4 presents the panel regression estimates of equation (2.1) with standard errors of t-statistics reported in parentheses. The results show that the coefficient on the variable *SIZE* is positive and statistically significant, indicating that larger firms tend to have higher carbon risk management. This is consistent with the argument that larger firms have a better bandwidth to adopt such practices, as they have more resources and expertise to devote to carbon risk management. The results suggest that the size of a firm is an important factor in determining its carbon risk management practices. This finding has implications for policymakers and regulators, who may need to consider the size of firms when designing policies and regulations to address climate change. In addition, the results also suggest that larger firms may be better positioned to adapt to the risks of climate change. This is because larger firms have more resources and expertise to invest in new technologies and processes that can help them reduce their carbon emissions. As a result, larger firms may be less vulnerable to the negative impacts of climate change than smaller firms.

The other two factors that may be driving carbon risk management are *CASH* and *TOBIN Q*. These two fundamental factors show a strong and positive association with a firm's carbon risk management score. Cash is a measure of a firm's financial resources. Firms with more cash are more likely to have the resources to invest in carbon risk management initiatives, such as reducing their carbon emissions or developing new technologies to mitigate the risks of climate change. Firms with a higher *TOBIN Q* are more likely to be valued by investors as being more efficient and innovative. These firms may be more likely to invest in carbon risk management initiatives as they see it as a way to improve their efficiency and innovation. The findings suggest that cash and *TOBIN Q* are important factors in determining a firm's carbon risk management practices.

**Table 2-4: Carbon Risk Management Score and Firm Characteristics**

This table presents panel regression results showing the association of key firm-level fundamental characteristics. The main dependent variable in all the models is the firm-level CRMS. The results are shown for the panel regressions done on the full sample (Column 1) and sub-samples of pre– (Column 2) and post-Paris Agreement (Column 3). All variables are explained in detail in Appendix 2.B. The models include the industry fixed effect (Sustainalytics Industry Classification) and quarter–year fixed effects. The standard errors are clustered by firm and by quarter. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels. The values in parentheses are the standard errors of the estimated coefficients.

| | Full<br>CRMS<br>(1) | Pre–Paris<br>CRMS<br>(2) | Post Paris<br>CRMS<br>(3) |
|---|---|---|---|
| *SIZE* | 0.861*** | 0.900*** | 0.801*** |
| | (0.100) | (0.110) | (0.112) |
| *LEVERAGE* | –0.829 | –1.264 | –0.269 |
| | (0.727) | (0.797) | (0.765) |
| *IVOL* | 17.780 | 23.916 | 14.313 |
| | (13.666) | (16.113) | (14.937) |
| *ROA* | –7.709* | –12.098** | –0.329 |
| | (3.904) | (5.441) | (3.209) |
| *CASH* | 2.353** | 1.889 | 3.403*** |
| | (1.036) | (1.160) | (1.119) |
| *TURNOVER* | 0.296 | 0.227 | 0.333 |
| | (1.036) | (1.051) | (1.291) |
| *PPE* | 0.243 | 0.523 | –0.406 |
| | (0.820) | (0.874) | (0.872) |
| *CAPEX* | 1.062 | 2.587 | –2.036 |
| | (2.209) | (2.321) | (3.304) |
| *TOBIN Q* | 0.320** | 0.333* | 0.314** |
| | (0.133) | (0.173) | (0.129) |
| *Industry FE* | Yes | Yes | Yes |
| *Quarter–Year FE* | Yes | Yes | Yes |
| *Observations* | 8,320 | 5,815 | 2,505 |
| *Adj.$R^2$* | 0.458 | 0.450 | 0.508 |

Finally, we also conducted the regression analyses, as described in equation 2.1, on two subsamples representing the pre- (Column 2) and post-Paris climate agreement periods (Column 3). We aim to examine how this significant event influenced firms' carbon risk management practices. These findings indicate that firms with greater asset value, increased cash holdings, and higher *TOBIN Q* were already committed to carbon risk management practices prior to the Paris Climate Agreement (December 2015). However, such practices may not have been material for the investors before the agreement and did not gain significant attention from the investors. The research in Chapter 3 on CDS spreads corroborates this statement, demonstrating that CDS investors began incorporating carbon risk management considerations primarily after the Paris Climate Accord.

### *2.3.5 Carbon Risk Management Score and Other ESG Risk Management Variables*

As CRMS variable has been extracted from the overall ESG score, it is imperative to assess CRMS within the broader ESG framework. This analysis aims to not only explore the correlations between CRMS and other ESG parameters but also to discern CRMS's independent contribution to firm sustainability assessments. To assess this relation, we use simple pairwise correlation analysis. The correlation analysis aimed to examine the relationship between CRMS and other ESG factors, shedding light on CRMS's independence within the broader ESG framework. We use five variables related to ESG to test their individual correlation with CRMS – overall ESG score (ESG), environmental risk management score (E Score), social risk management score (S Score), governance risk management score (G Score) and environmental risk management score excluding carbon risk management scores (E Score – CRMS).

As shown in Table 2-5, CRMS demonstrates a moderately strong positive correlation with ESG (67.2%) and E Score (69.6%), which is expected given the fact that CRMS is a constituent of overall ESG measure and within that it is a major constituent of environmental risk management score.

**Table 2-5: Correlation Matrix for CRMS and Different ESG Components**

This table shows the pooled Pearson correlation coefficient between *CRMS* and other ESG risk management components. *ESG* is the complete risk management score of a firm. *E Score* is the firm level environmental risk management score which also includes CRMS indicators. *S Score* represents the firm level social risk management score. *G Score* is the firm level governance risk management score. *E Score – CRMS* is the environmental risk management score excluding the *CRMS* indicators. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

| **Variables** | **CRMS** | **ESG** | **E Score** | **G Score** | **S Score** | **E Score - CRMS** |
|---|---|---|---|---|---|---|
| *CRMS* | 1 | | | | | |
| *ESG* | 0.672* | 1 | | | | |
| *E Score* | 0.696* | 0.862* | 1 | | | |
| *G Score* | 0.382* | 0.623* | 0.389* | 1 | | |
| *S Score* | 0.427* | 0.810* | 0.492* | 0.350* | 1 | |
| *E Score - CRMS* | 0.337* | 0.683* | 0.651* | 0.370* | 0.505* | 1 |

Notably, CRMS displayed a moderate positive correlation with Governance Score (38.2%), indicating that governance practices may have some role in driving carbon risk management practices. Similarly, CRMS shows a moderately positive correlation with Social Score (42.7%), highlighting its association with social responsibility initiatives as well. The correlation between Environmental Score (excluding CRMS) and CRMS (33.7%) implies a fairly positive relationship. Overall, the correlation analysis also indicates that around 60-70% of the variation within CRMS is uncorrelated with other environmental, social and governance risk management components.

These findings underscore CRMS's significance as an independent factor within the broader ESG framework. While closely correlated with other ESG parameters, CRMS possesses unique attributes that contribute distinctively to firm sustainability assessments.

Effective carbon risk management practices, as measured by CRMS, play a crucial role in enhancing overall corporate sustainability, complementing efforts across environmental, social, and governance domains.

### *2.3.6 Effectiveness of CRMS*

In this section, we test the effectiveness of carbon risk management, i.e. the ability of CRMS to reduce carbon emissions materially. We collect the firm-level carbon emission data from the Refinitiv *ESG* database, which provides data on Scope 1, Scope 2, and Scope 3 levels of carbon emissions and firm-level total carbon emissions. Because the Refinitiv *ESG* provides carbon emission data on an annual basis and our main sample considers a quarterly frequency, we use linear interpolation and the nearest value method to impute the carbon emission values and transform the annual frequency data to quarterly frequency data. Our main measure for carbon emission is the natural logarithm of total carbon emissions. The results in Table 2-6 show that better carbon risk management is related to lower subsequent total carbon emission levels, and that effect is significant only after the post-Paris Agreement. This evidence is consistent with firms adopting stronger carbon risk management practices in the post-Paris Agreement period to signal their ability to reduce carbon emissions credibly.

**Table 2-6: Effect of CRMS on Total Carbon Emission of the Firm**

This table shows the results of the impact of the Paris Agreement of December 2015 as the exogenous shock event on CRMS–$CO_2$ emission relation. The dependent variable is the natural logarithm of the one-quarter ahead total carbon emission (sum of SCOPE 1, 2, and 3 level carbon emission). The results are shown for the panel regressions done on the sub-samples of the pre-Paris Agreement (Column 1), post-Paris Agreement (Column 2), and full sample (Column 3). To measure the impact of the Paris Agreement, we use a dummy variable *POST,* which takes the value of one for the period after December 2015 and zero otherwise. The key variable in the model is *CRMS* × *POST,* an interaction term of *CRMS* and *POST.* The sample includes 405 firms located in the US from August 2009 to May 2018. All the models include the industry fixed effect (based on the Sustainalytics Industry Classification) and quarter-year fixed effects. The standard errors are clustered by firm and by quarter-year. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels. The values in parentheses are the standard errors of the estimated coefficients.

| | A. Pre-Paris Agreement | B. Post-Paris Agreement | C. Full Sample |
|---|---|---|---|
| | ln_$CO_2$_Total | ln_$CO_2$_Total | ln_$CO_2$_Total |
| | (1) | (2) | (3) |
| *CRMS* | –0.018 | –0.100*** | –0.021 |
| | (0.027) | (0.034) | (0.026) |
| *CRMS×POST* | | | –0.063*** |
| | | | (0.020) |
| *LEVERAGE* | 0.699 | 0.229 | 0.516 |
| | (0.522) | (0.467) | (0.440) |
| *IVOL* | –21.640** | –23.890** | –21.869** |
| | (10.426) | (9.613) | (8.508) |
| *SIZE* | 0.890*** | 0.825*** | 0.873*** |
| | (0.079) | (0.082) | (0.073) |
| *ROA* | 0.688 | –1.754 | –0.766 |
| | (2.750) | (2.547) | (2.343) |
| *CASH* | 0.257 | 0.740 | 0.423 |
| | (0.852) | (0.892) | (0.804) |
| *TURNOVER* | 2.269** | 2.253** | 2.221** |
| | (0.882) | (0.922) | (0.853) |
| *PPE* | 3.844*** | 3.542*** | 3.794*** |
| | (0.618) | (0.676) | (0.571) |
| *CAPEX* | –0.658 | 0.883 | –0.286 |
| | (2.071) | (2.301) | (1.932) |
| *Industry FE* | Yes | Yes | Yes |
| *Quarter-Year FE* | Yes | Yes | Yes |
| *Observations* | 4,472 | 1,917 | 6,389 |
| *Adj.$R^2$* | 0.777 | 0.756 | 0.766 |

### *2.3.7 Carbon Risk Management and Public Attention to Climate Change*

The temporal fluctuations in public attention to climate change, as indicated by various news indices, have been found to impact financial market participants (Ardia et al., 2022; Choi, Gao, and Jiang, 2020; Duan, Li, and Wen, 2021; Engle et al., 2020). Consequently, we anticipate that firms may respond to the growing prominence of carbon risk management, particularly during periods characterised by heightened public attention to climate change risk. However, it is important to acknowledge that implementing effective carbon risk management practices is not an immediate process. It typically requires a substantial investment of time and resources to materialise into robust practices. Therefore, it is plausible that substantial changes in a firm's carbon risk management score may not be evident during periods of increased focus on climate change. Therefore, it is an open empirical question whether firms react to heightened public attention to climate change risk and subsequently enhance their carbon risk management capabilities.

We use four proxies of climate change media attention to proxy for the heightened public attention to climate change risk. The first two proxies use the residuals from first-order autoregressive models using time series data on climate change innovation constructed in Engle et al. (2020) i.e. EGKLS. The first variable denoted as *CCN_WSJ_AR1*, is based on the climate news coverage in *The Wall Street Journal*. The WSJ Climate Change News Index assumes that more discussions about climate change occur when there is heightened climate risk. While this may be plausible in most cases, there is a risk of mistakenly interpreting positive climate news (e.g., news about new mitigation technologies or increased share of clean energy in the overall generation mix) as an increased risk. The other drawback of this measure is its reliance on a single source, which may restrict its ability to measure climate discourse among investors comprehensively. Hence, EGKLS provides another climate change news index that employs data from the Crimson Hexagon negative climate change news index. We denote this second EGKLS variable as *CCN_CHNN_AR1*. The third variable to proxy for public attention to climate change risk is *CPU_Index,* developed by Gavriilidis (2021). The final variable to measure the heightened attention to climate change is the monthly average of the daily aggregate of the Media Climate Change Concerns (MCCC) index constructed by Ardia et al. (2022).

We run the baseline regression in equation (2.1) after incorporating the vector of these time series variables and excluding the time-fixed effects to avoid the multi-collinearity with the time-fixed effect dummy and the variables representing climate change media attention. The results in Table 2-7 show that except for *CCN_CHNN_AR1*, the other three variables do not show any association with a firm's carbon risk management score.

**Table 2-7: Carbon Risk Management and Climate Change Media Attention**

This table presents regression results showing the effect of various time series or aggregate measures of climate change concern on the firm-level carbon risk management score. The first two columns use the residuals from first-order autoregressive models using series data for climate change innovation constructed by Engle et al. (2020). The key variable (*CCN_WSJ_AR1*) in Column (1) utilises news from the Wall Street Journal, while the variable (*CCN_CHNN_AR1*) in Column (2) employs data from the Crimson Hexagon negative climate change news index. The variable in Column (3) is the Climate Policy Uncertainty Index (*CPU_Index*) developed by Gavriilidis (2021). The variable (MCCC) in Column (4) is the monthly average of the daily aggregate Media Climate Change Concerns index constructed in Ardia et al. (2023). All the control variables are mentioned in Appendix 2.B. All the panel regression models include the firm- and macro-financial-level control variables. The standard errors are clustered by firm and by quarter. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively. The values in parentheses are the standard errors of the estimated coefficients.

| | CRMS (1) | CRMS (2) | CRMS (3) | CRMS (4) |
|---|---|---|---|---|
| *CCN_WSJ_AR1* | 0.016 | | | |
| | (0.014) | | | |
| *CCN_CHNN_AR1* | | 0.100** | | |
| | | (0.044) | | |
| *CPU_Index* | | | –0.001 | |
| | | | (0.001) | |
| *MCCC* | | | | 0.161 |
| | | | | (0.253) |
| *Control Variables* | Yes | Yes | Yes | Yes |
| *Industry FE* | Yes | Yes | Yes | Yes |
| *Observations* | 8,350 | 8,350 | 8,350 | 8,350 |
| *Adj.$R^2$* | 0.440 | 0.440 | 0.440 | 0.440 |

From the results in Column (2), we can say that only during the heightened negative news related to climate change firms may tend to improve their carbon risk management scores. These results suggest that public attention to climate change risk does not significantly impact firms' carbon risk management practices, except during heightened negative climate change news.

### *2.3.8 Carbon Risk Management and Alternative Firm-Level Climate Change Risk Measures*

We investigate whether the *CRMS* measure provides new insights into climate risk or simply measures the same information as other climate risk variables used in previous studies. To examine the incremental information about climate risk provided by *CRMS*, we assess its relationship with firm-level climate change risk exposures reported by SVLZ. The authors apply textual analytics to quarterly earnings conference call data and capture an elaborate keyword-based measure of firm-level exposures associated with different aspects of climate change. SVLZ constructed four sets of climate change bigrams. While the first construct is a broadly defined, (a) broad climate-change-measure, the next three are sub-measures focused on the following climate change shocks: (b) opportunity, (c) physical, and (d) regulatory. For each of these measures, they further construct "exposure", "risk", and "sentiment" sub-measures or scores.

We specifically choose the firm-level climate change exposure measure of SVLZ, as the authors find that such scores best capture firm-level variation in climate change exposure. Furthermore, these exposure measures are intrinsically forward-looking based on earnings calls, potentially revealing the management's business plans. We consider four firm-level exposure variables out of the total 12 variables described in SVLZ: (1) *CCExposure*; (2) $CCExposure^{Opp}$; (3) $CCExposure^{Reg}$; and (4) $CCExposure^{Phy}$. These capture the relative frequency of word combinations, or bigrams, referencing overall, opportunity, regulatory, and physical climate change shocks, respectively, in the transcripts of analyst conference calls. We conduct the analysis in two steps – Univariate tests and Regression Analysis.

#### ***2.3.8.1 Univariate Tests***

We first analyse the correlations between *CRMS* and different firm-level climate exposure variables. *CRMS* has low correlations with other measures of firm-level climate change exposure from SVLZ, with correlations ranging from 5.2% to 13.6% (tabulated in Table 2-8), showing that CRMS does not simply mirror climate change exposures.

We next examine the characteristics of the univariate-sorted portfolios based on quartile scores of *CRMS* versus the three firm-level risk measures from SVLZ, that is, *CCExposure*, $CCExposure^{Opp}$, and $CCExposure^{Reg}$. In Table 2-9, we find that firms with weak carbon risk management scores (i.e. low *CRMS*) have significantly higher risks, that is, higher idiosyncratic volatility (*IVOL*), and lower cash holdings (*CASH*), poor revenue (*TURNOVER*), and low growth potential (*TOBIN Q*). Firms with poorly managed carbon risk also have low firm-level climate risk exposures, as reflected by the climate change exposure scores. The relationship between *CRMS* and financial variables is also monotonic across portfolios. However, sorting by climate change exposure variables constructed by SVLZ yields no such clear and monotonic correspondence. Only the opportunity risk exposure ($CCExposure^{Opp}$) shows a direct relationship to *CRMS* and an inverse relationship to physical assets (firm-level risk and cash). Variations across other risk exposures show no material variation across financial variables. The results imply that the *CRMS* better captures heterogeneity across firms than risk exposure measures.

**Table 2-8: Correlation Matrix for CRMS and Different Firm–level Exposure Variables**

This table shows the pooled Pearson correlation coefficient between *CRMS* and climate change exposure measures constructed by Sautner et al. (2023). *CCExposure* measures the relative frequency with which bigrams related to climate change occur in the transcripts of analyst conference calls and other sub–measures. $CCExposure^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of analyst conference calls. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

| Variables | *CRMS* | *CCExposure* | $CCExposure^{Opp}$ | $CCExposure^{Reg}$ | $CCExposure^{Phy}$ |
|---|---|---|---|---|---|
| *CRMS* | 1 | | | | |
| *CCExposure* | 0.136*** | 1 | | | |
| $CCExposure^{Opp}$ | 0.135*** | 0.892*** | 1 | | |
| $CCExposure^{Reg}$ | 0.075*** | 0.656*** | 0.464*** | 1 | |
| $CCExposure^{Phy}$ | 0.052*** | 0.102*** | 0.034*** | 0.104*** | 1 |

The univariate results imply that the variation of *CRMS* across firms is associated with differences in firm characteristics and firm-level risk exposures. Hence, *CRMS* better captures heterogeneity across firms than risk exposure measures.

### *2.3.8.2 Regression Tests*

To investigate this relationship further, we consider the following regression model based on equation (2.1), where we include each type of firm-level climate change exposure ($CC_{i,t}$) as an additional regressor on *CRMS*:

$$CRMS_{i,t+1} = \alpha + \beta^{CC}CC_{i,t} + \beta^{X}X_{i,t} + \delta_j + \delta_t + \epsilon_{i,t+1}\ , \qquad (2.2)$$

where, $CRMS_{i,t+1}$ denotes firm *i*'s carbon risk management score in the next quarter. $CC_{i,t}$ represents three firm-level risk measures from Sautner et al. (2023): CCExposure, $CCExposure^{Opp}$, and $CCExposure^{Reg}$. $\beta^{CC}$ captures the association between SVLZ's firm-level climate change exposure measure and carbon risk management score. $X_{i,t}$ are the firm-specific common control vectors, all in the current quarter. $\beta^{X}$ captures the effect of various firm-level financial characteristics on carbon risk management score. $\delta_j$ and $\delta_t$ are industry (based on the Sustainalytics industry classification) and quarter-year fixed effects, respectively.

The objective of the regression analysis is to empirically test if the firm-level climate risk exposure of SVLZ is significantly related to the *CRMS* variable after conditioning for all controls that include firm-specific variables and industry and quarter-fixed effects. The results are reported in Table 2-9. We find that the overall climate change exposure variable is marginally significant at 10% (Model 1), and only the opportunity risk exposure ($CCExposure^{Opp}$) is significantly related (at 5% level) to *CRMS* (Model 2).

Additionally, we conduct a principal component analysis (PCA) of all three sub-exposure variables ($CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$) and use the first component (*PC1*) as the regressor shown in Table 2-9 (Model 5). *PC1*, which captures the common variation in all three exposure measures, is only weakly related to the *CRMS* variable. We also include principal components based on additional firm exposure variables from SVLZ.

## Table 2-9: Univariate Sorting Based on CRMS and Climate Change Exposure Measures of Sautner et al. (2023)

Univariate sorted portfolios of based on quartile scores of CRMS (Panel A), CCExposure (Panel B), CCExposure$^{Opp}$ (Panel C) and CCExposure$^{Reg}$ (Panel D). The last row in each panel presents the t–test of differences between high and low quartile values of each variable. All variables are explained in detail in Appendix 2.B. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels.

**Panel A: Univariate sorting based on *CRMS* score quartile**

| ***CRMS*** | *LEVERAGE* | *IVOL(%)* | *SIZE* | *ROA* | *CASH* | *TURNOVER* | *CAPEX* | *PPE* | *TOBIN Q* | *CCExposure* | *CCExposure$^{Opp}$* | *CCExposure$^{Reg}$* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Low CRMS* | 0.35 | 1.5 | 9.38 | 0.01 | 0.07 | 0.14 | 0.02 | 0.27 | 1.44 | 0.47 | 0.16 | 0.02 |
| *1* | 0.29 | 1.36 | 10.02 | 0.01 | 0.08 | 0.16 | 0.03 | 0.35 | 1.54 | 1.24 | 0.44 | 0.11 |
| *2* | 0.31 | 1.27 | 10.24 | 0.01 | 0.1 | 0.19 | 0.02 | 0.32 | 1.78 | 1.26 | 0.51 | 0.08 |
| *High CRMS* | 0.3 | 1.23 | 10.2 | 0.01 | 0.11 | 0.19 | 0.03 | 0.29 | 1.87 | 1.84 | 0.81 | 0.12 |
| **t–test (High–Low)** | 0.0455$^{***}$ | 0.2$^{***}$ | –0.767$^{***}$ | –0.007$^{***}$ | –0.04$^{4***}$ | –0.053$^{***}$ | –0.006$^{***}$ | –0.016 | –0.401$^{***}$ | –1.230$^{***}$ | –0.585$^{***}$ | –0.092$^{***}$ |
| **t–stat** | (–7.68) | (–8.5) | (–20.28) | (–15.05) | (–15.51) | (–11.65) | (–5.88) | (–1.77) | (–17.20) | (–12.44) | (–11.36) | (–9.16) |

**Panel B: Univariate sorting based on Sautner's Climate Change Exposure Measure (aggregate) quartile**

| ***CCExposure*** | *CRMS* | *LEVERAGE* | *IVOL(%)* | *SIZE* | *ROA* | *CASH* | *TURNOVER* | *CAPEX* | *PPE* | *TOBIN Q* | *CCExposure$^{Opp}$* | *CCExposure$^{Reg}$* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Low CCExposure* | 3.19 | 0.31 | 1.37 | 9.92 | 0.01 | 0.1 | 0.18 | 0.02 | 0.22 | 1.69 | 0.05 | 0 |
| *1* | 3.76 | 0.29 | 1.32 | 10.26 | 0.01 | 0.1 | 0.17 | 0.02 | 0.25 | 1.81 | 0.09 | 0.01 |
| *2* | 3.62 | 0.3 | 1.37 | 9.87 | 0.01 | 0.09 | 0.18 | 0.03 | 0.3 | 1.69 | 0.15 | 0.02 |
| *High CCExposure* | 4.35 | 0.33 | 1.27 | 9.99 | 0.01 | 0.07 | 0.15 | 0.04 | 0.47 | 1.52 | 1.66 | 0.31 |
| **t–test (High–Low)** | 0.127$^{***}$ | 0.001$^{***}$ | –0.1 | 0.001 | 0.035$^{***}$ | 0.028$^{***}$ | –0.016$^{***}$ | –0.242$^{***}$ | 0.173$^{***}$ | 0.173$^{***}$ | –1.608$^{***}$ | –0.303$^{***}$ |
| **t–stat** | (–5.51) | (–4.54) | (–1.81) | (–1.52) | (–14.05) | (–6.35) | (–16.74) | (–31.69) | (–8.01) | (–8.01) | (–31.83) | (–22.34) |

**Panel C: Univariate sorting based on Sautner's Climate Change Opportunity Exposure Measure (aggregate) quartiles**

| ***CCExposure$^{Opp}$*** | *CRMS* | *LEVERAGE* | *IVOL(%)* | *SIZE* | *ROA* | *CASH* | *TURNOVER* | *CAPEX* | *PPE* | *TOBIN Q* | *CCExposure* | *CCExposure$^{Reg}$* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Low CCExposure$^{Opp}$* | 3.34 | 0.3 | 1.37 | 9.92 | 0.01 | 0.1 | 0.17 | 0.02 | 0.26 | 1.7 | 0.31 | 0.02 |
| *2* | 4.16 | 0.29 | 1.3 | 10.14 | 0.01 | 0.09 | 0.18 | 0.02 | 0.3 | 1.76 | 0.7 | 0.05 |
| *High CCExposure$^{Opp}$* | 4.26 | 0.33 | 1.27 | 9.99 | 0.01 | 0.07 | 0.15 | 0.03 | 0.44 | 1.51 | 3.73 | 0.26 |
| **t–test (High–Low)** | –0.926$^{***}$ | –0.027$^{***}$ | 0.1$^{***}$ | –0.069$^{*}$ | 0.001$^{*}$ | 0.029$^{***}$ | 0.026$^{***}$ | –0.010$^{***}$ | –0.177$^{***}$ | 0.193$^{***}$ | (–3.420$^{***}$) | (–0.244$^{***}$) |
| **t–stat** | (–13.21) | (–5.85) | (–5.41) | (–1.98) | (–2) | (–12.11) | (–6.42) | (–11.28) | (–23.80) | (–9.5) | (–43.06) | (–23.52) |

**Panel D: Univariate sorting based on Sautner's Climate Change Regulatory Exposure Measure (aggregate) quartiles**

| ***CCExposure$^{Reg}$*** | *CRMS* | *LEVERAGE* | *IVOL(%)* | *SIZE* | *ROA* | *CASH* | *TURNOVER* | *CAPEX* | *PPE* | *TOBIN Q* | *CCExposure* | *CCExposure$^{Opp}$* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Low CCExposure$^{Reg}$* | 3.53 | 0.31 | 1.35 | 9.94 | 0.01 | 0.1 | 0.17 | 0.02 | 0.28 | 1.69 | 0.66 | 0.27 |
| *High CCExposure$^{Reg}$* | 4.66 | 0.31 | 1.27 | 10.12 | 0.01 | 0.05 | 0.13 | 0.04 | 0.53 | 1.43 | 6.15 | 2.36 |
| **t–test (High–Low)** | –1.214$^{***}$ | –0.011 | 0.1$^{**}$ | –0.197$^{***}$ | 0.002$^{***}$ | 0.046$^{***}$ | 0.042$^{***}$ | –0.013$^{***}$ | –0.259$^{***}$ | 0.265$^{***}$ | –5.922$^{***}$ | –2.304$^{***}$ |
| **t–stat** | (–11.58) | (–1.63) | (–2.94) | (–3.81) | (–3.82) | (–12.94) | (–6.9) | (–9.74) | (–23.77) | (–8.76) | (–52.61) | (–38.87) |

Specifically, we consider two textual analytics measures, i.e., sentiment and risk-based firm-level climate change scores, thus providing six variables overall (two textual analytics measures × three firm-level exposure variables), as reported by SVLZ and denoted as $CCSent^{Opp}$, $CCSent^{Reg}$, $CCSent^{Phy}$, $CCRisk^{Opp}$, $CCRisk^{Reg}$, and $CCRisk^{Phy}$. Using the above six variables, we extract the first three principal components (*PC2*, *PC3*, and *PC4*) and include them separately, as shown in Table 2-10 (Models 6, 7, and 8). We find no relationship between these variables and the *CRMS* variable.

In summary, we find that only one of SVLZ firm-level exposure variables, $CCExposure^{Opp}$, is significantly associated with CRMS. This is plausible, as firms exposed to opportunity shocks from climate change may be more focused on managing their carbon risk. Exploiting opportunities from climate change is one of the best ways to manage carbon risk. Overall, the lack of association between CRMS and Sautner's other climate change exposure measures suggests that CRMS captures additional information not captured by those measures.

As an additional robustness test, we repeat the above regression analysis by including a few other firm-level climate change risk measures. Specifically, we first employ the climate change transition and physical risk measure constructed by KLRW as alternative measures of climate change risk in place of Sautner's climate change exposure measures in equation (2.2). The results in Columns (1) and (2) of Table 2-11 show that though *CRMS* is negatively associated with the climate change risk measure, the relationship is not statistically significant. This suggests that the *CRMS* does not simply instrument the lower climate change risk proxied by the climate transition risk variable of KLRW. *Finally*, in columns (3) and (4), we show the results of the regression model (equation 2.2), where the main independent variables are the

**Table 2-10: The Relationship Between CRMS and Firm–level Climate Change Exposure constructed by Sautner et al. (2023)**

This table shows the effect of various climate change exposure scores constructed by Sautner et al. (2023) on a firm's carbon risk management practices using the model: $CRMS_{i,t} = \alpha + \beta^{CC_{i,t}} CC_{i,t} + \beta^{X} X_{i,t} + \beta^{Y} Y_t + \epsilon_{i,t+1}$ where $CC_{i,t}$ is one of the general scores constructed by Sautner et al. (2023). This includes *CCExposure*, *CCExposure*$^{Opp}$ and *CCExposure*$^{Reg}$. *CCExposure* measures the relative frequency with which bigrams related to climate change occur in the transcripts of analyst conference calls and other sub–measures. *CCExposure*$^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of analyst conference calls. *CCExposure*$^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of analyst conference calls. *CCExposure*$^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of analyst conference calls. The table also shows the effect of principal components constructed on Sautner et al. (2023) three climate change exposure measures and six risk and sentiment analytics-based sub–measures (Panel B). *PC1* captures the common variation in all three exposure measures: (i) *CCExposure*$^{Opp}$; (ii) *CCExposure*$^{Reg}$; and (iii) *CCExposure*$^{Phy}$. *PC2, PC3*, and *PC4* capture the common variation in six sub–measures of Sautner et al. (2023): *CCSent*$^{Opp}$; *CCSent*$^{Reg}$; *CCSent*$^{Phy}$; *CCRisk*$^{Opp}$; *CCRisk*$^{Reg}$; and *CCRisk*$^{Phy}$. All control variables are explained in detail in Appendix 2.B. All models include the industry fixed effect (Sustainalytics Industry Classification) and quarter fixed effects. The standard errors are clustered by firm and by quarter. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels. The values in parentheses are the standard errors of the estimated coefficients.

| | Panel A | | | | Panel B | | | |
|---|---|---|---|---|---|---|---|---|
| | CRMS | CRMS | CRMS | CRMS | CRMS | CRMS | CRMS | CRMS |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *CCExposure* | 0.061* | | | | | | | |
| | (0.031) | | | | | | | |
| *CCExposure*$^{Opp}$ | | 0.107** | | | | | | |
| | | (0.046) | | | | | | |
| *CCExposure*$^{Reg}$ | | | 0.116 | | | | | |
| | | | (0.157) | | | | | |
| *CCExposure*$^{Phy}$ | | | | 0.565 | | | | |
| | | | | (0.385) | | | | |
| *PC1* | | | | | 0.113* | | | |
| | | | | | (0.064) | | | |
| *PC2* | | | | | | 0.024 | | |
| | | | | | | (0.040) | | |
| *PC3* | | | | | | | 0.009 | |
| | | | | | | | (0.029) | |
| *PC4* | | | | | | | | 0.016 |
| | | | | | | | | (0.035) |
| *Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Industry FE* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Quarter–Year FE* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Observations* | 6,498 | 6,498 | 6,498 | 6,498 | 6,498 | 6,498 | 6,498 | 6,498 |
| *Adj.R*$^2$ | 0.490 | 0.490 | 0.488 | 0.488 | 0.489 | 0.488 | 0.488 | 0.488 |

first (*PC1_AllTr*) and second (*PC2_AllTr*) components constructed from all the available proxies of firm-level measures of climate change transition risk using the PCA. These proxies include

**Table 2-11: The Relationship Between CRMS and Other Climate Risk Measures**

This table shows the effect of various climate change exposure scores constructed by Kolbel et al. (2023) on a firm's *CRMS* using the model: $CRMS_{i,t} = \alpha + \beta^{CC_{i,t}} CR_{i,t} + \beta^{X} X_{i,t} + \beta^{Y} Y_{t} + \epsilon_{i,t+1}$ where $CR_{i,t}$ is the vector containing both climate physical ($CR_{PHY}$) and climate transition ($CR_{TR}$) risk scores constructed by Kolbel et al. (2023) based on Item 1.A in firms' 10–K fillings. All variables are explained in detail in Appendix 2.B. All models include the industry fixed effect (Sustainalytics Industry Classification) and quarter fixed effects. The standard errors are clustered by firm and by quarter. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively. The values in parentheses are the standard errors of the estimated coefficients.

| | CRMS<br>(1) | CRMS<br>(2) | CRMS<br>(3) | CRMS<br>(4) |
|---|---|---|---|---|
| $CR_{PHY}$ | –2.486 | | | |
| | (1.782) | | | |
| $CR_{TR}$ | | –1.572 | | |
| | | (1.234) | | |
| *PC1_AllTr* | | | –0.001 | |
| | | | (0.085) | |
| *PC2_AllTr* | | | | –0.193 |
| | | | | (0.125) |
| *LEVERAGE* | –1.356 | –1.406* | –1.202 | –1.081 |
| | (0.823) | (0.833) | (1.183) | (1.158) |
| *IVOL* | –9.799 | –8.832 | –8.557 | –10.800 |
| | (16.301) | (16.352) | (16.215) | (15.968) |
| *SIZE* | 0.857*** | 0.846*** | 0.562*** | 0.607*** |
| | (0.120) | (0.120) | (0.148) | (0.152) |
| *ROA* | –1.107 | –1.516 | 0.126 | 0.145 |
| | (4.747) | (4.703) | (4.448) | (4.402) |
| *CASH* | 3.198*** | 3.185*** | 2.968* | 3.013** |
| | (1.069) | (1.060) | (1.454) | (1.459) |
| *TURNOVER* | –0.899 | –0.966 | –2.710** | –2.646** |
| | (1.126) | (1.133) | (1.164) | (1.170) |
| *PPE* | 1.187 | 1.179 | 0.833 | 1.127 |
| | (0.976) | (0.987) | (1.392) | (1.341) |
| *CAPEX* | 2.349 | 2.667 | 3.539 | 3.348 |
| | (2.778) | (2.761) | (3.679) | (3.623) |
| *Industry FE* | Yes | Yes | Yes | Yes |
| *Quarter–Year FE* | Yes | Yes | Yes | Yes |
| *Observations* | 5,601 | 5,601 | 2,847 | 2,847 |
| *Adj.*$R^2$ | 0.513 | 0.513 | 0.463 | 0.466 |

Sautner's three aggregate measures of climate change exposure (*CCExposure, CCExposure*$^{Opp}$, and *CCExposure*$^{Reg}$), the KLRW measure ($CR_{TR}$) and the natural logarithm of firm-level total carbon emissions. The PCA generated two principal components that capture the common variation in all five exposure measures. The results show that though these variables are negatively related to *CRMS,* the association is insignificant.

Overall, the regression analysis done in this section, exploiting several firm-level climate change risk measures, shows that the CRMS variable is not statistically associated with any of these measures except for a weak association with the SVLZ climate change-related opportunity shock measure. This analysis suggests that the firm-level CRMS variable contains incremental information over the climate change risk measures rather than the climate change risk itself.

## 2.4 Conclusion

This chapter makes an important contribution to the growing literature on climate finance. We focus on a relatively understudied topic within climate finance: carbon risk management. The primary objective of the chapter is to disentangle the association of CRMS measures from various other climate change risk measures. The results indicate that the CRMS contains incremental information beyond existing measures of climate change exposure, in particular, the climate transition risk.

Several findings support this conclusion. First, the variance decomposition analysis shows that the vast majority of variation in the *CRMS* is explained by firm fixed effects, suggesting it quantifies heterogeneity at the firm level. Second, CRMS seems to be a prudent proxy for carbon risk management, given its statistically negative association with the total carbon emission of the firms, especially after the Paris Climate Agreement. Third, the regression analyses demonstrate a limited association between the CRMS and alternative climate risk indicators, except for opportunity exposure. Additional robustness tests employing principal components continue to find no significant relationship. These results suggest that *CRMS* is not subsumed by various other available measures proxying the climate transition risk.

By focusing specifically on risk management indicators from ESG ratings, this study avoids issues faced by aggregate ESG scores or climate risk measures in isolating the relevant dimension. It provides investors a tool to evaluate corporate transition strategies and identify leaders proactively managing carbon risks. As climate policies and low-carbon technologies accelerate the transition, effective risk oversight will be crucial for long-term financial performance. The findings indicate that CRMS can help investors distinguish firms actively adapting their business models to transform into a more sustainable company. Overall, the chapter makes an important step towards developing climate risk metrics that offer a more holistic view of opportunities within transition processes.

## Appendix 2.A. Measurement of Carbon Risk Management Performance

This table lists 13 indicators we use to measure carbon risk management practices adopted by firms. The information on these qualitative and quantitative indicators is collected from the Environmental dimension in the Sustainalytics *ESG* database. The Environmental dimension consists of about 59 indicators of environmental risk management practices, of which only 13 are relevant to carbon risk and the focus of this chapter. Sustainalytics provides a firm-level score for each of these indicators. The scores are industry adjusted weighted scores that are proprietary and assigned to a sub-industry depending on its exposure to individual carbon risk indicators. Our CRMS is the sum of the individual scores of the selected indicators.

**Carbon Risk Management Performance Indicators, *CRMS***

| **Component of Carbon Risk Management** | **Key Criteria Used for Evaluation by Sustainalytics** |
|---|---|
| *Formal Environmental Policy* | This includes a formal policy commitment to reduce emissions, implement energy efficiency practices, commit to environmental protection, and provide regular public disclosure of environmental issues. |
| *Environmental Management System (EMS)* | The formal management system should include programs to measure and manage emissions. The responsibilities and corresponding accountability of such programs should be delegated to management or board-level members. |
| *External Certification of EMS* | There should be an audit of the firm's EMS by an independent third-party agency that can certify whether the environmental management system adopted by the firm is appropriate. |
| *Participation in Carbon Disclosure Project (CDP)* | Relates to a firm's transparency regarding its progress on carbon emission reduction programs by responding to CDP's questionnaire on carbon emissions. |
| *Scope of Corporate Reporting on Reduce Greenhouse Gas (GHG) Emissions* | Evaluates whether the company reports on Scope 1 & 2 and discloses relevant information on Scope 3 GHG emissions. |
| *Programs and Targets to Reduce GHG Emissions from Own Operations* | The evaluation is based on policy commitment to reduce GHG emissions, initiatives to reduce GHG emissions, GHG reduction targets with deadlines, GHG emissions monitoring and measurement with regular GHG audits or verification. |
| *Programs and Targets to Increase Renewable Energy Use* | Assesses the firm's commitment to transition energy use in its operations to renewable energy. There must be formal programs within the firm to ensure such a transition. |
| *Carbon Intensity* | Assesses the relative performance of the firm compared to its peers on carbon intensity. |
| *Carbon Intensity Trend* | Evaluates the carbon intensity trend of the firm over the past three years. |
| *% Primary Energy Use from Renewables* | Measures the percentage of total energy consumption from renewable energy. |
| *Programs and Targets to Reduce GHG Emissions from Outsourced Logistics Services* | Evaluates Scope 3 emission reduction programs and targets of a firm by assessing its broader value chain. |
| *Revenue from Clean Technology or Climate Friendly Products* | Evaluates the material impact of a firm's transition to clean energy technologies and use of climate-friendly products by calculating the revenue generated from such a transition. |
| *Carbon Intensity of Energy Mix* | An additional criterion that assesses the carbon intensity of the firm across its value chain and wider energy usage mix. |

## Appendix 2.B. Variable Descriptions

This table describes the variables that we use in our analysis. Column 1 reports the variable names. Column 2 describes the variables, and column 3 provides the data sources.

| Variable | Description | Source |
|---|---|---|
| | ***Panel A: Carbon Risk Management Measure*** | |
| CRMS (Carbon Risk Management Score) | Weighted sum of scores of management indicators focusing exclusively on a firm's management of carbon risk related to its own operations. These carbon risk management parameters are extracted from the long list of environmental parameters within the overall *ESG* parameter provided by the Sustainalytics database. | Sustainalytics |
| | ***Panel B: Firm-level variables*** | |
| LEVERAGE | Total debt (DLTTQ + DLCQ) divided by total assets (ATQ) | Compustat |
| IVOL (Idiosyncratic volatility) | Standard deviation of daily excess returns, computed as the difference between a firm's stock return and the CRSP value-weighted return over the past 180 days | CRSP |
| SIZE | The natural logarithm of total asset value (ATQ) | Compustat |
| ROA (Return on Assets) | Income after taxes scaled by average total assets over the quarter | Compustat |
| CASH | Cash (CHQ) & Short-Term Investments (CHEQ) scaled by ATQ | Compustat |
| TURNOVER | Total revenues (REVTQ) scaled by ATQ | Compustat |
| PPE (Property, Plant and Equipment) | Gross property, plant, and equipment less accumulated reserves for depreciation, depletion, and amortisation (PPEGTQ) scaled by ATQ | Compustat |
| CAPEX | Capital expenditures representing the funds used to acquire fixed assets (CAPXY) scaled by ATQ | Compustat |
| TOBIN Q | (Total Assets (ATQ) – Book value of equity (CEQQ) + Market value of equity (MKVALTQ))/ ATQ | Compustat |
| | ***Panel C: Aggregate Measures of Climate Change Risk*** | |
| CCN_WSJ_AR1 | Residuals from first-order autoregressive models using climate change innovation series data constructed by EGKLS using climate news coverage in The Wall Street Journal | Engle et al. (2020) |
| CCN_CHNN_AR1 | Residuals from first-order autoregressive models using climate change innovation series data constructed by EGKLS using data from the Crimson Hexagon negative climate change news index | Engle et al. (2020) |
| CPU_Index | Climate Policy Uncertainty Index | Gavriilidis (2021) |
| MCCC | Monthly average of daily aggregate Media Climate Change Concerns measured as the heightened attention to climate change | |
| | ***Panel D: Firm-level Climate Change Exposure Variables of Sautner et al. (2023)*** | |
| CCExposure | Relative frequency with which bigrams related to climate change occur in the transcripts of analyst conference calls. | CCExposure |

| | | |
|---|---|---|
| | Authors count the number of such bigrams and divide by the total number of bigrams in the transcripts. | |
| $CCExposure^{Opp}$ | Relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of analyst conference calls. Authors count the number of such bigrams and divide by the total number of bigrams in the transcripts. | $CCExposure^{Opp}$ |
| $CCExposure^{Reg}$ | Relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of analyst conference calls. Authors count the number of such bigrams and divide by the total number of bigrams in the transcripts. | $CCExposure^{Reg}$ |
| $CCExposure^{Phy}$ | Relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of analyst conference calls. Authors count the number of such bigrams and divide by the total number of bigrams in the transcripts. | $CCExposure^{Phy}$ |
| $CCSent^{Opp}$ | Relative frequency with which bigrams that capture opportunities related to climate change are mentioned together with the positive and negative tone words in one sentence in the transcripts of analyst conference calls. | $CCSent^{Opp}$ |
| $CCSent^{Reg}$ | Relative frequency with which bigrams that capture regulatory shocks related to climate change are mentioned together with the positive and negative tone words that are summarised in one sentence in the transcripts of analyst conference calls. | $CCSent^{Reg}$ |
| $CCSent^{Phy}$ | Relative frequency with which bigrams that capture physical shocks related to climate change are mentioned together with the positive and negative tone words that are summarised in one sentence in the transcripts of analyst conference calls. | $CCSent^{Phy}$ |
| $CCRisk^{Opp}$ | Relative frequency with which bigrams that capture opportunities related to climate change are mentioned together with the words "risk" or "uncertainty" (or synonyms thereof) in one sentence in the transcripts of analyst conference calls. | $CCRisk^{Opp}$ |
| $CCRisk^{Reg}$ | Relative frequency with which bigrams that capture regulatory shocks related to climate change are mentioned together with the words "risk" or "uncertainty" (or synonyms thereof) in one sentence in the transcripts of analyst conference calls. | $CCRisk^{Reg}$ |
| $CCRisk^{Phy}$ | Relative frequency with which bigrams that capture physical shocks related to climate change are mentioned together with the words "risk" or "uncertainty" (or synonyms thereof) in one sentence in the transcripts of analyst conference calls. | $CCRisk^{Phy}$ |

**Appendix 2.C. Summary of other Climate Risk Measures used in Prior Literature**

| Climate Change Risk Measure | Papers | Source/Database |
|---|---|---|
| Corporate Carbon Emission (Scope 1, Scope 2, and Scope 3 emissions) | • Bolton and Kacperczyk, 2021<br>• Azar et al., 2021 | Trucost, Thomson Reuter's Asset 4 |
| Carbon Intensity (total carbon emission divided by company revenue) | • Bolton and Kacperczyk, 2021<br>• Ilhan, Sautner, and Vilkov, 2020<br>• Capasso, Gianfrate, and Spinelli (2020)<br>• Duan, Li, and Wen, 2021 | Trucost, Thomson Reuter's Asset 4 |
| Carbon Risk Factor (constructed through various pillars of environmental scores provided by several *ESG* databases) | • Görgen et al. (2020) | CDP, MSCI, Thomson Reuters, Sustainalytics |
| Climate Physical Risk Measures (sea level rise, drought, etc.) | • Alok, Kumar, and Wermers (2020)<br>• Bernstein, Gustafson, and Lewis (2019)<br>• Huynh, Nguyen, and Truong (2020)<br>• Painter (2020) | Spatial Hazard and Loss Database for the United States (SHELDUS), Palmer Drought Severity Index (PDSI), Geographic Mapping Software for sea–level rise |

# Chapter 3: Do Firms Benefit from Carbon Risk Management? Evidence from the Credit Default Swaps Market

'Incorporating climate change risks into the existing risk management framework is likely to be the best way to ensure that the impact of climate change is properly considered in decision making.'

*Climate Change Risk Management in Financial Services*

*(White paper published by Parker Fitzgerald/Accenture, 11/2019, p. 2)*

## 3.1 Introduction

Investors are increasingly concerned about the climate risk exposure of financial asset prices. Such concerns have led investors and regulators to exert significant pressure on carbon-intensive firms to curb their carbon emissions (Azar et al., 2021; Krueger, Sautner, and Starks, 2020). [11] At the same time, several climate coalitions and initiatives have encouraged firm directors to adopt management practices that can help them avoid the foreseeable and costly carbon transition risk. [12] While the implications of carbon emission risk for corporate performance are generally well understood (Bolton and Kacperczyk, 2021; Duan, Li, and Wen, 2021; Ilhan, Sautner, and Vilkov, 2020), there is little evidence on the benefits of firms'

[11] Recently formed consortium of Wall Street banks and the Risk Management Association, intends to develop standards for measuring and managing climate risk ("Big Banks Band Together to Measure and Manage Climate Risk" ; Wall Street Journal, 01/12/2022). The US Security Exchange Commission (SEC) also proposed stringent disclosure requirements on greenhouse-gas emissions and risks related to climate change for publicly traded companies ("SEC Floats Mandatory Disclosure of Climate-Change Risks, Emissions" ; Wall Street Journal, 03/21/2022). Related findings in Downar et al. (2021) show that UK firms affected by the carbon disclosure requirement in 2013 witnessed a reduction in their subsequent emissions.

[12] The climate initiatives include Climate Action 100+, RE100, Task Force on Climate-related Financial Disclosures (TCFD), United Nations Principles for Responsible Investments (UN-PRI), Science Based Targets Initiative (SBTi), and the Glasgow Climate Pact (or COP 26).

proactive management of carbon emission risk. We fill this gap in the literature by examining whether firms that are prudent in managing their carbon emissions and, hence, better positioned to tackle carbon transition risk are favourably assessed in the credit markets.

The relevance of carbon risk management for credit risk assessment arises from the importance of carbon emissions in driving firm credit risk. Following the Merton (1974) framework, carbon emissions can affect the underlying credit risk in multiple ways. *First*, firms with disproportionately high $CO_2$ emissions may be exposed to carbon pricing risk and other regulatory interventions to limit emissions, leading to higher operational costs and lower cash flows. *Second*, as carbon emissions are tied to fossil fuel energy usage, instability in fossil fuel prices injects uncertainty into operational costs, leading to increases in cash flow volatility. *Third*, fossil fuel-dependent firms are highly exposed to carbon transition risks. The transition to lower-cost clean energy technology results in rapid obsolescence of the existing carbon-intensive assets, turning them into non-performing or financially stranded assets. The stranded assets can intensify sunk capital costs and induce bankruptcies, thereby resulting in a loss in firm value. Firms with stranded or non-investible assets may attract costly penalties (e.g., via a potential carbon tax, emission trading schemes, or cap-and-trade policies), and/or regulations mandating early retirement of firms' fossil fuel power plants and, thereby, face the risk of being excluded from investor portfolios. In summary, carbon pricing and other transition risks can reduce corporate cash flows, increase cash flow volatility and obsolescence, and hence, cause high carbon emission firms *ceteris paribus* to exhibit higher credit risk.

The effectiveness of carbon risk management on credit risk depends on the relative strength of two competing hypotheses (Flammer, 2021). On one hand, the "signaling hypothesis" (Flammer, 2013; Klassen and McLaughlin, 1996; Krueger, 2015) implies that stronger firms indicate their relative strength and commitment to mitigate climate risk through better carbon risk management. As a result, firms with better carbon risk management are favourably assessed in the credit market, reflected by lower credit spreads. On the other hand, the "greenwashing hypothesis" suggests that firms tend to inflate or misrepresent their carbon risk management practices, which may reflect inadequate public enforcement mechanisms (Berrone, Fosfuri, and Gelabert, 2017; Liang, Sun, and Teo, 2022). Unsubstantiated claims of risk management, or window-dressing efforts by overzealous firms, can be counterproductive as financial market participants may penalise any misleading claims about a company's environmental commitment. Hence, claims of better carbon risk management by window-dressing firms can significantly increase credit spreads. The ultimate effect of carbon risk management on credit risk is, therefore, an open empirical question.

We address this question by examining whether firms with better carbon risk management scores (*CRMS* thereafter) are favourably assessed in the CDS market. The US credit market provides a plausible setting to investigate the impact of firms' carbon risk management given its robust size ($10.3 trillion in corporate debt outstanding as of December quarter 2022)[13] and potential exposure to climate change risk. We consider the *CDS* market because it offers several advantages for our empirical work. The *CDS* market is primarily dominated by sophisticated investors with the capacity to integrate climate risks into their analysis. Elevated climate transition risks on account of inadequate carbon risk management can also pose tail risks for the firms that can be better captured by the *CDS* contracts. *CDS* are actively traded instruments that reflect changes in credit risk more accurately and quickly than corporate bond yield spreads (Blanco, Brennan, and Marsh, 2005). CDS instruments are less impacted by non-default components

[13] Source: SIFMA - https://www.sifma.org/resources/research/us-corporate-bonds-statistics/

compared to corporate bonds that are subject to high illiquidity (Zhang, Zhou, and Zhu, 2009). In addition, unlike corporate bond spreads, CDS spreads are free of specification issues arising from the correct specification of a benchmark risk-free yield curve (Ericsson, Jacobs, and Oviedo, 2009).[14] Finally, findings in the CDS market can inform pricing in the primary debt market securities, and influence the firms' borrowing costs (Augustin et al., 2014; Goldstein, Hotchkiss, and Pedersen, 2019).

We investigate the importance of carbon risk management for corporate CDS spreads using a sample of 405 US firms over the period from August 2009 to May 2018. We rely on the Sustainalytics database on ESG criteria to evaluate the carbon risk management practices adopted by these firms. Specifically, we extract 13 firm-level indicators related to carbon risk management from the broader 59 environmental parameters related to ESG. These indicators offer a relative assessment of firms' preparedness and performance in managing carbon risk. Our key firm-level variable is a carbon risk management score, which is the sum of the individual industry adjusted scores for these 13 indicators. A higher CRMS value indicates that a firm performs favourably in managing carbon transition risk relative to its peers.

We investigate the impact of CRMS primarily on the 5-year benchmark CDS spreads of the firms as they are traded more frequently compared to the CDS of other maturities (Augustin and Izhakian, 2020; Das, Kalimipalli, and Nayak, 2014; Ericsson, Jacobs, and Oviedo, 2009; Galil et al., 2014). Our primary findings reveal a statistically significant and negative relationship between CRMS and the CDS spread of the firm. The results are also economically significant; a one-standard deviation increase in a firm's *CRMS* variable reduces

[14] Extant literature shows that CDS spreads reflect: (i) forward looking expectations of subjective or perceived credit risk; (ii) better market calibration due to frequent trading (Ederington, Guan, and Yang, 2015; Ericsson, Jacobs, and Oviedo, 2009; Finnerty, Miller, and Chen, 2013) and (iii) improved standardisation in terms of maturities, debt seniority levels, and restructuring events (Norden and Weber, 2009).

the 5-year *CDS* spread by 10.31 basis points, which is equivalent to 7.26% of the average value of the 5-year *CDS* spread value.

To address potential endogeneity concerns regarding the relationship between *CRMS* and *CDS* spread, we employ two quasi-natural experiments: the Paris Agreement of December 2015 and the staggered adoption of State Climate Adaptation Plans adopted by 15 states in the US. The Paris Agreement, considered the most ambitious climate agreement ever signed (Bolton and Kacperczyk, 2021; Capasso, Gianfrate, and Spinelli, 2020). It serves as a major exogenous shock to the financial market's attention to a firm's exposure to climate risk, especially in terms of climate transition or carbon risk. The Paris Agreement hence results in a significant change in the perception related to climate change risk materiality and the importance of risk management within the investor community. We find that *CRMS* exerts a stronger impact on credit spread in the post-Paris Agreement period. We then perform a difference-in-differences (DiD) analysis where we match treatment (high *CRMS*) firms with comparable control (low *CRMS*) firms based on propensity score matching. We observe that treatment firms have significantly lower credit spreads compared to control firms, and incrementally so after the Paris Agreement. These findings suggest that the credit markets favourably assess firms that show prudence in carbon risk management.

Next, we utilise the staggered adoption of State Climate Adaptation Plans (*SCAP*) in 15 states over our sample period from August 2009 to May 2018 as an additional quasi-natural setting for our analysis. *SCAP* represents government interventions through a combination of legislative actions, executive orders by governors, and engagement with all stakeholders, aimed at enhancing preparedness and resilience to the impacts of climate change. The staggered *SCAP* implementation events enhance carbon transition risk for firms with poor carbon risk management and highlight the associated cost of transition risk. Employing a stacked regression approach, we find that the role of proactive carbon risk management practices play a more significant role in reducing the credit spread for firms headquartered in states with formalised *SCAPs*. This finding implies that the credit markets favourably assess the climate change implications on firms headquartered in states where the government has implemented climate protection policies and plans.

We further investigate the possibility of alternative explanations and examine the robustness of our findings. *First*, it is possible that our results are driven by underlying firm-level climate risks. We leverage a few results from chapter 3 where we compare the *CRMS* to firm-level climate change risk exposure measures of Sautner et al. (2023), based on textual analysis of firms' quarterly earnings conference calls. We find that the effect of *CRMS* on *CDS* spread is robust even after controlling for Sautner et al. (2023) measures, suggesting that *CRMS* conveys additional information not captured by the firm-level climate change risk variables.

*Second*, given that well-governed firms invest more in environmental and social policies (Ferrell, Liang, and Renneboog, 2016), it is possible that our results are driven by firms' governance risks or social policies and practices. We find that after the Paris Agreement, *CRMS* have a favourable impact on *CDS* spreads even after controlling for governance and social risk management risk scores. We additionally include environmental measures unrelated to carbon risk management as controls and find our results to be robust. These findings validate our conjecture that carbon risk management practices within environmental pillar have become prominent after the Paris Agreement and are associated with lower subsequent credit risks for underlying firms.

In the final set of analysis, we explore the possible channels underlying the *CRMS–CDS* spread relation. We find that for firms with the highest quartile of industry leverage, higher *CRMS* is associated with lower subsequent credit risk valuations, mainly in the post-Paris Agreement period. Additionally, we find that better carbon risk management is associated with lower total carbon emission levels, especially following the Paris Agreement.

Our findings contribute to the existing literature in several ways. *First*, we add to the growing body of research that examines the link between climate change risk and financial markets. Prior work in this emerging literature highlights the importance of carbon emissions, carbon risk factors, or hedging of climate change news in determining financial asset value or returns (Amiraslani et al., 2022; Bolton and Kacperczyk, 2021; Ehlers, Packer, and de Greiff, 2022; Engle et al., 2020; Görgen et al., 2020; Huynh and Xia, 2020; Kölbel et al., 2024; Monasterolo and de Angelis, 2020; Wu and Tian, 2022). We differ from these studies by emphasizing the important impact of *prudent carbon emission management* by a firm on its CDS spread.

This chapter is also closely related to Seltzer, Starks, and Zhu (2022) who show that stricter regulatory enforcement amplifies the effect of corporate environmental profile on credit ratings and bond yield spreads. Compared to Seltzer, Starks, and Zhu (2022), the use of CDS in our analysis provides a more accurate measurement from secondary market of credit risk, that is less affected by non-default or estimation issues (Blanco, Brennan, and Marsh, 2005; Ericsson, Jacobs, and Oviedo, 2009; Zhang, Zhou, and Zhu, 2009). In addition, Seltzer, Starks, and Zhu (2022) consider the overall environmental profile of a firm while we show that the influence of CRMS on credit spread is much stronger than other environmental indicators, and also independent of indicators of governance, social, or firm-level climate change exposure

(Sautner et al., 2023). Our findings suggest that among a comprehensive set of risk management indicators that inform the overall environmental profile of a firm, attributes linked to the management of carbon risk play a key role for the CDS spreads. Furthermore, our approach of concentrating solely on carbon risk management indicators within the broader spectrum of ESG risk management indicators is intended to prevent or reduce the problem of aggregate confusion (Berg, Kölbel, and Rigobon, 2022; Ehlers, Gao, and Packer, 2021) that may arise when studying hundreds of risk management indicators associated with E, S, and G together.

*Second*, our chapter contributes to the extant literature on risk management by focusing on carbon risk management. Previous research shows that managing risk in the presence of imperfect capital markets can be value enhancing for firms by: (i) reducing expected taxes (Graham and Rogers, 2002), (ii) decreasing cash flow and earnings volatility (Beatty, Petacchi, and Zhang, 2012; Giambona and Wang, 2020), (iii) lowering the costs of financial distress (Campello et al., 2011; Gilje and Taillard, 2017), (iv) decreasing the cost of capital (Smith and Stulz, 1985), (v) mitigating financial constraints (Froot, Scharfstein, and Stein, 1993), (vi) increasing the optimal debt capacity (Leland, 1998) as well as investment productivity (Cornaggia, 2013), and (vii) alleviating the underinvestment problem (Bessembinder, 1991; Gilje and Taillard, 2017; Pérez-González and Yun, 2013). Risk management can also lower agency costs and tail risks (Ellul and Yerramilli, 2013; Kumar and Rabinovitch, 2013). This chapter extends this strand of literature by highlighting the effects of improved carbon risk management by firms. Firms with higher *CRMS* scores exhibit superior preparedness and performance levels with respect to lower carbon emissions, and hence carry reduced transition risks as reflected in favourable CDS spreads.

The remaining chapter is structured as follows: Section 3.2 describes the data and key variables used in the study; Sections 3.3, 3.4 and 3.5 provide the empirical results on the relationship between *CRMS* and *CDS* spreads; Section 3.6 provides various robustness tests and channel analyses; and Section 3.7 provides tests for signaling effect hypothesis. Finally, in Section 3.8, we offer our conclusions.

## 3.2 Data

### *3.2.1 Carbon Risk Management Score*

In this chapter, we utilise the CRMS as the primary independent variable. As the CRMS was developed in Section 2.2.1 of this thesis, please refer thereto for details on its construction from Sustainalytics' ESG risk management indicators. Specifically, the CRMS quantifies two dimensions of corporate climate transition risk management efforts: preparedness demonstrated through carbon emission policies and systems, as well as performance reflected in relative emissions reductions and clean energy utilisation. Appendix 2.A further specifies the risk management practices and achievements captured by this metric.

### *3.2.2 Credit Risk Measure*

We utilise IHS Markit database to obtain data on single-name *CDS* spreads across tenors of 1, 5, 10, and 30 years. We use single-name *CDS* spread data of firms headquartered in the US during the period between August 2009 and May 2018. The beginning of the period is determined by availability of the *CRMS* data from Sustainalytics. To be consistent with quarterly firm-level control variables, we employ daily CDS spreads which are then averaged over each quarter.

### *3.2.3 Control Variables*

In order to isolate the impact of *CRMS* on credit spread, we select several firm-specific and non-firm specific common control variables that have been identified in the literature as having an impact on the credit spread of a firm. Drawing from structural credit risk models, particularly by Merton (1974), we include the theoretical determinants of the credit spread such as asset value, asset volatility, and firm leverage. Asset value is the total assets of the firm reported quarterly. We use the natural logarithm of asset value (*SIZE*) in our regression analysis. To proxy for asset volatility, we follow Kaviani et al. (2020) and Campbell and Taksler (2003) and use idiosyncratic equity volatility (*IVOL*), which is measured as the standard deviation of daily excess returns over the preceding 180 days. Firm leverage is approximated by the average book value of the firm's debt, calculated as the total value of short- and long-term debt divided by total assets (*LEVERAGE*).

We also control for various firm-level fundamental determinants of credit spread, following Bharath and Shumway (2008) and Bai and Wu (2016). These control variables include the return on assets (*ROA*) to capture the profitability of the firm, cash and cash equivalent scaled by total assets (*CASH*) to capture firm liquidity, revenue or turnover of the firm scaled by total assets (*TURNOVER*), capital expenditure scaled by total assets (*CAPEX*), and property, plant, and equipment scaled by assets (*PPE*) to capture the tangibility of the firm. Data for all these variables were obtained from the Compustat-North America quarterly database.

Finally, we use the excess stock market return (*MktRET*), one-year US treasury rates (*Yield1Yr*), and government treasury yield curve (*YieldCurve*) as the macro-financial variables that we expect to be influencing *CDS* spreads, as per Zhang, Zhou, and Zhu (2009). We obtain data on excess market returns from the Kenneth French data library. The one-year US treasury bill rate and the yield curve slope, which is the difference between ten- and two-year US treasury bond rates, are from the US Federal Reserve website. Appendix 3.A provides further description and data sources for all variables.

#### *3.2.4 Sample Construction*

We follow prior studies (Bai and Wu, 2016; Ericsson, Jacobs, and Oviedo, 2009; Griffin, Hong, and Kim, 2016) to clean the *CDS* data as follows: (1) remove *CDS* which are denominated in currencies other than US dollars; (2) keep only the senior unsecured obligations as they are the most liquid trading *CDS* contracts; (3) keep only those *CDS* contracts which have a modified restructuring (MR) documentation clause prior to April 2009 ("CDS Big Bang") and no restructuring clause afterwards; (4) exclude *CDS* contracts which have a spread of more than 10,000 basis points (Bai and Wu, 2016) to minimize any measurement errors as such contracts are mostly illiquid due to bilateral arrangements for up-front payments; (5) remove any *CDS* entry that does not have an observation for *CDS* spread for any of the tenors. The final *CDS* data set consists of 483 unique single-name or firm-level daily *CDS* spreads distributed across 1-, 5-, 10-, and 30-year tenors.

In the next step, we merge the *CDS* spread data with the *CRMS* data from the Sustainalytics database and firm-level control variables data from the Compustat database. For each firm we aggregate monthly averages of *CRMS* for a given quarter over the sample period. We then merge the three datasets across common firms and corresponding quarters of a particular year using common identifiers such as GVKey and REDCODE. [15] We remove all observations where the asset value of any firm is either nonpositive or missing.

The final sample consists of 405 unique firms with a quarterly frequency starting from August 2009 to May 2018, providing a total of 9,407 firm-quarter observations. The sample size is similar to previous studies on climate change risk impact on *CDS* spreads (Kölbel et al., 2024). Finally, all continuous variables are winsorised at the 1st and 99th percentile to mitigate the effect of either data errors or outliers.

### *3.2.5 Descriptive Statistics*

We present summary statistics on all main variables used in the analysis in Table 3-1. The *CDS* spreads are reported in basis points to facilitate interpretation. The median of the 5-year *CDS* spread is 90.53 basis points. Firms in our sample have a median asset size of $16.78 billion. Our descriptive statistics of key variables in the sample, such as median leverage of 29% and median idiosyncratic volatility of 1.19%, are similar to those in other recent papers focusing on credit spreads (Kaviani et al., 2020; Kölbel et al., 2024).

Table 3-2 presents pooled quarterly Pearson correlation coefficients of the key variables. Correlations between the *CDS* spread of all maturities and *CRMS* are negative and statistically significant. This finding provides some initial indication of a negative relationship between *CRMS* and *CDS* spreads. The correlation coefficients of the *CDS* spread with the other control variables are quantitatively the same to those established in previous literature and

[15] In cases, where the common identifiers are not available, we apply the fuzzy-logic Python code to match the firm names and import corresponding identifiers to map the different datasets.

theory. For instance, for our sample period the correlations of 5-year *CDS* spread with idiosyncratic volatility and leverage are 58.8% and 27.6%, respectively.[16]

**Table 3-1: Descriptive Statistics**

This table provides the summary statistics of the test variables for a sample of 405 single–*CDS* of firms in the US for the period from August 2009 to May 2018. Note that the log-transformed *CDS* spread is reported in real values and expressed in basis points (bps). *CDS1*, *CDS5*, *CDS10*, and *CDS30* are the daily averages of *CDS* spread across 1-, 5-, 10-, and 30-year tenor in each quarter. *CRMS* denotes the sum of the scores of each of the carbon risk management practices adopted by a firm. *LEVERAGE* is the ratio of total liabilities to total assets. *IVOL* is the idiosyncratic volatility of a firm; it is the standard deviation of daily excess returns, computed as the difference between a firm's stock return and the CRSP value-weighted return over the past 180 days. *Total Asset Value* is the firm's size measured by total assets. We use the natural logarithm of *Total Asset Value* denoted as *SIZE* in our regression analysis. *ROA* is the return on assets, *PPE* is the property, plant, and equipment scaled by the total assets of the firm, and *CAPEX* is the capital expenditure scaled by total assets. *CASH* and *TURNOVER* are the cash & short-term investments and total revenue of the firm, respectively, both scaled by the total assets of the firm. *Yield1Yr* is the 1-year US Treasury rate and *YieldCurve* is the difference between 10-year and 2-year US Treasury rate. *MktRET* is the quarterly excess return of the market. The details of these variables are provided in Appendix 3.A. All continuous variables except *CRMS* are winsorised at the 1st and 99th percentile.

| | Obs. | Mean | Median | min | p5 | p95 | max | Std. Dev. |
|---|---|---|---|---|---|---|---|---|
| | | | *CDS Spread (bps) across Tenors* | | | | | |
| CDS1 | 9,407 | 51.11 | 22.92 | 3.36 | 5.11 | 196.84 | 546.36 | 82.94 |
| CDS5 | 9,407 | 141.91 | 90.53 | 19.35 | 28.09 | 447.10 | 898.62 | 150.39 |
| CDS10 | 9,407 | 178.82 | 127.92 | 42.44 | 52.40 | 505.10 | 887.28 | 154.10 |
| CDS30 | 9,407 | 190.12 | 141.73 | 50.29 | 61.63 | 513.37 | 861.37 | 151.12 |
| | | | *Carbon Risk Management Score* | | | | | |
| CRMS | 9,407 | 3.71 | 3.40 | 0.00 | 0.000 | 8.76 | 16.00 | 2.73 |
| | | | *Firm Level Variables* | | | | | |
| LEVERAGE | 8,716 | 0.312 | 0.29 | 0.02 | 0.067 | 0.61 | 0.87 | 0.17 |
| IVOL (%) | 9,407 | 1.39 | 1.19 | 0.42 | 0.71 | 0.94 | 1.60 | 2.78 |
| Total Asset Value (in billion $) | 9,407 | 55.86 | 16.78 | 2.26 | 3.463 | 235.50 | 841.37 | 130.82 |
| ROA | 9,403 | 0.01 | 0.01 | –0.06 | –0.010 | 0.04 | 0.05 | 0.02 |
| CASH | 9,407 | 0.09 | 0.06 | 0.00 | 0.005 | 0.28 | 0.49 | 0.09 |
| TURNOVER | 9,359 | 0.19 | 0.15 | 0.01 | 0.025 | 0.54 | 0.92 | 0.17 |
| PPE | 8,625 | 0.31 | 0.22 | 0.00 | 0.009 | 0.81 | 0.88 | 0.26 |
| CAPEX | 9,397 | 0.03 | 0.01 | 0.00 | 0.000 | 0.09 | 0.17 | 0.03 |
| | | | *Macro-Financial Variables* | | | | | |
| Yield1Yr (%) | 9,407 | 0.45 | 0.26 | 0.10 | 0.100 | 1.70 | 2.27 | 0.47 |
| YieldCurve (%) | 9,407 | 1.72 | 1.70 | 0.47 | 0.560 | 2.72 | 2.77 | 0.65 |
| MktRET (%) | 9,407 | 1.13 | 0.78 | –7.59 | –5.570 | 6.96 | 9.54 | 3.47 |

[16] Our bivariate correlations are qualitatively similar to those observed by (Ericsson, Jacobs, and Oviedo, 2009) and (Augustin and Izhakian, 2020).

**Table 3-2: Correlation Matrix**

This table shows pooled Pearson correlation coefficients for major variables used in our empirical analyses. All variables are explained in detail in Appendix 3.A. The sample includes 405 firms located in the US from August 2009 to May 2018. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels.

| Variables | *CDS1* | *CDS5* | *CDS10* | *CDS30* | *CRMS* | *Yield1Yr* | *Yield_Curve* | *LEVERAGE* | *IVOL* | *MktRET* |
|---|---|---|---|---|---|---|---|---|---|---|
| *CDS1* | 1.000 | | | | | | | | | |
| *CDS5* | 0.887*** | 1.000 | | | | | | | | |
| *CDS10* | 0.833*** | 0.990*** | 1.000 | | | | | | | |
| *CDS30* | 0.797*** | 0.977*** | 0.996*** | 1.000 | | | | | | |
| *CRMS* | –0.062*** | –0.105*** | –0.116*** | –0.122*** | 1.000 | | | | | |
| *Yield1Yr* | –0.056*** | –0.072*** | –0.063*** | –0.055*** | –0.058*** | 1.000 | | | | |
| *Yield_Curve* | 0.048*** | 0.037*** | 0.012 | 0.001 | 0.088*** | –0.668*** | 1.000 | | | |
| *LEVERAGE* | 0.126*** | 0.276*** | 0.313*** | 0.330*** | –0.090*** | 0.081*** | –0.103*** | 1.000 | | |
| *IVOL* | 0.412*** | 0.588*** | 0.605*** | 0.609*** | –0.066*** | 0.003 | 0.005 | 0.204*** | 1.000 | |
| *MktRET* | –0.026** | –0.028*** | –0.036*** | –0.039*** | 0.019* | –0.054*** | 0.141*** | –0.016 | 0.037*** | 1.000 |

## 3.3 Baseline Regression Results

We analyse how the carbon risk management practices of a firm affects *CDS* spreads. We use the following general model specification to test the relationship between the one-quarter-ahead of the *5*-year *CDS* spread for the *i*-th firm ($CDS_{i,t+1}$) and the current quarter *CRMS* ($CRMS_{i,t}$) as follows:

$$\ln\left(CDS_{i,t+1}\right) = \alpha + \beta^{CRMS} CRMS_{i,t} + \beta^{X} X_{i,t} + \beta^{Y} Y_t + \epsilon_{i,t+1}\,, \tag{3.1}$$

where, $X_{i,t}$ and $Y_t$ are firm specific and macro-financial factors, respectively. Consistent with prior studies (Bai and Wu, 2016; Bharath and Shumway, 2008), we use the natural logarithm of *CDS* spreads to mitigate the impact of outliers. We control all panel regression models using quarter and industry-fixed effects. The use of fixed effects ensures that we control for time-specific or industry-specific factors that could affect credit spread. Since non-firm-specific common factors have the same value for all firms in the same quarter of the same year, these variables get absorbed when we use model specification with quarter-fixed effects. Thus, we estimate specifications with and without time-fixed effects in our analysis.

We do not consider firm-level fixed effects due to the persistence of the key carbon risk management score variable. The industry fixed effects are based on the industry classification provided by Sustainalytics.[17] Carbon risk management practices could concentrate across firms and over time; therefore, we cluster standard errors at the firm and the quarter-year level to account for cross-sectional and serial correlation in the error terms (Petersen, 2009).

We investigate the impact of carbon risk management on the 5-year *CDS* spread as it is the most liquid maturity *CDS* instrument traded. Table 3-3 reports the main regression results examining the impact of carbon risk management on the 5-year *CDS* spread in Model (1) (with industry fixed effects but without quarter fixed effects) and Model (2) (with both industry and quarter fixed effects). We observe a significant and negative relationship between the carbon risk management score and the 5-year *CDS* spread in these two models. Models (3) and (4) augment Models (1) and (2) respectively by including several firm characteristics and macro-financial variables as additional control variables. In both models, we observe a significant and negative relationship between *CRMS* and 5-year *CDS* spreads, implying that carbon risk management practices have a risk mitigation impact on firms' credit risk.

Our results are also economically significant. We assess the economic significance of these findings by estimating the expected change in *CDS* spread due to a one standard deviation

[17] Results are robust when we use industry classification based on the 2-digit Standard Industrial Classification (SIC2).

change in the *CRMS*. [18] Specifically, for the results using quarter fixed effects (Model 4), a one standard deviation (2.73) increase in the *CRMS* (see Table 3-1) reduces the 5-year *CDS* spread by 10.31 basis points in a quarter, which is 7.26% of the mean of the 5-year *CDS* spread (or in dollar terms by about $72,600 for a $1 million notional *CDS* contract). We also run the baseline regression of Table 3-3 using industry × quarter fixed effects. We further re-estimate the baseline model using the average time-series values of credit spreads, *CRMS*, and other control variables at the firm level. The results presented in Appendix Table 3-1 show that the negative relationship between CRMS and credit spreads still holds. Hence, the regression results support our hypothesis that carbon risk management performance is associated with significantly lower *CDS* spreads. [19] Our results provide evidence consistent with the signalling hypothesis and imply that credit risk management by firms is interpreted favourably by credit markets.

Turning to the control variables, we find that *CDS* spreads are higher for firms with higher leverage (*LEVERAGE*) and volatility (*IVOL*) and lower for larger firms (*SIZE*). The results are consistent with credit risk structural models and associated theories (Ericsson, Jacobs, and Oviedo, 2009; Merton, 1974). The other firm-level determinants of credit spreads, such as *ROA* and *PPE*, also show a negative relationship with the *CDS* spread as established in the related literature (Bai and Wu, 2016; Ericsson, Jacobs, and Oviedo, 2009). The explanatory power of regressions for 5-year *CDS* spread levels is up to 65.8%, in terms of adjusted $R^2$. Previous research on the pricing of *CDS* spreads report a similar explanatory power (Augustin

[18] Given the dependent variable is the natural logarithm of 5-year CDS spread, the coefficient estimates of CRMS of –0.027 in Model 4 of Table 3-3 suggests that a one unit increase in CRMS leads to a change of: –2.66% x (exp(–0.027)) in the CDS spread. Thus, a one standard deviation change in CRMS (2.73) will lead to a change of: –7.26% (–2.66% x 2.73) in the CDS spread. Given the average value of CDS spread of 141.91 basis points (from Table 3-1), this is equivalent to a reduction of 10.31basis points (–7.26% x 141.91) in the CDS spread.

[19] We obtain consistent results when we exclude financial firms from our sample. We report the results including the financial firms in our sample as these firms are equally exposed and under pressure from activist investors to act against carbon transition risk.

and Izhakian, 2020; Ericsson, Jacobs, and Oviedo, 2009). Macro-financial variables get absorbed after the inclusion of quarter fixed effects due to perfect collinearity. As time (quarter)

**Table 3-3: The Relationship between CRMS and 5-Year CDS Spread**

This table presents the results from the panel regression of the natural logarithm of daily average of 5-year senior unsecured *CDS* spread level (*CDS5*) in a quarter on the CRMS, structural variables such as leverage (*LEVERAGE*), idiosyncratic volatility (*IVOL*), excess market return (*MktRET*), and other control variables. All variables are explained in detail in Appendix 3.A. The sample includes 405 firms located in the US from August 2009 to May 2018. All the models include the industry fixed effect (based on Sustainalytics Industry Classification). Models (2) and (4) include quarter-year fixed effects. The standard errors are clustered by firm and by quarter-year. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively. The values in parentheses are the standard errors of the estimated coefficients.

| | CDS5 | CDS5 | CDS5 | CDS5 |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *CRMS* | –0.059*** | –0.067*** | –0.026** | –0.027*** |
| | (0.020) | (0.019) | (0.010) | (0.010) |
| *LEVERAGE* | | | 1.305*** | 1.352*** |
| | | | (0.170) | (0.166) |
| *IVOL* | | | 47.620*** | 48.117*** |
| | | | (5.122) | (4.726) |
| *SIZE* | | | –0.178*** | –0.165*** |
| | | | (0.025) | (0.025) |
| *ROA* | | | –7.996*** | –8.485*** |
| | | | (1.231) | (1.218) |
| *CASH* | | | –0.240 | –0.308 |
| | | | (0.221) | (0.223) |
| *TURNOVER* | | | 0.127 | 0.091 |
| | | | (0.165) | (0.163) |
| *PPE* | | | –0.558*** | –0.588*** |
| | | | (0.195) | (0.196) |
| *CAPEX* | | | 0.380 | 0.746 |
| | | | (0.717) | (0.672) |
| *Yield1Yr* | | | –15.259** | |
| | | | (6.843) | |
| *YieldCurve* | | | 10.739* | |
| | | | (5.788) | |
| *MktRET* | | | –0.560 | |
| | | | (0.882) | |
| *Industry FE* | Yes | Yes | Yes | Yes |
| *Quarter-Year FE* | No | Yes | No | Yes |
| *Observations* | 9,407 | 9,407 | 8,350 | 8,350 |
| *Adj.$R^2$* | 0.181 | 0.261 | 0.614 | 0.658 |

fixed effect is meant to capture most of the impact of aggregate time-series trends (including trend in the macro-financial control variables), we use Model (4) as our main specification for subsequent analyses.

**3.4 Endogeneity Test: The Impact of the Paris Agreement**

Our baseline regression results show that better carbon risk management is significantly associated with lower *CDS* spreads. However, there might be endogeneity issues as, for example, some unobservable variables correlated with CRMS may also be important for perceived credit risks. Alternatively, firms that perform better financially may also manage their carbon risk performance accordingly. To address such concerns, we use the Paris Agreement of 2015 as a quasi-natural experiment to examine how *CDS* spreads change after a potentially exogeneous shock to the value of *CRMS*.[20] The Paris Agreement had the primary goal of curbing global temperature rise in this century to 1.5 degrees Celsius above pre-industrial levels. Moreover, the Paris Agreement is considered as the most significant event in the climate finance history as it spurred discussions about climate change widely within the investor community (Bolton and Kacperczyk, 2021; Delis, De Greiff, and Ongena, 2019; Seltzer, Starks, and Zhu, 2022). Hence, the 2015 Paris Agreement serves as a major exogenous shock to firms' exposure to climate risk, especially climate transition risk or carbon risk. Therefore, if the Paris Agreement strengthens the effect of carbon risk on a firm's default risk, firms with better and proactive carbon risk management practices should be in a better position

[20] The Paris Climate Agreement (https://www.un.org/en/climatechange/paris-agreement), the most ambitious climate agreement ever signed - officially known as the COP21, was the twenty-first session of the Conference of the Parties (COP21) hosted by the United Nations which took place in Paris from November 30 to December 12, 2015. It is also referred as Paris Climate Accord or Paris Agreement on Climate Change.

to mitigate their credit spread risk after the Paris Agreement. As such, the impact of carbon risk management on *CDS* spreads should be more pronounced after the Paris Agreement.

To test for this hypothesis, we estimate the following regression model:

$$\ln(CDS_{i,t+1}) = \alpha + \beta^{CRMS} CRMS_{i,t} + \beta^{POST} POST_t + \beta^{CRMS\times POST} CRMS_{i,t} \times POST_t + \beta^{X} X_{i,t} + \beta^{Y} Y_t + \epsilon_{i,t+1}\,, \tag{3.2}$$

where, *POST* is a binary dummy variable which takes the value of one for all quarters after the Paris Agreement, that is all quarters post-December 2015, and zero otherwise. The key coefficient in equation (3.2) is $\beta^{CRMS\times POST}$, which captures the change in the *CDS* spread due to the change in the *CRMS* around the Paris Agreement. A negative and significant coefficient estimate would indicate a stronger effect of better carbon risk management score in mitigating credit risk following the Paris Agreement.

We first discuss the results of Model (1) and Model (2) in Table 3-4. Since the dummy variable *POST* is highly correlated with the quarter fixed effect dummy variable, we do not include the *POST* variable in the regression. We observe a negative and significant relationship between *CRMS* and *CDS* spreads. The results suggest that *CDS* markets incorporate the carbon risk management exposure in credit spreads, confirming our baseline results that carbon risk management performance mitigates a firm's credit spread.[21] More importantly, the coefficient estimates for the interaction term, $\beta^{CRMS\times POST}$, is negative and significant. This finding indicates that the effect of carbon risk management on *CDS* spread becomes stronger after the Paris Agreement. We perform a similar analysis in Model (2) with the exception that we exclude quarter fixed effects and include macro-financial variables as controls. Consistent with

[21] Additionally, when we split our sample into the pre-Paris Agreement and post-Paris Agreement period, we find that the relevance of carbon risk management for credit risk becomes significant only after the climate accord.

the results in Model (1), we still observe a negative and significant coefficient estimates for the interaction term *POST* × *CRMS*.

Next, we perform the DiD analysis to compare changes in the *CDS* spread of firms with most prudent carbon risk management versus those with poor carbon risk management. To compare the credit spreads of firms with similar characteristics, we use propensity score matching (PSM) before performing the DiD analysis. *First*, we classify firms into *treatment* firms if their *CRMS* value in 2014 is above the median *CRMS* value and *control* firms if their *CRMS* value in 2014 is below the median *CRMS* value in 2014. We choose 2014 (one year before the Paris Agreement) to mitigate the effect of the possible anticipation of the outcome of the Paris Agreement planned in December 2015. We only keep firms present in the sample in the year 2014. We then estimate the probability of firms being assigned to the treatment or control using a logit regression with all firm-level variables as specified in the baseline regression (equation 3.1) and use propensity scores to match to the nearest control sample.[22] Next, we compare the *CDS* spread of firms in the treatment versus control groups in the periods before and after the Paris Agreement by estimating the following DiD regression model:

$$\ln\left(CDS_{i,t+1}\right) = \alpha + \beta^{TREAT} TREAT_{i,t} + \beta^{POST} POST_t$$
$$+\beta^{TREAT \times POST} TREAT_{i,t} \times POST_t + \beta^{X} X_{i,t} + \beta^{Y} Y_t + \epsilon_{i,t+1}, \qquad (3.3)$$

where, $TREAT_i$ is an indicator variable for the *i*-th firm which equals one for any treatment firm and zero otherwise. Other variables are as defined in equations (3.1) and (3.2).

[22] We use the propensity score to perform one-to-one nearest-neighbor-matching method without replacement along with caliper matching using a caliper of 10%. This algorithm excludes all matches where the distance is above 10% by imposing a maximum propensity score distance of 10%.

**Table 3-4: The Impact of the Paris Agreement on the CRMS–CDS spread Relation**

This table shows the results using the Paris Agreement of December–2015 as the exogenous event. The dependent variable is the natural logarithm of the daily average of *5-year CDS* spread level (*CDS5*) in a quarter. To measure the impact of the Paris Agreement, we use a dummy variable *POST* which takes value of one for the period after December 2015 and zero otherwise. The key variable in the model (Columns 1 and 2) is *CRMS × POST* which is an interaction term of *CRMS* and *POST*. Model (3) and (4) show the results of difference-in-differences (DiD) analysis. The key variable in the models (Columns 3 and 4) is *TREAT × POST* which is an interaction term of *TREAT* and *POST*. *TREAT* takes the value of one if a firm's *CRMS* is above the median *CRMS* value in the year 2014, and zero' otherwise. All firms which are not available in 2014 gets dropped to create the *TREAT* dummy. Further, we use one-to-one nearest-neighbor-matching method without replacement along with caliper matching with a caliper of 10% to match treatment and control firms based on all firm characteristics in Table 3-3. All variables are explained in detail in Appendix 3.A. The model includes the industry fixed effect (Sustainalytics Industry Classification) and quarter-year fixed effects. The standard errors are clustered by firm and by quarter-year. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively. The values in parentheses are the standard errors of the estimated coefficients.

| | CDS5<br>(1) | CDS5<br>(2) | CDS5<br>(3) | CDS5<br>(4) |
|---|---|---|---|---|
| *POST × CRMS* | –0.023** | –0.020** | | |
| | (0.010) | (0.009) | | |
| *CRMS* | –0.022** | –0.022** | | |
| | (0.010) | (0.011) | | |
| *POST × TREAT* | | | –0.225*** | –0.210*** |
| | | | (0.075) | (0.059) |
| *TREAT* | | | –0.118** | –0.123** |
| | | | (0.059) | (0.059) |
| *POST* | | –0.109 | | -0.091 |
| | | (0.088) | | (0.097) |
| *LEVERAGE* | 1.364*** | 1.325*** | 1.328*** | 1.032*** |
| | (0.167) | (0.171) | (0.261) | (0.217) |
| *IVOL* | 47.952*** | 47.970*** | 58.286*** | 53.764*** |
| | (4.730) | (5.104) | (4.379) | (4.794) |
| *SIZE* | –0.164*** | –0.175*** | –0.145*** | –0.152*** |
| | (0.025) | (0.025) | (0.034) | (0.033) |
| *ROA* | –8.496*** | –7.972*** | –8.152*** | –8.548*** |
| | (1.195) | (1.216) | (1.461) | (1.367) |
| *CASH* | –0.285 | –0.223 | 0.261 | –0.136 |
| | (0.225) | (0.222) | (0.327) | (0.302) |
| *TURNOVER* | 0.092 | 0.125 | 0.180 | 0.101 |
| | (0.163) | (0.165) | (0.180) | (0.187) |
| *PPE* | –0.589*** | –0.558*** | –0.564** | –0.422* |
| | (0.196) | (0.194) | (0.275) | (0.222) |
| *CAPEX* | 0.768 | 0.373 | -0.001 | –1.356 |
| | (0.670) | (0.708) | (0.982) | (0.834) |
| *Macrofinancial Controls* | Yes | Yes | Yes | Yes |
| *Industry FE* | Yes | Yes | Yes | Yes |
| *Quarter-Year FE* | Yes | No | Yes | No |
| *Observations* | 8,350 | 8,350 | 2,432 | 2,433 |
| *Adj.$R^2$* | 0.659 | 0.617 | 0.617 | 0.577 |

The regression results based on equation (3.3) for both specifications (Models (3) and Model (4)) of Table 3-4 show that the 5-year *CDS* spread is lower for treatment firms compared to control firms. The coefficient estimates for the interaction term *POST* × *TREAT* is negative and significant in both models, with or without quarter-fixed effects. These results imply that the Paris Agreement led *CDS* markets to view firms with high carbon risk management performance more positively. It also implies that climate risk received more attention from investors post-Paris Agreement, when governments initiated stricter regulatory measures.

### *3.4.1 Test for Change in CDS Spread Around the Paris Agreement*

We next interact the dummy variable for *treatment* firms (*TREAT*) with dummy variables indicating each of the eight quarters before (from October 2013 to September 2015) and after (from January 2016 to December 2017) the Paris Agreement, following the model below:

$$ln(CDS_{i,t+1}) = \sum_{n=-8}^{-1} \beta_n [\mathbb{1}(t = n) \times TREAT_i] + \sum_{n=1}^{8} \beta_n [\mathbb{1}(t = n) \times TREAT_i] + \beta^X X_{i,t} + \epsilon_{i,t+1}, \quad (3.4)$$

where, *n* is the specific quarter in the two-year pre- and post-Paris Agreement window. This time indicator variable ($n$) does not include the quarter (October 2015-December 2015) with Paris Agreement, so all the treatment effects are relative to this quarter. Other variables are as defined in equations (3.1) and (3.2).

The coefficient estimates of the interaction terms can be interpreted as the effect of being a firm with high carbon risk management score on the credit default swap spreads in each period relative to the Paris Agreement of December 2015. We plot these coefficient estimates in Figure 3-1. As depicted in the figure, the coefficients of the interaction between TREAT and dummy variables for quarters after the Paris Agreement become more negative in subsequent quarters following the Paris Agreement, confirming that high *CRMS* firms experience lower *CDS* spreads compared to low *CRMS* firms after the Paris Climate Agreement.

### *3.4.2 Placebo Test for Paris Agreement*

To further allay the possibility of finding significant results due to random chance, we run a placebo or falsification test on the Paris Agreement event. To test the null hypothesis that there is no treatment effect (*TREAT* × *POST*), we conduct randomisation inference test where we generate a distribution of placebo treatment effects by randomizing the *POST* dummy variable, and then compare the estimate of the true treatment effect to this empirically derived distribution of placebo treatment effects. We thereby assess the null of whether the sample realisation of the treatment effect is consistent with the numerically inferred distribution (Campbell and Taksler, 2003; MacKinnon and Webb, 2020; White and Webb, 2021). Results are reported in Panel A of Table 3-5. Our test shows that *p*-value is zero implying that there is only a zero percent chance that a randomly shuffled *POST* would generate a treatment effect as extreme as observed in the actual data. Hence, our null of no treatment effect is overwhelmingly rejected. This finding supports our assertion that the Paris Agreement is the major catalyst event affecting the relationship between the *CDS* spread and carbon risk management performance.

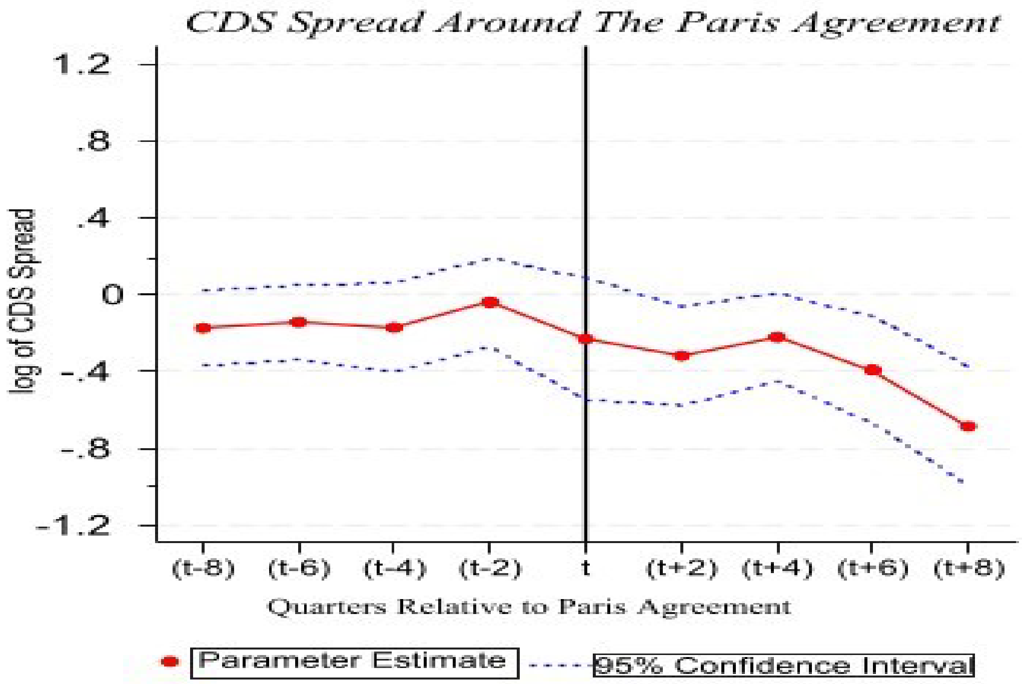
We further examine the impact of two other quasi-exogenous events that occur after the Paris Agreement that could dilute the impact of carbon transition risk on firms in the US due to lax regulatory risk environment. A lenient carbon transition risk regime may dilute the

**Figure 3-1: CDS Spread Around the Paris Climate Agreement**

This figure plots the $\beta_n$ coefficient from the equation:

$$CDS_{i,t+1} = \sum_{n=-8}^{-1} \beta_n[\mathbb{1}(t = n) \times TREAT_i] + \sum_{n=1}^{8} \beta_n[\mathbb{1}(t = n) \times TREAT_i] + \beta^X X_{i,t} + \epsilon_{i,t+1},$$

*TREAT* equal to one for firms whose *CRMS* value in the year 2014 (one year prior to the Paris Agreement) is above the median *CRMS* value of the sample in 2014 (*TREAT group*) and else it takes the value zero for the firms in the which have the *CRMS* value below the median in year 2014 (*CONTROL group*). All the firms in the *TREAT* and *CONTROL* group are matched with similar firm characteristics using the propensity score matching (PSM) before performing the regressions. The chart shows time eight quarters (from October 2013 to September 2015) before the Paris Agreement and eight quarters (from January 2016 to December 2017) after the Paris Agreement. The chart excludes the quarter for Paris Agreement (October 2015 to December 2015). The regression coefficient $\beta_n$ can be interpreted as the effect of being a firm with high carbon risk management score on the credit default swap spreads in each period relative to the Paris Agreement of December 2015.




impact of *CRMS* on *CDS* spreads. We first consider whether the election of President Trump in November 2016, who advocated for loosening environmental regulations and potential withdrawal of the US from the Paris Agreement during his election campaign, played any role in the effect of *CRMS* on credit spreads. We also examine whether the actual policy announcement of the US withdrawal from the Paris Agreement in June 2017 has any moderating impact of *CRMS* on *CDS* spread. These events may alter market expectations regarding climate regulatory requirements, and potentially mitigate the effect of *CRMS* on credit spread.

**Table 3-5: Placebo Test for the Paris Agreement and Effect of Events indicating potential US withdrawal from Paris Agreement on CRMS–CDS Spread relation**

Panel A presents the results of the placebo test using randomisation inference method to ascertain the impact of the Paris Agreement of December 2015. '*POST'* takes value of one for the period after December 2015 and zero otherwise and '*TREAT*' takes the value of one if a firm's *CRMS* is above the median *CRMS* value in the year 2014, and zero' otherwise. The test in Panel A of this table re-samples or permutes the Paris Agreement dummy variable '*POST*' leading to re-estimation of the statistic of main difference-in-difference interaction variable '*TREAT × POST*'. '*T(obs)*' is the realisation of the test statistic in the data; '*c*' is the count of under how many of the re-sampled iterations, the realisation of the test-statistic was more extreme than '*T(obs)*'; '*n*' is the total count of re-samplings; '*p=c/n*' is the actual randomised inference based *p*-value; '*SE(p)*' is the standard-error of the *p*-value estimate; '*95% Conf. Interval*' is an estimated confidence interval for the *p*-value.
Panel B presents the results of the effect of the events indicating potential US withdrawal from the Paris Agreement on *CRMS–CDS spread* relation. We use the dummy variable *Post Trump Election* which takes value of one for the period after the presidential candidate Donald Trump won the US elections in November 2016, indicating a potential withdrawal of the US from Paris Climate Agreement, and zero otherwise. We use another dummy variable *Post Paris Withdrawal Announcement* which takes the value of one for the period after June 2017 when the US government formally announced its withdrawal from the Paris Climate Agreement, and zero otherwise. All variables are explained in detail in Appendix 3.A. The model includes the industry fixed effect (Sustainalytics Industry Classification) and quarter-year fixed effects. The standard errors are clustered by firm and by quarter-year. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively. The values in parentheses are the standard errors of the estimated coefficients.

Panel A

| T(obs) | c | n | p=c/n | SE(p) | [95% Conf. Interval] | |
|---|---|---|---|---|---|---|
| -0.146 | 0 | 500 | 0.000 | 0.000 | 0.000 | 0.007 |

Panel B

| | CDS5<br>(1) | CDS5<br>(2) |
|---|---|---|
| *CRMS* | –0.025** | –0.026** |
| | (0.010) | (0.010) |
| *Post Trump Election × CRMS* | –0.020* | |
| | (0.010) | |
| *Post Paris Withdrawal Announcement × CRMS* | | –0.019 |
| | | (0.012) |
| *Controls* | Yes | Yes |
| *Industry FE* | Yes | Yes |
| *Quarter-Year FE* | Yes | Yes |
| *Observations* | 8,350 | 8,350 |
| *Adj.$R^2$* | 0.658 | 0.658 |

To test the effect of the President Trump election and the actual announcement of US withdrawal from the Paris Agreement, we perform regression model similar to that in equation (3.2), but replacing *POST* by either *Post Trump Election* (a dummy variable for periods after the election of Donald Trump on November 8, 2016) or *Post Paris Withdrawal Announcement* (a dummy variable for periods after the US government officially announced its withdrawal from the Paris Agreement on June 1, 2017.

The results in columns (1) and (2) in Panel B of Table 3-5, respectively, for the interaction term *Post Trump Election* × *CRMS* and *Post Paris Withdrawal Announcement* × *CRMS* are not positive and significant. These findings suggest that we do not observe a reversal in the impact of *CRMS* on credit spread post-President Trump election or post formal announcement of the US withdrawal from the Paris Agreement. The weaker and insignificant results for these events compared to the Paris Agreement also suggest that although regulatory risk can be reduced for firms with poor carbon risk management profile, major curbs in $CO_2$ emissions are likely in the future (Bolton and Kacperczyk, 2021). Therefore, the companies that are poorly managing their carbon emission risks would still be potentially affected by the regulatory restrictions.

### 3.5 Endogeneity Test: Firms Headquartered in States with State Climate Adaptation Plans

The US states face a diverse set of climate change-related challenges due to geographical factors. In any given year, some states face drought-related issues while others grapple with catastrophes caused by hurricanes and floods. This heterogeneity in climate challenges, and arguably insufficient support at the federal level, has forced several states in the US to pass their own SCAPs that vary in scope, goals, and strategies. However, all SCAPs share a common goal to combat climate change risk and make their respective states more resilient and better prepared to mitigate the disastrous effects of climate change. A total of 15 states finalised their first climate adaptation policies during our sample period, most of which adopted their first SCAP before 2015 but on staggered dates. SCAPs are government induced interventions that can have wide-ranging direct and indirect material effects on corporate policy and action. [23]

Credit markets are particularly sensitive to carbon emission activities of firms headquartered in states with formal plans to mitigate climate change issues, due to their susceptibility to climate change regulatory violations and associated costs. At the same time, by encouraging and facilitating prudent carbon risk management practices, a state's climate adaptation plans and initiatives may increase the value of a firm's assets (Chen, 2008; Konar and Cohen, 2001; Porter and Van der Linde, 1995a, 1995b), thus reducing the credit risk of those firms. Ex-ante, we expect that the mitigating impact of carbon risk management on corporate credit spread to become stronger in states that have adopted a *SCAP*.

To test this hypothesis, we use the stacked regression framework suggested in Baker et al. (2022). It involves creating event-specific "clean 2×2" datasets, which include the outcome variable and controls for the treated cohort and other relevant observations. Each clean 2×2 dataset is given a dataset-specific identifying variable. These datasets are then combined or "stacked" together, and a two-way fixed effect DiD regression is performed on the stacked

[23] *SCAP* goals can be broadly divided into three categories: planning and capacity building; law and policy; and post-implementation monitoring (Ray and Grannis, 2015). The first category includes awareness campaigns and collaborative dialogues with local businesses, with the potential to impact voluntary corporate behavior toward climate issues. The second category includes binding guidance, code changes, new design standards, and zoning modifications. The resulting new regulations and their post-implementation monitoring have a direct effect on the cost of doing business in these states (see, for example, Ilhan (2020); Heo (2021)). Appendix 3.B. provides details on the dates when individual states of the firms in our sample adopted *SCAP*.

dataset, incorporating unit and time-fixed effects specific to each dataset. The stacked regression estimates the DiD effect for each clean 2×2 dataset and applies variance weighting to efficiently combine treatment effects across cohorts. It is a practical solution to produce aggregated treatment effect estimates using ordinary least squares (OLS) while addressing issues related to staggered treatment timing and treatment effect heterogeneity. In summary, the stacked regression is an event-by-event analysis which estimates separate treatment effects for each of the events. [24]

To implement the above framework, we first create an event-specific quarter-year state panel dataset where our event is the date when a state has adopted its *SCAP*. Each event or cohort *d*-specific dataset includes the treated states and all other clean control states for a 16-quarter panel event by time ($t$ = -8, -7, …. , 7, 8) with the SCAP adoption date at quarter $t$ = 0. Clean control states are those without any SCAP implementation ever in the full sample time period. For each event *d*, we run the following regression model to assess whether carbon risk management practices of firms become more important and significant in states that have adopted *SCAP*s:

$$\ln\left(CDS_{i,t+1}^{d}\right) = \alpha + \sigma_{ds}^{d} + \Theta_{dt}^{d} + \sum_{k=-8}^{-1} \mu_{l}^{d} D_{it}^{k} + \sum_{k=0}^{8} \mu_{l}^{d} D_{it}^{k} + \beta_{CRMS}^{d} HCRMS_{i,t}^{d} + \beta_{POSTSCAP}^{d} POSTSCAP_{t}^{d} + \beta_{CRMS\times POSTSCAP}^{d} POSTSCAP_{t}^{d} \times HCRMS_{i,t}^{d} + \beta_{X}^{d} X_{i,t} + \epsilon_{i,t+1}\,, \qquad (3.5)$$

where, for every cohort $d$, $\sigma_{ds}^{d}$ and $\Theta_{dt}^{d}$ are the interaction of *d*, an identifier for each of the cohort-specific datasets, with either the state or the industry fixed effects and quarter-year fixed effects, respectively; $D_{it}^{k} = \mathbb{I}[t - \mathrm{E_i} = k]$ is an indicator for a firm *I* in cohort $E_i$ (period of treatment) being *k* periods from the start of the *SCAP* implementation. The first summation

[24] We use a Stata package (*stackedev*) written by Joshua Bleiberg to implement the stacked regression discussed in Baker et al. (2022).

captures the quarters leading up to the *SCAP* implementation ('leads') and the second summation captures the quarters after *SCAP* implementation.

The indicator *POSTSCAP* takes the value of one if a firm is headquartered in a state with a *SCAP* and in the years post implementation; and takes a value of zero if a firm is either in a state without a *SCAP* or in the years pre-*SCAP* implementation in that state. The *HCRMS* is the categorical variable which takes the value of one if the *CRMS* value of a firm is at the top quartile in a quarter. As an alternative, we also construct *HCRMS* by sorting the *CRMS* quartiles within each state. Our key variable of interest, *HCRMS* × *POSTSCAP*, captures the heterogeneous effect of high carbon risk management performance on the credit spread of the treatment firms vis-à-vis control firms.

The results in Table 3-6 show that the 5-year *CDS* spreads are particularly sensitive to the carbon risk management performance of the firms headquartered in states with SCAP implemented. The coefficients of the interaction variable *HCRMS* × *POSTSCAP* are negative and statistically significant, suggesting that the staggered adoption of climate plans by US states enhances the importance of carbon risk management practices by mitigating the credit spread of the firms. The results overall indicate that credit markets have been sensitive to climate related interventions of state governments where firms operate.[25]

[25] In unreported results, we find that the coefficient estimates for POSTSCAP × CRMS remain negative and significant even after including the post-Paris Agreement period dummy, which helps alleviate the concern that the results of state climate adaptation plans could be driven by the effect of the Paris Agreement.

**Table 3-6: Impact of State Climate Adaptation Plans on the CRMS–CDS spread Relationship – Stacked Regression Approach**

Using the stacked analysis, this table assess the relation between firms' carbon risk management performance i.e. *CRMS* and *CDS* spreads exploiting the impact of State Climate Adaptation Plans (*SCAP*s) adopted by 15 states in the US till May 2018 (sample end period). For each event date when a state adopts an *SCAP* (treatment cohort period), a window of +/– eight quarters is formed around that event date. The dataset includes the firms which are headquartered in the states which have adopted *SCAP* (treated firms) as well as the firms which are headquartered in states which never adopted *SCAP* (clean controlled firms). Similar datasets are created for each of the cohort treatment periods and then all these smaller datasets are stacked together in relative time periods. For the stacked dataset, baseline regression of Table 3-3 is repeated after including the interaction variable '*HCRMS × POSTSCAP*' which is our main variable of interest in this table. *P*OSTSCAP is an indicator variable which takes the value of 1 after a state has implemented an SCAP, else it takes the value of 0. *HCRMS* is a categorical variable that divides firms into two groups: those in the top quartile of *CRMS* values (assigned the value 1) and those in the bottom quartile (assigned the value 0). We use two different ways to calculate *HCRMS*: one based on the quartiles of *CRMS* values within each quarter ($HCRMS_{Qtr}$) and the other based on the quartiles of *CRMS* values within each state ($HCRMS_{State}$). The dependent variable is the natural logarithm of the daily average of 5-year CDS spread level (CDS5) in a quarter. All variables are explained in detail in Appendix 3.A. Furthermore, the model includes fixed effect based on the interaction of cohort indicator with the state fixed effect (Column 1 and 3), industry fixed-effect (Column 2 and 4) and quarter-year fixed effect (all the models). The standard errors are clustered by state interacted with quarter-year. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively. The values in parentheses are the standard errors of the estimated coefficients.

| | CDS5<br>(1) | CDS5<br>(2) | CDS5<br>(3) | CDS5<br>(4) |
|---|---|---|---|---|
| $HCRMS_{Qtr}$ | –0.196*** | –0.147*** | | |
| | (0.023) | (0.016) | | |
| $HCRMS_{Qtr}$ × *POSTSCAP* | –0.235*** | –0.232*** | | |
| | (0.053) | (0.032) | | |
| $HCRMS_{State}$ | | | –0.181*** | –0.080*** |
| | | | (0.013) | (0.016) |
| $HCRMS_{State}$ × *POSTSCAP* | | | –0.233*** | –0.278*** |
| | | | (0.051) | (0.040) |
| *POSTSCAP* | 0.131*** | 0.037 | 0.192*** | 0.118*** |
| | (0.050) | (0.040) | (0.046) | (0.041) |
| *Pre–SCAP Quarter–Year Dummies* | Yes | Yes | Yes | Yes |
| *Post–SCAP Quarter–Year Dummies* | Yes | Yes | Yes | Yes |
| *Control Variables* | Yes | Yes | Yes | Yes |
| *Cohort × State FE* | Yes | No | Yes | No |
| *Cohort × Industry FE* | No | Yes | No | Yes |
| *Cohort × Quarter–Year FE* | Yes | Yes | Yes | Yes |
| *Observations* | 12,339 | 12,328 | 12,117 | 12,106 |
| *Adj.*$R^2$ | 0.650 | 0.701 | 0.617 | 0.664 |

## 3.6 Economic Channels, Alternative Explanations and Robustness Checks

### *3.6.1 Evaluating the CRMS Measure*

To ensure that *CRMS* captures significantly new information and does not simply instrument other climate risk variables used in prior studies, we leverage the results of analysis conducted in Chapter 2. The analysis compares the *CRMS* measure with the firm-level climate change risk exposures reported in Sautner et al. (2023). The authors apply textual analytics to quarterly earnings conference call data and capture an elaborate keyword-based measure of firm-level exposures associated with different aspects of climate change. Sautner et al. (2023) construct four sets of climate change bigrams. While the first construct is a broadly defined, (a) broad climate-change-measure; the next three are sub-measures focused on the following climate change shocks: (b) opportunity, (c) physical, and (d) regulatory. For each of these measures, they construct "exposure", "risk", and "sentiment" sub-measures or scores.

We specifically choose the firm-level climate change exposure measure of Sautner et al. (2023), as the authors find that such scores best capture firm-level variation than carbon intensities or ratings. Furthermore, these exposure measures are intrinsically forward-looking as they are based on earnings calls, potentially revealing the management's future business plans. We consider four firm-level exposure variables out of the total 12 variables described in Sautner et al. (2023): (1) *CCExposure*; (2) $CCExposure^{Opp}$; (3) $CCExposure^{Reg}$; and (4) $CCExposure^{Phy}$. These capture relative frequency of word combinations, or bigrams, referencing overall, opportunity, regulatory, and physical climate change shocks, respectively, in the transcripts of analyst conference calls.

The analysis in Chapter 2 first conducts a univariate test (Table 2-8) to analyse the correlations between CRMS and different firm-level climate exposure variables of Sautner et al. (2023). The univariate test findings imply that the *CRMS* better captures heterogeneity across firms in comparison to risk exposure measures constructed by Sautner et al. (2023).

Subsequently, the regression analysis test the relationship between the firm-level climate risk exposure measures from Sautner et al. (2023) and the CRMS variable. These tests were conducted after conditioning for all controls that include firm specific variables and industry and quarter-year fixed effects. Model 2, as presented in Table 2-9 of Chapter 2, indicate that only opportunity risk exposure ($CCExposure^{Opp}$) exhibits a statistically significant association with *CRMS*. Furthermore, Model 5 includes a principal component as main independent variable capturing the common variation of exposure variables which include $CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$. The results show a weak association of the principal component with *CRMS*. Finally, models 6, 7, and 8 of the analysis, which expanded to include PCA components from additional firm exposure variables, show no significant association with CRMS.

In conclusion, the results show that only the $CCExposure^{Opp}$ stands out as a significant predictor, suggesting that firms exposed to climate change opportunities prioritize carbon risk management. Other climate exposure measures of Sautner et al. (2023), including those from PCA, do not provide any additional insights that are not already captured by *CRMS*.

Next, to investigate if *CRMS* is not instrumenting other firm-level climate change risks, we consider the baseline regression models based on equation (2.1) and add the opportunity risk exposure ($CCExposure^{Opp}$) as an additional regressor. We examine whether the relationship between *CRMS* and credit risk is diluted after including the $CCExposure^{Opp}$ variable as the control. We conduct this analysis for the full sample, subsample of the pre-Paris time-period and subsample of the post-Paris time-period. The results (Model 1, 2, and 3) in

Table 3-7 show that the opportunity risk variable loads insignificantly, and the relationship between *CRMS* and *CDS* spread is robust to the inclusion of the opportunity risk variable. We also examine whether sorting $CCExposure^{Opp}$ into high and low categories based on its median score values and its interaction with *CRMS* has an impact on the information content in *CRMS* in both pre- and post-Paris Agreement periods. First, we create a dummy variable called $High\_CCExposure^{Opp}$ which takes the value of one if the $CCExposure^{Opp}$ value of a firm in any quarter is higher than the median value of $CCExposure^{Opp}$ of all firms in that quarter, otherwise it takes the value of zero. *Second*, we interact $High\_CCExposure^{Opp}$ with *CRMS* to construct $High\_CCExposure^{Opp} \times CRMS$, the main control variable for the analysis. We find no significance for the interaction $High\_CCExposure^{Opp} \times CRMS$ on *CDS* spreads (refer to Models 4, 5 and 6 in Table 3-7). These results suggest that the *CRMS–CDS* spread relationship is robust when we control for the climate change opportunity exposure variable of Sautner et al. (2023), either standalone or conditioned on *CRMS*. Thus, our analyses provide supportive evidence that *CRMS* is not subsuming information from firm-level climate change variables of Sautner et al. (2023).

Furthermore, we examine the effect of orthogonalised measure of *CRMS* on the 5-year CDS spread. The orthogonalised measures of *CRMS* are obtained as the residuals of regression of *CRMS* on various measures of climate change exposure constructed by Sautner et al. (2023). In Models (1) – (4) of Table 3-8, we find that the orthogonalised measures of *CRMS* are all negatively and significantly related to the 5-year CDS spread. These results suggest that the *CRMS–CDS* spread relationship is robust when we control for the climate change exposure variables of Sautner et al. (2023). Thus, our analyses provide supportive evidence that *CRMS* is not subsuming information from firm-level climate change variables of Sautner et al. (2023).

**Table 3-7: CRMS and the Firm-level Climate Change Exposure Measures Constructed by Sautner et al. (2023)**

This table shows the effect of *CRMS* of the firm on the natural logarithm of daily average of 5-year senior unsecured *CDS* spread level (*CDS5*) in a quarter after controlling for the $CCExposure^{Opp}$ constructed by Sautner et al. (2023). $CCExposure^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of analyst conference calls. $High\_CCExposure^{Opp}$ is a dummy variable which takes the value of one if the $CCExposure^{Opp}$ value of a firm in any quarter is higher than the median value of $CCExposure^{Opp}$ of all the firms in that quarter, and zero otherwise. $High\_CCExposure^{Opp} \times CRMS$ is an interaction term between $High\_CCExposure^{Opp}$ and *CRMS*. Models (1) to (3) are similar to the baseline regression model in Table 3-3 and control for $CCExposure^{Opp}$. Models (4) to (6) show the regression results of the *CRMS–CDS* spread relationship conditional on $High\_CCExposure^{Opp}$. The results are shown for the panel regressions done on the full sample and sub-samples of pre- and post-Paris Agreement. All variables are explained in detail in Appendix 3.A. All models include the industry fixed effect (Sustainalytics Industry Classification) and quarter-year fixed effects. The standard errors are clustered by firm and by quarter-year. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively. The values in parentheses are the standard errors of the estimated coefficients.

| | Full<br>CDS5<br>(1) | Pre–Paris<br>CDS5<br>(2) | Post-Paris<br>CDS5<br>(3) | Full<br>CDS5<br>(4) | Pre–Paris<br>CDS5<br>(5) | Post-Paris<br>CDS5<br>(6) |
|---|---|---|---|---|---|---|
| *CRMS* | –0.029*** | –0.018* | –0.069*** | –0.034*** | –0.023* | –0.073*** |
| | (0.011) | (0.011) | (0.014) | (0.012) | (0.012) | (0.017) |
| $CCExposure^{Opp}$ | 0.006 | 0.006 | 0.015 | | | |
| | (0.016) | (0.015) | (0.021) | | | |
| $High\_CCExposure^{Opp}$ | | | | –0.054 | –0.052 | –0.054 |
| | | | | (0.045) | (0.052) | (0.056) |
| $High\_CCExposure^{Opp} \times CRMS$ | | | | 0.011 | 0.012 | 0.013 |
| | | | | (0.010) | (0.011) | (0.014) |
| *Control Variables* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Industry FE* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Quarter-Year FE* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Observations* | 6,498 | 4,505 | 1,993 | 6,498 | 4,505 | 1,993 |
| $Adj.R^2$ | 0.675 | 0.703 | 0.655 | 0.675 | 0.703 | 0.654 |

**Table 3-8: Impact of Orthogonalised Measure of CRMS on CDS Spread**

This table shows the effect of orthogonalised measure of *CRMS* (obtained as residuals of regression of CRMS on various measures of climate change exposure constructed by Sautner et al. (2023)) on the 5-year CDS spread using the baseline regression of Table 3-3. The transformed measures of *CRMS* - *OCRMS_CCE*, $OCRMS\_CCE^{Opp}$, $OCRMS\_CCE^{Reg}$, $OCRMS\_CCE^{Phy}$ are orthogonal to *CCExposure*, $CCExposure^{Opp}$, $CCExposure^{Reg}$ and $CCExposure^{Phy}$, respectively. *CCExposure* measures the relative frequency with which bigrams related to climate change occur in the transcripts of analyst conference calls and other sub-measures. $CCExposure^{Opp}$ measures the relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Reg}$ measures the relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of analyst conference calls. $CCExposure^{Phy}$ measures the relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of analyst conference calls. All variables are explained in detail in Appendix 3.A. All models include the industry fixed effect (Sustainalytics Industry Classification) and quarter-year fixed effects. The standard errors are clustered by firm and by quarter-year. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively. The values in parentheses are the standard errors of the estimated coefficients.

| | *CDS5* | *CDS5* | *CDS5* | *CDS5* |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *OCRMS_CCE* | –0.030** | | | |
| | (0.011) | | | |
| $OCRMS\_CCE^{Opp}$ | | –0.029** | | |
| | | (0.011) | | |
| $OCRMS\_CCE^{Reg}$ | | | –0.029** | |
| | | | (0.010) | |
| $OCRMS\_CCE^{Phy}$ | | | | –0.030** |
| | | | | (0.010) |
| *Control Variables* | Yes | Yes | Yes | Yes |
| *Industry FE* | Yes | Yes | Yes | Yes |
| *Quarter-Year FE* | Yes | Yes | Yes | Yes |
| *Observations* | 6,498 | 6,498 | 6,498 | 6,498 |
| *Adj.$R^2$* | 0.675 | 0.675 | 0.675 | 0.680 |

Finally, we examine whether *CCExposure* or $CCExposure^{Opp}$ moderates the relationship between *CRMS* and CDS spreads. To the extent *CRMS* signals a firm's relative strength and commitment to mitigate climate risk through better carbon risk management, such signaling should be more beneficial for firms with more exposure to climate change. We therefore postulate that the relationship between CRMS and CDS spread should be stronger among firms more exposed to climate change. To test for our conjecture, we examine the relationship between CDS spread and *CRMS* for firms in the top (High CCE) versus bottom (Low CCE) quartiles of *CCExposure* in each industry; or the top (High $CCE^{Opp}$) versus bottom (Low $CCE^{Opp}$) quartiles of *CCExposure*$^{Opp}$ in each industry. The results in Table 3-9 show that *CRMS* is negatively related to subsequent CDS spread in the subsamples of High CCE or High $CCE^{Opp}$ firms, and insignificant for the subsamples of Low CCE and Low $CCE^{Opp}$ firms.

**Table 3-9: CRMS-CDS Relationship for subsamples based on Top and Bottom Quartiles of Firm Level Climate Change Exposure Measures constructed by Sautner et al. (2023)**

This table presents the results for the CRMS-CDS relationship in Table 3-3 separately for firms in the top and bottom quartiles of Sautner et al. (2023) climate change exposure measures sorted within each industry. Columns 1 and 2 show the relationship of CDS and CRMS for the top (High CCE) and bottom (Low CCE) quartiles of *CCExposure* in each industry, respectively. Similarly, columns 3 and 4 show the relationship of CDS and CRMS for the top (High $CCE^{Opp}$) and bottom (Low $CCE^{Opp}$) quartiles of *CCExposure*$^{Opp}$ in each industry, respectively. All variables are explained in detail in Appendix 3.A. All models include the industry fixed effect (based on Sustainalytics Industry Classification) and quarter-year fixed effects except Model (3). The standard errors are clustered by firm and by quarter-year. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively. The values in parentheses are the standard errors of the estimated coefficients.

| | High CCE<br>CDS5<br>(1) | Low CCE<br>CDS5<br>(2) | High $CCE^{Opp}$<br>CDS5<br>(3) | Low $CCE^{Opp}$<br>CDS5<br>(4) |
|---|---|---|---|---|
| *CRMS* | –0.043*** | 0.000 | –0.036*** | 0.023 |
| | (0.015) | (0.016) | (0.012) | (0.022) |
| *LEVERAGE* | 1.830*** | 1.038*** | 1.764*** | 0.419 |
| | (0.232) | (0.375) | (0.225) | (0.497) |
| *IVOL* | 39.190*** | 41.008*** | 35.571*** | 71.142*** |
| | (11.686) | (7.736) | (9.797) | (10.127) |
| *SIZE* | –0.140*** | –0.235*** | –0.164*** | –0.188*** |
| | (0.030) | (0.046) | (0.031) | (0.049) |
| *ROA* | –6.551*** | –6.279*** | –9.473*** | –8.631** |
| | (1.725) | (1.933) | (1.559) | (3.749) |
| *CASH* | –0.617** | 0.372 | –0.516* | 1.667* |
| | (0.273) | (0.495) | (0.261) | (0.835) |
| *TURNOVER* | –0.078 | –0.298 | –0.251 | –1.101 |
| | (0.190) | (0.425) | (0.154) | (0.802) |
| *PPE* | –0.421 | –0.485 | –0.924*** | –0.725 |
| | (0.298) | (0.373) | (0.226) | (0.647) |
| *CAPEX* | 0.808 | 1.613 | 0.939 | 2.655* |
| | (1.141) | (1.074) | (1.178) | (1.465) |
| *Industry FE* | Yes | Yes | Yes | Yes |
| *Quarter-Year FE* | Yes | Yes | Yes | Yes |
| *Observations* | 1,637 | 1,096 | 1,384 | 461 |
| *Adj.*$R^2$ | 0.643 | 0.694 | 0.677 | 0.698 |

These results are consistent with our hypothesis and indicate that the role of *CRMS* is most pronounced among firms that would benefit most from the signalling of commitment to mitigate climate risk through better carbon risk management.

### *3.6.2 Impact of Governance, Social and other Environmental Risk Management Factors*

Recall that the focus of this chapter is to investigate the impact of climate change-related risk management, or more precisely, carbon risk management practices, in mitigating the credit spread of firms. However, it is plausible that our results are driven by firm-level corporate governance characteristics, as firms that are well-governed invest more in environmental and social policies (Ferrell, Liang, and Renneboog, 2016). As carbon risk management is one of the many *ESG* practices, it is pertinent to control for the governance effect, if any, to show that carbon risk management practices are not driven by implicit governance quality. In addition, we also control for the social factor as social issues are also correlated (44%) with carbon risk management practices.

Sustainalytics provides the individual scores on Environmental, Social and Governance risk management pillars to arrive at the total *ESG* score of a firm. We extract the scores on Social (S) and Governance (G) risk management practices out of the overall *ESG* scores for the robustness test. Sustainalytics evaluates firms' social and governance risk management considering several dimensions. For instance, some of the dimensions to evaluate social risk management include firm policy on freedom of association, human capital development, data privacy and security, human rights, and product responsibility. Governance risk management includes attributes such as management quality, board structure, remuneration, business ethics, and shareholder governance, among many other dimensions. The scores on these dimensions are aggregated to arrive at the individual social and governance scores. Similar to our main measure, the carbon risk management score, the social and governance management scores are also adjusted for industry to allow for comparison across firms in different industries.

As a further robustness check, we also examine whether the *CRMS* effect holds after controlling for the rest of environmental risk management measures from Sustainalytics. We define a new variable *E-CRMS* that pools remaining environmental variables. Specifically, *E-CRMS* is obtained as the sum of 46 *non-CRMS* environmental variables (i.e., all 59 environmental variables excluding the 13 *CRMS* variables).[26]

The results in Table 3-10 highlight that carbon risk management scores become insignificant after we control for the governance, social and *E-CRMS* variables. However, post-Paris Agreement, improved carbon risk management bears a strong negative relationship with CDS spreads even after controlling for governance, social and remaining environmental risk management effects. These results provide comfort that our findings are not driven by omitted environment variables, social and governance risk management variables, and carbon risk management has become more relevant in the post-2015 Paris Agreement period.

[26] E-CRMS variables include wider environmental indicators such as company's policies and programs to reduce hazardous waste, air emissions, and water use, sustainability related products, percentage of recycled raw materials used, targets to protect biodiversity etc. We find that the correlation between CRMS and E-CRMS is 0.337. This relatively low correlation indicates that although the two variables positively correlated, the information content in CRMS is not captured in other Environmental risk management measures from Sustainalytics.

**Table 3-10: The Relationship between CRMS and 5-Year CDS Spread, Controlling for Governance, Social and other Environmental Risk Management Scores**

This table shows the effect of *CRMS* of a firm on the natural logarithm of daily average of 5–year senior unsecured *CDS* spread level (*CDS5*) in a quarter after controlling for the governance (*Governance Score*), social (*Social* Score) and remaining environmental risk management variables (*E–CRMS*). The results are shown for the baseline panel regressions done on the full sample (Column 1), baseline full sample regression with '*CRMS × POST*' as key variable and baseline panel regressions on sub–samples of pre– (Column 3) and post–Paris Agreement (Column 4). We use a dummy variable *POST* which takes value of one for the period after December 2015 and zero otherwise. All variables are explained in detail in Appendix 3.A. All the models include the industry fixed effect (Sustainalytics Industry Classification) and quarter-year fixed effect. The standard errors are clustered by firm and by quarter-year. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively. The values in parentheses are the standard errors of the estimated coefficients.

| | A. Full Sample | B. Full Sample | C. Pre–Paris Agreement | D. Post–Paris Agreement |
|---|---|---|---|---|
| | CDS5 | CDS5 | CDS5 | CDS5 |
| | (1) | (2) | (3) | (4) |
| *CRMS* | –0.011 | –0.006 | –0.003 | –0.038*** |
| | (0.010) | (0.010) | (0.010) | (0.014) |
| *CRMS × POST* | | –0.022** | | |
| | | (0.010) | | |
| *E–CRMS* | 0.002 | 0.003 | –0.001 | 0.013 |
| | (0.008) | (0.008) | (0.008) | (0.011) |
| *Governance Score* | –0.006** | –0.006** | –0.004 | –0.009** |
| | (0.003) | (0.003) | (0.003) | (0.005) |
| *Social Score* | –0.006** | –0.005** | –0.006** | –0.007* |
| | (0.002) | (0.002) | (0.003) | (0.004) |
| *Controls* | Yes | Yes | Yes | Yes |
| *Industry FE* | Yes | Yes | Yes | Yes |
| *Quarter-Year FE* | Yes | Yes | Yes | Yes |
| *Observations* | 8,263 | 8,263 | 5,732 | 2,531 |
| *Adj.* $R^2$ | 0.661 | 0.662 | 0.687 | 0.645 |

### *3.6.3 Impact of Carbon Risk Management on CDS of Different Maturities*

We use the 5-year *CDS* spread in our main analysis. As a robustness check, we use *CDS* spreads of 1-year, 10-year, and 30-year single-name *CDS* of the firms in the sample as alternative dependent variables. We repeat our baseline analysis based on equation (3.1) to understand if the risk mitigation impact of carbon risk management performance is consistent across *CDS* spreads of other maturities.

Similar to our baseline results, we observe a negative relationship between CRMS and CDS spreads of 1-year, 10-year and 30-year single-name CDS, shown in Table 3-11. In terms of economic significance, a one standard deviation (2.73) increases in *CRMS* (Table 3-1) reduces the quarterly spread of 10-year and 30-year maturity *CDS* spreads by 9.18 and 8.74 basis points, respectively. The impact of *CRMS* on *CDS* spreads also become stronger after the Paris Agreement. While controlling the governance and social factors, we also test for the impact of the 2015 Paris Agreement on *CDS* spreads of other maturities. We present the results of this analysis in Appendix Table 3-2. We find that the interaction term *CRMS* × *POST* has a significant impact on 10-year and 30-year maturity *CDS* spreads but not on 1-year *CDS* spreads, suggesting that carbon risk management has a material impact on credit spreads with longer-term maturity but does not show similar mitigation effect on short-term credit risk. This is consistent with the conjecture that climate risk affects financial markets in the long term. [27]

### *3.6.4 Evaluating Alternative Channels for the Relationship Between CRMS and CDS Spreads*

In this section, we examine possible financial characteristics channels that can induce the relationship between CRMS and CDS spreads. We examine the differential effect of high versus low leverage on the association between CRMS and CDS spreads. [28]

Table 3-12 presents the results. We find that better carbon managed firms with the highest quartile of industry leverage have lower subsequent credit risk valuations in the post-Paris Agreement period.

[27] We perform three additional robustness checks and present the results in the Appendix Table 3-3. *First*, we include lagged *CRMS* variable in Model (1) to control for possible persistence in *CRMS*. We use two quarters lagged (*CRMS_lag*) with respect to *CDS* spread as the main independent variable in place of our main *CRMS* variable. *Second*, we examine whether high credit risk on account of poor carbon risk management is simply a reflection of illiquidity in the *CDS* market. We implement Model (2) augmented by *CDS* market liquidity (*CDS_Depth*) proxied by the number of contributors in the 5-year *CDS* market. *Third*, we use VIX as an additional market risk conditioning variable. In all additional robustness tests, the previous finding of negative significant relationship between *CRMS* and *CDS* spreads still holds.
[28] We find qualitatively similar results when we divide the sample based on the median values of leverage of firms in each quarter.

**Table 3-11: Robustness Checks using CDS Spreads of Different Maturities**

This table shows the effect of carbon risk management practices of firms on *CDS* spreads over different time periods after controlling for governance and social factors. The results are shown for the panel regressions done on the full sample (Column 1–3) and sub-samples of pre- (Column 4–6) and post-Paris Agreement (Column 7–9). The dependent variable is the natural logarithm of the daily average of *CDS* spreads of 1-year, 10-year and 30-year maturities in a quarter. All variables are explained in detail in Appendix 3.A. All models include the industry fixed effect (Sustainalytics Industry Classification) and quarter-year fixed effects. The standard errors are clustered by firm and by quarter-year. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively. The values in parentheses are the standard errors of the estimated coefficients.

| | A. Full Sample | | | B. Pre-Paris Agreement | | | C. Post-Paris Agreement | | |
|---|---|---|---|---|---|---|---|---|---|
| | CDS1 | CDS10 | CDS30 | CDS1 | CDS10 | CDS30 | CDS1 | CDS10 | CDS30 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *CRMS* | –0.045*** | –0.019** | –0.017** | –0.036** | –0.012 | –0.011 | –0.070*** | –0.043*** | –0.039*** |
| | (0.015) | (0.008) | (0.008) | (0.015) | (0.009) | (0.008) | (0.020) | (0.011) | (0.010) |
| *LEVERAGE* | 1.256*** | 1.230*** | 1.167*** | 1.351*** | 1.334*** | 1.247*** | 0.942*** | 0.985*** | 0.960*** |
| | (0.218) | (0.138) | (0.128) | (0.232) | (0.142) | (0.134) | (0.312) | (0.202) | (0.183) |
| *IVOL* | 54.797*** | 40.966*** | 38.224*** | 58.551*** | 45.314*** | 42.599*** | 47.821*** | 34.839*** | 32.479*** |
| | (5.362) | (3.959) | (3.727) | (6.090) | (3.897) | (3.760) | (7.838) | (6.148) | (5.609) |
| *SIZE* | –0.214*** | –0.119*** | –0.103*** | –0.218*** | –0.114*** | –0.103*** | –0.214*** | –0.128*** | –0.100*** |
| | (0.035) | (0.020) | (0.019) | (0.036) | (0.021) | (0.020) | (0.044) | (0.027) | (0.025) |
| *ROA* | –9.601*** | –7.040*** | –6.548*** | –11.916*** | –8.364*** | –7.909*** | –5.379** | –4.394*** | –3.927*** |
| | (1.650) | (0.991) | (0.918) | (1.602) | (0.962) | (0.905) | (2.200) | (1.326) | (1.182) |
| *CASH* | 0.118 | –0.339* | –0.308* | 0.221 | –0.241 | –0.210 | 0.065 | –0.422* | –0.405** |
| | (0.333) | (0.188) | (0.174) | (0.343) | (0.199) | (0.188) | (0.415) | (0.221) | (0.198) |
| *TURNOVER* | –0.287 | 0.177 | 0.201 | –0.165 | 0.253* | 0.261* | –0.786*** | –0.115 | –0.046 |
| | (0.211) | (0.138) | (0.129) | (0.206) | (0.138) | (0.132) | (0.283) | (0.162) | (0.147) |
| *PPE* | –0.651*** | –0.475*** | –0.442*** | –0.789*** | –0.429*** | –0.387** | –0.249 | –0.550** | –0.513** |
| | (0.223) | (0.168) | (0.160) | (0.212) | (0.156) | (0.151) | (0.317) | (0.233) | (0.214) |
| *CAPEX* | 0.284 | 0.587 | 0.491 | –0.235 | –0.064 | –0.174 | 2.147* | 2.409*** | 2.290*** |
| | (0.749) | (0.569) | (0.535) | (0.802) | (0.581) | (0.549) | (1.096) | (0.781) | (0.719) |
| *Industry FE* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Quarter-Year FE* | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Observations* | 8,350 | 8,350 | 8,350 | 5,826 | 5,826 | 5,826 | 2,524 | 2,524 | 2,524 |
| *Adj.* $R^2$ | 0.630 | 0.653 | 0.639 | 0.663 | 0.679 | 0.667 | 0.523 | 0.640 | 0.627 |

This implies that, in the in the post-Paris Agreement period, superior carbon risk management firms are associated with lower subsequent credit risk assessments despite being highly leveraged.

**Table 3-12: Exploring Alternative Channels for CRMS and CDS Spread Relation**

This table presents the results to verify alternative channels inducing the relationship between *CRMS* and *CDS* spreads. It presents the effects of *CRMS* on one quarter ahead 5-year *CDS* spreads interacted with *High-Leverage* (a high vs. low leverage dummy) and *POST*, the Paris Agreement dummy. The key variables are *CRMS* × *High-Leverage* (interacting *CRMS* and *High-Leverage* dummy) and *CRMS* × *POST* × *High-Leverage* (interacting *CRMS*, *POST*, and *High-Leverage* dummy). Models (1) to (3) use dummy (*High-Leverage*) classified using highest versus lowest leverage quartile portfolios. All variables are explained in detail in Appendix 3.A. The model includes the industry fixed effect (Sustainalytics Industry Classification) and quarter-year fixed effects. The standard errors are clustered by firm and by quarter-year. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively. The values in parentheses are the standard errors of the estimated coefficients.

| | CDS5<br>(1) | CDS5<br>(2) | CDS5<br>(3) |
|---|---|---|---|
| *CRMS* | 0.003 | 0.007 | 0.002 |
| | (0.017) | (0.017) | (0.017) |
| *High-Leverage* | 0.580*** | 0.601*** | 0.543*** |
| | (0.118) | (0.117) | (0.118) |
| *CRMS* × *High-Leverage* | –0.016 | –0.010 | –0.001 |
| | (0.024) | (0.023) | (0.023) |
| *CRMS* × *POST* | | –0.014 | 0.005 |
| | | (0.016) | (0.019) |
| *CRMS* × *POST* × *High-Leverage* | | –0.039** | –0.077*** |
| | | (0.015) | (0.025) |
| *High-Leverage* × *POST* | | | 0.208* |
| | | | (0.121) |
| *Control Variables* | Yes | Yes | Yes |
| *Industry FE* | Yes | Yes | Yes |
| *Quarter-Year FE* | Yes | Yes | Yes |
| *Observations* | 4,023 | 4,023 | 4,023 |
| *Adj.*$R^2$ | 0.681 | 0.684 | 0.685 |

We further examine whether the *CRMS–CDS* spread relationship is driven by underlying poor performance or insolvency of the firms. Distressed firms are likely to have high credit risks and be lax in committing to any carbon risk management practices. Therefore, we empirically test whether our results are driven mainly by the effect of distressed firms. We follow Demiroglu and James (2015) and Subrahmanyam, Tang, and Wang (2014) in identifying firms in financial distress. If a stock return of a firm in our sample is in the bottom

10% of the overall market for two consecutive years, we classify it as financially distressed in the third year. We find that there are 10 firms in our sample that can be classified as distressed firms. We use a dummy variable called *DistressedFirms* which takes a value of one if a firm is classified as distressed, otherwise it takes a value of zero.

We find in Model (1) of Appendix Table 3-4 that for the distressed firms, better carbon risk management has no diminishing effect on *CDS* spreads. We also evaluate the post-Paris Agreement impact of distressed firms on *CRMS–CDS* spread relationship (see Model (2) in Appendix Table 3-4). We find our results on *CRMS–CDS* spread relationship post-Paris Agreement are robust, and not driven by the distressed firms as indicated by the lack of significance of triple interaction term *DistressedFirms* × *CRMS* × *POST*. In summary, we rule out the significance of our results as arising from firm distress.

### 3.7 Signaling Effect of Carbon Risk Management

We assess the efficacy of carbon risk management as a signalling mechanism for underlying firms. This is done by examining the correlation between CRMS and subsequent carbon emission levels. Additionally, we conduct a separate analysis, studying the relationship between CRMS and CDS for varying carbon emission levels.

The signalling hypothesis implies that firms' commitment to carbon risk management would be associated with lower carbon emissions. We leverage the test conducted in Section 2.3.6 to understand the relationship between CRMS and subsequent total carbon emission levels of the firm. The results in Table 2-6 show that better carbon risk management is related to lower subsequent total carbon emission levels and that effect is significant only after the post-Paris Agreement. This finding supports the notion that firms have adopted more robust carbon risk management practices in the post-Paris Agreement era, effectively signalling their capacity to curb carbon emissions.

Next, we investigate the relationship between CRMS and CDS spread, considering firms' varying levels of carbon emissions. If risk reduction is possible through better carbon risk management, the signalling hypothesis implies that better CRMS scores could be especially critical in lowering credit risks for high compared to low carbon emitters (Signaling hypothesis). On the other hand, it is possible that high carbon emitters indulge in "window-dressing" by providing wrong information to ESG rating agencies to inflate their CRMS scores and overstate their carbon risk management commitment (Green-washing hypothesis). If so, management of high carbon emitting firms would employ CRMS activities for their own reputation-building purposes. Once investors discover their true intentions, they could penalize such errant companies by charging them higher CDS spreads.

We sort firms into quartile groups based on their annual total carbon emission levels. The top quartile firms are the ones having the highest carbon emissions, and the one at the bottom quartiles have lowest emissions compared to other firms in each time period. Then, we employ the baseline regression of equation (3.1) separately for each of these quartiles. We report the results for the top and bottom quartiles in Table 3-13. We find that the strong negative relationship between CRMS and subsequent CDS spreads is mainly evident for the highest quartile carbon-emitting firms. Furthermore, we observe the relationship for the top quartile sample primarily after the Paris Agreement. This implies that CRMS scores reported by high emitters are credible signals of their lower transition risks and, hence, are reflected in reduced CDS spreads. Our evidence is once again consistent with the Signaling hypothesis.

**Table 3-13: CRMS-CDS Relationship for subsamples based on Firm-level total Carbon Emissions**

This table presents the results for the CRMS-CDS relationship in Table 3-3 separately for firms in the top quartile of annual total carbon emissions (Top CO2 sample) and the bottom quartile of annual carbon emissions (Bottom CO2). Panel A shows the results for the subsamples of top and bottom quartile across the full time period. Panel B and C show the results of top and bottom quartile CO2 subsamples for the pre- and post-Paris Climate Agreement periods, respectively. All variables are explained in detail in Appendix 3.A. All models include the industry fixed effect (based on Sustainalytics Industry Classification) and quarter-year fixed effects except Model (3). The standard errors are clustered by firm and by quarter-year. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively. The values in parentheses are the standard errors of the estimated coefficients.

| | A. Full Period | | B. Pre Paris | | C. Post Paris | |
|---|---|---|---|---|---|---|
| | Top CO2 | Bottom CO2 | Top CO2 | Bottom CO2 | Top CO2 | Bottom CO2 |
| | CDS5 | CDS5 | CDS5 | CDS5 | CDS5 | CDS5 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *CRMS* | –0.035** | –0.002 | –0.036* | 0.008 | –0.046** | –0.036 |
| | (0.016) | (0.016) | (0.018) | (0.014) | (0.019) | (0.039) |
| *LEVERAGE* | 1.362** | 0.840* | 1.744*** | 1.076** | 0.550 | 0.128 |
| | (0.532) | (0.441) | (0.533) | (0.465) | (0.694) | (0.751) |
| *IVOL* | 72.390*** | 41.452*** | 85.152*** | 43.637*** | 52.368*** | 43.193*** |
| | (14.836) | (6.020) | (15.386) | (7.628) | (15.124) | (8.567) |
| *SIZE* | –0.112 | –0.121* | -0.078 | –0.133** | –0.134 | –0.125* |
| | (0.076) | (0.062) | (0.076) | (0.060) | (0.096) | (0.070) |
| *ROA* | –6.633*** | –8.591*** | –6.930*** | –8.325*** | –5.750** | –5.742* |
| | (1.884) | (2.179) | (1.667) | (2.508) | (2.486) | (2.776) |
| *CASH* | 1.330* | –0.251 | 0.738 | –0.559 | 1.934** | 0.013 |
| | (0.703) | (0.331) | (0.861) | (0.369) | (0.775) | (0.400) |
| *TURNOVER* | 0.214 | –0.003 | 0.315 | 0.108 | 0.157 | –0.083 |
| | (0.410) | (0.172) | (0.359) | (0.154) | (0.818) | (0.309) |
| *PPE* | –1.093* | –0.321 | –1.348** | –0.814 | –0.110 | 0.545 |
| | (0.596) | (0.771) | (0.530) | (0.938) | (0.873) | (0.691) |
| *CAPEX* | 1.652 | –4.139 | 1.954 | –3.282 | 4.456 | –5.488 |
| | (1.180) | (3.454) | (1.269) | (3.902) | (2.696) | (4.655) |
| *Industry FE* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Quarter-Year FE* | Yes | Yes | Yes | Yes | Yes | Yes |
| *Observations* | 1,335 | 945 | 988 | 702 | 347 | 240 |
| *Adj.$R^2$* | 0.677 | 0.687 | 0.752 | 0.689 | 0.484 | 0.722 |

### 3.8 Conclusion

We examine whether firms prudently managing their carbon emissions are favourably assessed in the credit markets. We find that firms' proactive carbon transition risk engagement is associated with their lower subsequent *CDS* spreads. Our results are robust when we control for established credit risk determinants and industry- and time-level unobservable heterogeneity. We find that the importance of carbon risk management performance has gained prominence following the Paris Climate Agreement of December 2015. We also find that carbon risk management practices play a greater role in credit risk mitigation for firms headquartered in states that have implemented climate adaptation plans. These findings suggest that effective carbon risk management following enhanced regulatory regime can lead to lower subsequent credit risk assessment, and lower cost of borrowing. Further analysis shows that the impact of carbon risk management performance on *CDS* spreads is neither driven by the role of governance or social factors, nor subsumed by other firm-level climate change exposure measures used in the prior literature. Finally, we show that firms with better carbon risk management have improved future growth opportunities, cash liquidity, and lower carbon emission levels.

Our study extends prior research by demonstrating that the credit market does not only respond to carbon emission risk, but also incorporates the effectiveness of firms' carbon risk management to mitigate the carbon transition risk. Our findings have implications for regulators, corporations, investors, and credit rating agencies. Specifically, our findings can inform the decision-making of regulatory bodies, such as the SEC, on the effectiveness of proposed climate risk disclosures on the firm risk. Firms can be motivated to adopt and enhance their carbon risk management to help mitigate credit risks. In addition, long-term investors may beneficially adjust their portfolios based on the adequacy of a firm's carbon risk management. Moreover, given that carbon risk management can potentially lower firms' credit risks, credit rating agencies may consider carbon risk management performance in their rating assessment. Providing direct evidence for these implications is an important question for future research.

Finally, the chapter incorporates perspectives from a range of key stakeholders in assessing the implications of firms' carbon risk management practices. By examining the relationship between carbon risk management scores and corporate CDS spreads, the findings reflect the valuation placed by sophisticated investors in the credit derivatives market. This market is primarily dominated by large institutional investors that have both the ability and incentive to closely analyze firms' exposure to climate transition risks. In addition, the use of quasi-natural experiments around the Paris Agreement and state climate adaptation plans helps capture how regulatory bodies and environmental policymakers view the importance of proactive carbon risk management. Broader stakeholder views could also be gleaned to some extent, as firms with better risk management of their carbon emissions may face less pushback from environmental groups concerned about climate change. Strong carbon practices could also provide reassurance to individual ESG-conscious investors evaluating firms' exposure to long-term sustainability risks.

Overall, our chapter provides empirical evidence consistent with the signalling hypothesis. The findings do not support the view that carbon risk management practices are merely a tool for greenwashing concerns. However, there is currently no direct method available to identify greenwashing at the firm level. Greenwashing detection becomes further difficult in the absence of ESG regulations and green taxonomies. Hence, big data science and machine learning methods in detecting firm greenwashing is a promising avenue for future research.

## Appendix 3.A. Variable Description

This table describes the variables that we use in our analysis. Column 1 reports the variable names. Column 2 provides the description of the variables and column 3 provides the data sources.

| Variable | Description | Source |
|---|---|---|
| | ***Panel A: Carbon Risk Management Measure*** | |
| CRMS (Carbon Risk Management Score) | Weighted sum of scores of management indicators focusing exclusively on a firm's management of carbon risk related to its own operations. These carbon risk management parameters are extracted from the long list of environmental parameters within the overall *ESG* parameter provided by the Sustainalytics database. | Sustainalytics |
| | ***Panel B: CDS Spread and CDS_Depth*** | |
| CDSX | Spread on *CDS* with maturity X years | IHS Markit |
| CDS_Depth | *CDS* market liquidity proxied by the number of contributors in the 5-year *CDS* market | IHS Markit |
| | ***Panel C: Firm-level variables*** | |
| LEVERAGE | Total debt (DLTTQ + DLCQ) divided by total assets (ATQ) | Compustat |
| IVOL (Idiosyncratic volatility) | Standard deviation of daily excess returns, computed as the difference between a firm's stock return and the CRSP value-weighted return over the past 180 days | CRSP |
| SIZE | The natural logarithm of total asset value (ATQ) | Compustat |
| ROA (Return on Assets) | Income after taxes scaled by average total assets over the quarter | Compustat |
| CASH | Cash (CHQ) & Short-Term Investments (CHEQ) scaled by ATQ | Compustat |
| TURNOVER | Total revenues (REVTQ) scaled by ATQ | Compustat |
| PPE (Property, Plant and Equipment) | Gross property, plant, and equipment less accumulated reserves for depreciation, depletion, and amortisation (PPEGTQ) scaled by ATQ | Compustat |
| CAPEX | Capital expenditures representing the funds used to acquire fixed assets (CAPXY) scaled by ATQ | Compustat |
| | ***Panel D: Macro-Financial Variables*** | |
| Yield1Yr | One-year US Treasury rate | Federal Reserve Board |
| YieldCurve | The difference in the yields of ten- and two-year Treasury bonds | Federal Reserve Board |
| MktRET | Monthly excess return of the market factor | K. French data library |
| VIX | CBOE S&P500 Volatility Index - Close | CBOE |
| | ***Panel E: Governance and Social Variables*** | |
| Governance Score | Sum of the weighted scores of the governance risk management performance of a firm | Sustainalytics |
| Social Score | Sum of the weighted scores of the social risk management performance of a firm | Sustainalytics |
| | ***Panel F: Firm-level Climate Change Exposure Variables of Sautner et al. (2023)*** | |
| CCExposure | Relative frequency with which bigrams related to climate change occur in the transcripts of analyst conference calls. | Sautner et al. (2023) |

| | | |
|---|---|---|
| | Authors count the number of such bigrams and divide by the total number of bigrams in the transcripts. | |
| $CCExposure^{Opp}$ | Relative frequency with which bigrams that capture opportunities related to climate change occur in the transcripts of analyst conference calls. Authors count the number of such bigrams and divide by the total number of bigrams in the transcripts. | Sautner et al. (2023) |
| $CCExposure^{Reg}$ | Relative frequency with which bigrams that capture regulatory shocks related to climate change occur in the transcripts of analyst conference calls. Authors count the number of such bigrams and divide by the total number of bigrams in the transcripts. | Sautner et al. (2023) |
| $CCExposure^{Phy}$ | Relative frequency with which bigrams that capture physical shocks related to climate change occur in the transcripts of analyst conference calls. Authors count the number of such bigrams and divide by the total number of bigrams in the transcripts. | Sautner et al. (2023) |
| $CCSent^{Opp}$ | Relative frequency with which bigrams that capture opportunities related to climate change are mentioned together with the positive and negative tone words in one sentence in the transcripts of analyst conference calls. | Sautner et al. (2023) |
| $CCSent^{Reg}$ | Relative frequency with which bigrams that capture regulatory shocks related to climate change are mentioned together with the positive and negative tone words that are summarised in one sentence in the transcripts of analyst conference calls. | Sautner et al. (2023) |
| $CCSent^{Phy}$ | Relative frequency with which bigrams that capture physical shocks related to climate change are mentioned together with the positive and negative tone words that are summarised in one sentence in the transcripts of analyst conference calls. | Sautner et al. (2023) |
| $CCRisk^{Opp}$ | Relative frequency with which bigrams that capture opportunities related to climate change are mentioned together with the words “risk” or “uncertainty” (or synonyms thereof) in one sentence in the transcripts of analyst conference calls. | Sautner et al. (2023) |
| $CCRisk^{Reg}$ | Relative frequency with which bigrams that capture regulatory shocks related to climate change are mentioned together with the words “risk” or “uncertainty” (or synonyms thereof) in one sentence in the transcripts of analyst conference calls. | Sautner et al. (2023) |
| $CCRisk^{Phy}$ | Relative frequency with which bigrams that capture physical shocks related to climate change are mentioned together with the words “risk” or “uncertainty” (or synonyms thereof) in one sentence in the transcripts of analyst conference calls. | Sautner et al. (2023) |

## Appendix 3.B. State Climate Adaptation Plans by US States

The information on state climate adaptation plans is compiled by the Georgetown Climate Center at https://www.georgetownclimate.org/adaptation/plans.html. The dates mentioned are the first time an individual state in which the firms in our sample are located adopted a *SCAP* during our sample period (August 2009 to May 2018).

| **State** | **Date Finalised** |
|---|---|
| Alaska | January 2010 |
| California | September 2009 |
| Colorado | November 2011 |
| Connecticut | July 2013 |
| Delaware | March 2015 |
| Florida | October 2008 |
| Maine | February 2010 |
| Maryland | July 2008 |
| Massachusetts | September 2011 |
| New Hampshire | March 2009 |
| New York | November 2010 |
| Oregon | December 2010 |
| Pennsylvania | January 2011 |
| Virginia | December 2008 |
| Washington | April 2012 |

## Appendix 3.C. Additional Regression Results

**Appendix Table 3-1: Cross-Sectional Regression and Baseline Regression with Industry × Quarter Fixed Effects**

This table presents the results from the panel regression of the natural logarithm of daily average of 5-year senior unsecured *CDS* spread level (*CDS5*) in a quarter on the carbon risk management score, structural variables such as leverage (*LEVERAGE*), idiosyncratic volatility (*IVOL*), Excess Market Return (*MktRET*), and other control variables. Column 1 presents results for the cross-sectional regression in which all variables are averaged across time at the firm level. Column 2 presents the baseline regression of Table 3-3 with industry × quarter-year fixed effects as an additional fixed effect control. All variables are explained in detail in Appendix 3.A. The sample includes 405 firms located in the US from August 2009 to May 2018. The standard errors are clustered by firm and by quarter-year. ***, ** and * indicate statistical significance at the 0.01, 0.05 and 0.10 level, respectively. The values in parentheses are the standard errors of the estimated coefficients.

| | CDS5<br>(1) | CDS5<br>(2) |
|---|---|---|
| *CRMS* | –0.035*** | –0.034*** |
| | (0.011) | (0.012) |
| *LEVERAGE* | 0.913*** | 1.307*** |
| | (0.157) | (0.189) |
| *IVOL* | 44.761*** | 50.624*** |
| | (10.17) | (6.077) |
| *SIZE* | –0.142*** | –0.156*** |
| | (0.024) | (0.028) |
| *ROA* | –19.821*** | –9.558*** |
| | (3.989) | (1.546) |
| *CASH* | –0.017 | –0.232 |
| | (0.339) | (0.277) |
| *TURNOVER* | 0.003 | 0.002 |
| | (0.18) | (0.177) |
| *PPE* | –0.61*** | –0.581** |
| | (0.196) | (0.232) |
| *CAPEX* | 3.274 | 0.620 |
| | (2.162) | (1.015) |
| *Industry FE × Quarter-Year FE* | No | Yes |
| *Observations* | 374 | 7,732 |
| *Adj.$R^2$* | 0.647 | 0.644 |

**Appendix Table 3-2: The Impact of the Paris Agreement on the CRMS–CDS Spreads (1-, 5-, 10-, 30-year maturity) Relation**

This table shows the results of the impact of the Paris Agreement of December 2015 as the exogeneous shock event on *CRMS–CDS* spread relationship after controlling for the Governance and Social factors. The dependent variable is the natural logarithm of the daily average of *1–year*, *10–year* and *30–year CDS* spread in a quarter. To measure the impact of the Paris Agreement, we use a dummy variable *POST* which takes value of one for the period after December 2015 and zero otherwise. The key variable in the model is *CRMS × POST* which is an interaction term of *CRMS* and *POST.* All variables are explained in detail in Appendix 3.A. The sample includes 405 firms located in the US from August 2009 to May 2018. All the models include the industry fixed effect (based on Sustainalytics Industry Classification) and quarter-year fixed effects. The standard errors are clustered by firm and by quarter-year. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively. The values in parentheses are the standard errors of the estimated coefficients.

| | CDS1<br>(1) | CDS5<br>(2) | CDS10<br>(2) | CDS30<br>(3) |
|---|---|---|---|---|
| *CRMS* | –0.019 | –0.005 | –0.001 | –0.001 |
| | (0.013) | (0.011) | (0.009) | (0.009) |
| *CRMS × POST* | –0.014 | –0.025** | –0.020** | –0.017** |
| | (0.012) | (0.010) | (0.008) | (0.008) |
| *Governance_Score* | –0.015*** | –0.011*** | –0.008*** | –0.007*** |
| | (0.004) | (0.003) | (0.002) | (0.002) |
| *Social_Score* | –0.003 | –0.001 | –0.001 | –0.002 |
| | (0.003) | (0.002) | (0.002) | (0.002) |
| *Controls* | Yes | Yes | Yes | Yes |
| *Industry FE* | Yes | Yes | Yes | Yes |
| *Quarter-Year FE* | Yes | Yes | Yes | Yes |
| *Observations* | 8,348 | 8,348 | 8,348 | 8,348 |
| *Adj.$R^2$* | 0.649 | 0.669 | 0.661 | 0.649 |

**Appendix Table 3-3: Baseline Regression with Lagged CRMS, CDS Liquidity, and VIX**

This table presents the results of baseline results of Table 3-3 with two quarter lagged *CRMS* variable with respect to 5-year *CDS* spread (*CDS5*) as the main independent variable in Model (1), *CDS_Depth* as a measure of *CDS* liquidity in Model (2), and *VIX* as a measure of market expectation of volatility in Model (3) as additional control variables. All variables are explained in detail in Appendix 3.A. The sample includes 405 firms located in the US from August 2009 to May 2018. All models include the industry fixed effect (based on Sustainalytics Industry Classification) and quarter-year fixed effects except Model (3). The standard errors are clustered by firm and by quarter-year. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively. The values in parentheses are the standard errors of the estimated coefficients.

| | CDS5 | CDS5 | CDS5 |
|---|---|---|---|
| | (1) | (2) | (3) |
| *CRMS* | | –0.021** | –0.028** |
| | | (0.009) | (0.011) |
| *CRMS_Lagged* | –0.027*** | | |
| | (0.010) | | |
| *CDS_Depth* | | –0.061*** | |
| | | (0.009) | |
| *VIX* | | | 0.018*** |
| | | | (0.004) |
| *SIZE* | –0.162*** | –0.131*** | –0.176*** |
| | (0.025) | (0.025) | (0.026) |
| *ROA* | –8.163*** | –8.483*** | –8.419*** |
| | (1.159) | (1.177) | (1.240) |
| *CASH* | –0.292 | –0.458** | –0.213 |
| | (0.226) | (0.216) | (0.222) |
| *TURNOVER* | 0.091 | 0.195 | 0.115 |
| | (0.163) | (0.166) | (0.167) |
| *PPE* | –0.572*** | –0.547*** | –0.546*** |
| | (0.197) | (0.191) | (0.197) |
| *CAPEX* | 0.612 | 0.815 | 0.171 |
| | (0.636) | (0.661) | (0.682) |
| *Yield1Yr* | | | –12.560** |
| | | | (5.777) |
| *Yield_Curve* | | | 6.217 |
| | | | (5.548) |
| *MktRET* | | | 0.599 |
| | | | (0.659) |
| *Industry FE* | Yes | Yes | Yes |
| *Quarter-Year FE* | Yes | Yes | No |
| *Observations* | 7,994 | 8,289 | 8,350 |
| *Adj.* $R^2$ | 0.663 | 0.676 | 0.624 |

**Appendix Table 3-4: Implication of Distressed Firms on CRMS–CDS spread Relation**

This table shows the result of implications of distressed firms on the *CRMS–CDS* relation. The dummy variable *DistressedFirms* takes the value of one if a firm in the sample has been at the bottom 10% of stock returns in the previous two consecutive years considering the overall listed firms' stock returns in the US market, otherwise it takes value of zero. Model (1) estimates the impact of distressed firms on *CRMS–CDS* spread relationship via interaction variable *DistressedFirms* × *CRMS*. Model (2) estimates the impact of distressed firms on *CRMS–CDS* spread relationship post Paris Agreement. We use a dummy variable *POST* which takes value of one for the period after December 2015 and zero otherwise to measure the impact of the Paris Agreement. The main variable in the model is *DistressedFirms* × *CRMS* × *POST* variable, which is a triple interaction between the variables *DistressedFirms*, *CRMS*, and *POST*. All variables are explained in detail in Appendix 3.A. The sample includes 405 firms located in the US from August 2009 to May 2018. All models include the industry fixed effect (based on Sustainalytics Industry Classification) and quarter-year fixed effects. The standard errors are clustered by firm and by quarter-year. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively. The values in parentheses are the standard errors of the estimated coefficients.

| | CDS5<br>(1) | CDS5<br>(2) |
|---|---|---|
| *CRMS* | –0.027*** | –0.022** |
| | (0.010) | (0.011) |
| *CRMS* × *POST* | | –0.023** |
| | | (0.010) |
| *DistressedFirms* | –0.289 | –0.277 |
| | (0.190) | (0.273) |
| *DistressedFirms* × *CRMS* | 0.159*** | 0.110 |
| | (0.051) | (0.137) |
| *DistressedFirms* × *CRMS* × *POST* | | 0.040 |
| | | (0.131) |
| *DistressedFirms* × *POST* | | 0.139 |
| | | (0.255) |
| *Controls* | Yes | Yes |
| *Industry FE* | Yes | Yes |
| *Quarter-Year FE* | Yes | Yes |
| *Observations* | 8,350 | 8,350 |
| *Adj.*$R^2$ | 0.658 | 0.659 |

# Chapter 4: Bond Short Selling and CDS Spread

## 4.1 Introduction

The emerging research suggests that bond short selling (Duong, Kalev, and Tian, 2023; Hendershott, Kozhan, and Raman, 2020) is becoming more informative, especially after the global financial crisis (GFC). This information was not apparent during the period examined in the research conducted by Asquith et al. (2013). Surprisingly, Hendershott, Kozhan, and Raman (2020) suggest that the informational value of bond short sellers appears limited to the bond market alone, as their results show no evidence regarding the impact of bond short sellers on cross-asset class prediction, especially concerning future stock returns. In this chapter, we aim to examine further the potential cross-asset informational role of bond short positions. Specifically, we investigate whether bond short-selling activity can predict changes in CDS spreads.

This chapter analyses the information flows from the short-selling activity in the corporate bond market to the CDS market. It is related to the literature on bond short selling as well as on the price discovery in the CDS market on account of the information flows from the markets of other financial instruments of the underlying firms (Acharya and Johnson, 2007; Griffin, Hong, and Kim, 2016; Hilscher, Pollet, and Wilson, 2015; Kryzanowski, Perrakis, and Zhong, 2017; Marsh and Wagner, 2016). Specifically, we build upon the work of (Griffin, Hong, and Kim, 2016), who demonstrate the predictive role of short sellers in the equity market on CDS returns by showing the predictive role of bond short sellers in influencing the CDS spreads. While the information content of CDS markets for underlying bonds is well understood, we provide evidence on how information generated by bond short selling is significantly related to subsequent CDS spreads.

Short selling a bond or a synthetic short through a CDS are both methods that allow individuals to profit from the risk of default or decrease in the valuation of a corporate bond and hedge against credit risk exposure. These strategies require upfront costs, carry counterparty risks, and allow investors to express negative views about an issuer's creditworthiness. However, short selling a bond is relatively costly and time-consuming compared to synthetic shorts through CDS, as stated by Czech (2021) and Sambalaibat (2022). According to Sambalaibat (2022), a search framework suggests that the total search cost of short selling a bond is considerably higher than that of synthetic shorts through CDS. Short selling requires multiple search stages; in each stage, investors must trade a bond in a potentially limited supply. Despite the arduous and expensive nature of bond short selling, the fact that short sellers are active in the bond market implies that compelling reasons must drive such behaviour. The higher cost of directly shorting a bond compared to buying a CDS suggests that short sellers may have access to additional information regarding the credit issues of underlying bonds or firms. Consequently, investors in other related asset classes, such as CDS investors, may find information on bond short interest as value-relevant for them. This is the primary motivation for exploring the impact of bond short interest on the CDS spread.

The investigation is further motivated by the theoretical construct of Duffie and Lando (2001) model, which suggests that the pricing of a CDS instrument depends on the likelihood and severity of firm default and the quality of the information available to CDS counterparties about firm value. Although CDS investors can exploit pricing inefficiencies and access privileged information through private communications with company managers (Acharya and

Johnson, 2007), they may still benefit from incorporating short sellers' information in their credit risk assessment. This was shown to be true in the case of equity short selling, as demonstrated by (Griffin, Hong, and Kim, 2016). Therefore, the next empirical question is whether bond short sellers convey additional information in the CDS market. We conjecture that bond short interest can also provide information that can impact CDS spreads beyond what the equity short interest conveys. Suppose high or increasing short selling in the bond market indicates bad news about the firm beyond what is already conveyed by equity short sellers. In that case, CDS investors are likely to factor this information into their evaluation of CDS spreads. We test this conjecture by examining the ability of firm-level bond short interest to predict five-year *CDS* spreads in the next one-month period.

Short sellers, whether in the equity or bond markets, generally indicate a belief in the downside risk associated with the underlying firm, making it pertinent to assess their impact on asset markets, which are more concerned about the downside risk of the firm. Griffin, Hong, and Kim (2016) have already provided evidence on the role of equity short interest in predicting the future CDS return. Since CDSs are an asset class highly relevant and specific to credit risk and default probabilities associated with a firm, they provide a more appropriate market setting for studying the effect of bond short sellers on CDS spreads. Therefore, it is the next logical step in exploring the impact of short selling on the credit market.

Surprisingly, there is little literature on short selling in bond markets, considering that the bond market is much larger than the stock market globally. One of the main reasons for the lack of studies on bond short selling has been the lack of availability of data as bond short selling is completely an over-the-counter market, and we understand that study of any OTC market is relatively difficult (Asquith et al., 2013). The importance of the research question is underscored by the significant size of the US corporate bond market and CDS market,[29] the limited amount of existing research on corporate bond short selling, and expectations from *CDS* counterparties and market dealers, given their sophistication, to understand the role of bond short interest.

We utilise data on bond short selling and 5-year *CDS* spreads from Markit to answer our main research question. Our final sample includes 59,958 firm-month observations for 648 distinct firms from February 2006 to December 2020. The key independent variable is firm-level bond short interest, which is the value-weighted (bond offering amount scaled by the sum of offering amounts of all the bonds issued by a firm) bond short interest quantity (quantity of bond short interest scaled by the bond offering amount) of all the bonds issued by a firm in a month. The key dependent variable is the spread level of a 5-year tenor CDS contract. We investigate the impact of bond short interest primarily on the 5-year benchmark CDS spreads of the firms as they are traded more frequently compared to the CDS of other maturities (Augustin and Izhakian, 2020; Das, Kalimipalli, and Nayak, 2014; Ericsson, Jacobs, and Oviedo, 2009).

First, the firm-level bond short interest is positively and significantly related to the month ahead of a 5-year *CDS* spread. These results remain strong after controlling for several variables, such as firm characteristics and macro-financial variables, as well as firm- and time-fixed effects. The relationship between *CDS* spread and firm-level bond short interest is also economically significant – a one-standard-deviation increase in firm-level bond short interest

[29] As of June 2022, the total outstanding corporate bonds in the US amounts to US$10.1 trillion (Source: https://www.sifma.org/resources/research/us-corporate-bonds-statistics/). As of June 2022, the global outstanding notional amount of CDS contracts is valued at US$9.3 trillion, with US counterparties holding positions in CDS contracts worth US$2.1 trillion (Source: https://stats.bis.org/statx/srs/table/d10.5?f=pdf).

increases the 5-year *CDS* spread by 19.21 basis points, 12% of the mean value of the 5-year *CDS* spread. The main baseline results are robust using alternative CDS spread and bond short-selling measures. We further find that the influence of firm-level bond short selling on the *CDS* spread is independent of the influence of equity short interest and put options volume. The baseline results are robust even after controlling for the persistence in CDS spread or the stocks and bonds return and risk variables.

We perform two additional analyses to mitigate the potential endogeneity concerns. We first use the propensity score matching approach to match firms with high bond short interest (above monthly median) to comparable firms with low bond short interest. We still find bond short interest positively related to future CDS spread for the matched sample. We also perform an internal instrumental variable analysis following the method of Lewbel (2012), in which the heterogeneity in the error term of the first stage regression is used to generate instruments from within the existing model. Our results show that the instrumented bond short interest still positively affects future CDS spread.

Having documented a robust relationship between bond short interest and one-month-ahead CDS spread, we further examine this relationship's time series and cross-sectional variation. In the first test, we consider how the relationship varies following natural disaster periods versus other periods. We expect that large-scale disasters serve as exogenous shocks to the supply of bonds available for shorting. The decrease in bond ownership primarily arises from insurance companies liquidating their bond holdings to meet insurance claims, as they are naturally one of the largest lenders of corporate bonds (Foley-Fisher, Gissler, and Verani, 2019). Consequently, the decreased availability of bonds for shorting should result in a decrease in bond short interest, indicating a reduction in the amount of information accessible within the shorting market. Supporting our conjectures, we find that the supply of bonds available for shorting and bond short interest declines after natural disasters. More importantly, we show that the relationship between CDS spread and bond short interest is weaker during the disaster period.

In the second test, we analyse whether the borrowing cost, i.e., the fee of short selling a bond, affects the impact of short selling on credit default swap spreads. Previous studies on stock short selling suggest that higher short-selling fees improve the informational value of equity short interest and that equity loan fees are accurate predictors of stock market returns. Extending this reasoning to the bond market, we find that the relationship between CDS spread and bond short interest is present only in the high fee subsample.

Next, we assess the impact of CDS liquidity on the relationship between the bond short interest and CDS spread. We use Markit computed CDS depth score as the proxy for the liquidity of the CDS contracts of the underlying firms. CDS depth measures the number of contributors, typically large institutions — such as commercial and investment banks — actively trading in CDS contracts. Increased contributors lead to potentially enhanced trading and, thereby, higher underlying liquidity. Our analysis contemplates two potential outcomes: Firstly, we anticipate that in more liquid CDS markets, the information conveyed by bond short sellers is more readily reflected in subsequent CDS spreads, owing to improved access to trading. Conversely, it's plausible that bond short interest holds stronger predictive power in less liquid CDS markets, where information flow from bond short sellers may be more enduring or robust. In addressing this empirical question, we find that the relationship between CDS spread and bond short interest is predominantly observed in firms with highly liquid CDS markets.

We also consider the possible channels underlying the relationship between the firm-level bond short interest and *CDS* spread. We argue that bond short sellers conduct an in-depth analysis of different firms' underlying economics or fundamentals before taking short positions in their bonds. This suggests that bond short sellers can predict certain firm-level financial variables pertinent to credit risk evaluation. We test whether bond short sellers can predict the key financial variables such as leverage, volatility, and future growth options and accordingly decide to take a short position in the underlying bond. We find that the firms with higher bond short-selling activities have higher leverage, higher idiosyncratic volatility, lower value of growth options and lower returns on assets, implying higher credit risk profiles for such firms.

Our main analyses demonstrate the important informational role of bond short selling for the secondary market assessment of firms' credit risk. In the final analysis, we analyse the informational role of bond short interest for the investors in the primary bond market and lenders in the bank loan market. Higher bond short-selling activities of a firm lead to higher costs of raising new bonds or higher interest rates on bank loans. These results indicate that bond short sellers possess value-relevant information for investors in the primary debt markets, especially the banks.

The primary and most notable contribution of this chapter is that we are the first to demonstrate the value of bond short-seller information beyond the bond market. Prior work by Hendershott, Kozhan, and Raman (2020) and Duong, Kalev, and Tian (2023) has focused mainly on the role of bond short selling in the bond market. Hendershott, Kozhan, and Raman (2020) show that bond short interest is irrelevant to predicting future stock returns. We build on their work by highlighting the role of bond short interest in cross-asset information. The CDS is a better market setting than stocks because equity market returns could be driven by several other factors beyond the factors related to credit or default risk. Our research provides evidence that bond short sellers possess information that may be relevant for cross-market assets, i.e., CDSs. We demonstrate that despite controlling for equity short interest, put options trading, firm characteristics, and security pricing measures, bond short interest has a robust and positive association with the CDS spread of the underlying firm.

Previous literature on information linkages between bonds and CDS markets finds that CDS markets have leading information content for corporate bonds. For example, Hull, Predescu, and White (2004) study the information impact of CDS spreads on bond market ratings and find that credit spreads provide helpful information in estimating the probability of negative credit rating changes. Blanco, Brennan, and Marsh (2005) find that the CDS market leads the bond market in determining the price of credit risk. Baba and Inada (2009) find that CDS spreads play a bigger role in price discovery than bond spreads for Japanese banks. Norden and Weber (2009) find that CDS spreads explain syndicated loan rates much better than spreads of similar-rated bonds. Forte and Pena (2009) study the long-run equilibrium relations between bond, CDS, and stock market implied spreads and find that stocks lead CDS and bonds more frequently than the reverse and that the CDS market leads the bond market. Norden and Weber (2009) find that stock returns lead to CDS and bond spread changes and that the CDS market contributes more to price discovery than the bond market. Hence, our study represents a novel contribution, as it is the first study that shows that the bond short sellers may have the leading informational content for the CDS market.

The subsequent chapter is structured as follows: Section 4.2 describes the data and key variables utilised in the chapter. Section 4.3 presents empirical results on the relationship between bond short selling and CDS spread. Section 4.4 provides the results of robustness tests.

Section 4.5 discusses the results of endogeneity tests. Section 4.6 presents the results of the time series and cross-sectional variance analysis. Section 4.7 presents the results on the information content of bond short interest for future firm performance and financing costs. Finally, Section 4.8 concludes the chapter.

### 4.2 Data and Sample

We use Markit as the primary data source for corporate bond lending and *CDS* spreads. We source corporate bond data from the TRACE and FISD. We source firm-specific financial information from the Compustat North America Quarterly Database, macro-financial control variables from the St. Louis Federal Reserve Economic Data (FRED) and Kenneth French database, and stock price information from the Center for Research in Security Prices (CRSP). We also collect information on equity short-selling activity from the Compustat database, which provides information on stock short interest across the New York Stock Exchange, American Stock Exchange, and NASDAQ.

The corporate bond lending data come from the Markit securities lending database. It collects this information from many of the largest custodians and prime brokers in the securities lending industry. The data set comprises the security-level daily information for the US corporate bonds from February 2006 to December 2020. We use the information on the quantity and value of borrowed bond securities, the percentage of securities on loan out of total securities available for lending and indicator score on a daily fee or rebate charged by the agent lender. The dataset also provides information on the supply-side indicators of bond short selling, which includes the value and quantity of the current inventory available from beneficial owners and the number of custodians and lending agents with open transactions. The other variables in the dataset include the utilisation value or quantity of shorted bonds.

Our main variable is the bond short interest of a firm at the end of every month (*BONDSS*), which is the value-weighted bond short interest of all the bonds issued by a firm in a month. We first calculate the average daily quantity of bonds on loan in a month and scale it by each bond's offering amount. We multiply the monthly bond short interest by the value weights. The value weights are the offering amount of the shorted bond divided by the sum of the offering amounts of all the shorted bonds of the firm. Finally, we take the aggregate of monthly value-weighted bond level short interest of all the shorted bonds of a firm to arrive at the firm-level bond short interest. The bond short-selling data are available for 1,603 firms between Feb-2006 and Dec-2020.

Next, we use the Markit database to obtain single-name 5-year *CDS* spread data. The single-name *CDS* are the most common credit derivative contracts, accounting for almost a third of the trading activity in the *CDS* market (Ericsson, Jacobs, and Oviedo, 2009). Furthermore, we use a 5-year *CDS* contract as it is the most liquid *CDS* instrument traded. We use single-name *CDS* spread data of firms headquartered in the US between Feb 2006 and Dec 2020. The availability of the bond short-selling data from Markit determines the beginning of the period.

Markit provides information on *CDS* contracts of over 5,670 firms across 119 countries. We start with the *CDS* contracts of 2,151 unique firms headquartered in the US, given our dataset for the bond short selling is only available for the US market. Following prior studies (Bai and Wu, 2016; Ericsson, Jacobs, and Oviedo, 2009; Griffin, Hong, and Kim, 2016), we clean the *CDS* data as follows: (i) retain only the US denominated contracts; (ii) keep only the senior unsecured obligations as they are the most liquid *CDS* contracts; (iii) keep only those *CDS* contracts which have a modified restructuring (MR) documentation clause before April 2009 ("*CDS* Big Bang") and no restructuring clause afterwards; (4) exclude *CDS* contracts which have a spread of more than 2,000 basis points to minimize any measurement errors as such contracts are mostly illiquid due to bilateral arrangements for up-front payments. Finally, we transform the daily *CDS* spread data into monthly frequency data, as the data on bond lending are available every month as provided by our data vendor. We report results based on end-of-month *CDS* spreads (*CDS5*). However, all results are robust to using other measures of *CDS* spread, such as monthly averages of daily *CDS* spread and the natural logarithms of *CDS* spread, as shown in the robustness tests.

We first incorporate each dataset's PERMNO identifier from the CRSP database to merge the CDS spread dataset with bond short-selling data. The merge of the *CDS* dataset and the firm-level bond short interest dataset using the PERMNO identifier generates a *CDS5-BONDSS* sample of 59,958 firm-month bond short interest observations for 648 unique single-name or firm-level *CDS* spread.

Further, we use two sets of explanatory variables identified in the literature as influencing the credit spread of a firm – firm-specific fundamental variables and aggregate macro-financial variables. Following structural credit risk models (Merton, 1974), we include the theoretical determinants of credit risk pricing, such as asset value, volatility, and firm leverage. Asset value is the total assets of the firm reported quarterly. Our regression analysis uses the natural logarithm of asset value (*SIZE*). To proxy asset volatility, we follow Kaviani et al. (2020) and Campbell and Taksler (2003) and utilise the idiosyncratic equity volatility (*IVOL*), measured as the standard deviation of daily excess returns over the past 180 days. We use the average book value of the firm's debt as the proxy for firm leverage. We calculate this variable (*LEVERAGE)* as the total value of short- and long-term debt divided by the firm total assets.

Following Bharath and Shumway (2008) and Bai and Wu (2016), we also include the return on assets (*ROA*) to capture the profitability of the firm, cash and cash equivalent scaled by total assets (*CASH*) to capture firm liquidity, revenue or turnover of the firm scaled by total assets (*TURNOVER*), capital expenditure scaled by total assets (*CAPEX*), Market to Book ratio (*MTB*), measure of firm's growth option captured by *TOBINQ*, and property, plant, and equipment scaled by assets (*PPE*) to capture the tangibility of the firm. Data to measure these variables were obtained from the Compustat-North America quarterly database.

Finally, we include the excess stock market return (*MKTRET*), one-year US treasury rates (*TSYIELD*), government treasury yield curve (*TSSLOPE*) and market expectation of volatility (*VIX*) as the macro-financial variables that may influence *CDS* spreads, as per Zhang, Zhou, and Zhu (2009). We obtain data on excess market returns from the Kenneth French data library. The one-year US treasury bill rate and the yield curve slope, which is the difference between ten- and two-year US treasury bond rates, are from the FRED website. The data for *VIX,* the CBOE S&P500 volatility index (closing), are obtained from the Chicago Board Options Exchange.

Table 4-1 reports the summary statistics of key variables where all the continuous variables are winsorised at the $1^{st}$ and $99^{th}$ percentile to mitigate any possible effects of either data errors or outliers. The statistics are based on the 59,958 firm-month observations. The mean and median of the monthly *CDS_SPREAD* are 156 bps and 93 bps, respectively.

**Table 4-1: Descriptive Statistics**

Panel A of the table provides the summary statistics of the key variables for a sample of 648 single *CDS*s of US firms from Feb 2006 to Dec 2020. *CDS_SPREAD* is reported in real values and expressed in basis points (bps). *BOND_SS* is an aggregate of value-weighted average (the number of bonds shorted over the bond offering amount) of the daily short interest of all the bonds of firm *i* in month *t–1*. *LEVERAGE* is the ratio of total liabilities to total assets. *IVOL* is the idiosyncratic volatility of a firm; it is the standard deviation of daily excess returns, computed as the difference between a firm's stock return and the CRSP value-weighted return over the past 180 days. *Total Asset Value* is the firm's size measured by total assets. Our regression analysis uses the natural logarithm of *Total Asset Value* denoted as *SIZE*. *ROA* is the return on assets, *TANGIBILITY* is the property, plant, and equipment scaled by the firm's total assets, and *CAPEX* is the capital expenditure scaled by total assets. *CASH* and *TURNOVER* are the cash & short-term investments and total revenue of the firm, respectively, both scaled by the total assets of the firm. *TSYIELD1* is the 1-year US Treasury rate, and *TSSLOPE* is the difference between the 10-year and 2-year US Treasury rates. *MKTRET* is the monthly excess return of the market. The details of these variables are provided in Appendix 4.A. All continuous variables are winsorised at the 1st and 99th percentile.

| | N | Mean | SD | p25 | Median | p75 | Max |
|---|---|---|---|---|---|---|---|
| | | | | *5–Year CDS Spread at the End of Month* | | | |
| CDS5 (bps) | 59,958 | 156 | 179 | 52 | 93 | 180 | 1,049 |
| | | | | *Firm Level Bond Short Interest Measure* | | | |
| BONDSS (%) | 59,958 | 1.65 | 2.28 | 0.28 | 0.84 | 1.94 | 12.33 |
| | | | | *Firm Characteristic Variables* | | | |
| SIZE | 58,455 | 9.72 | 1.40 | 8.71 | 9.60 | 10.53 | 13.76 |
| LEVERAGE | 54,502 | 0.31 | 0.16 | 0.19 | 0.29 | 0.41 | 0.82 |
| TANGIBILITY | 54,892 | 0.31 | 0.26 | 0.09 | 0.23 | 0.52 | 0.89 |
| CASH | 51,970 | 0.16 | 0.15 | 0.05 | 0.11 | 0.23 | 0.70 |
| ROA | 53,149 | 0.03 | 0.02 | 0.02 | 0.03 | 0.04 | 0.09 |
| MTB | 58,181 | 3.16 | 4.84 | 1.34 | 2.20 | 3.63 | 33.73 |
| TOBIN Q | 58,181 | 1.64 | 0.72 | 1.12 | 1.42 | 1.90 | 4.63 |
| CAPEX | 58,236 | 0.03 | 0.03 | 0.01 | 0.02 | 0.04 | 0.18 |
| TURNOVER | 57,315 | 0.20 | 0.17 | 0.08 | 0.16 | 0.26 | 0.92 |
| IVOL | 59,925 | 0.07 | 0.05 | 0.04 | 0.06 | 0.08 | 0.29 |
| | | | | *Macro–Financial Variables* | | | |
| MKT_RET (%) | 59,958 | 0.79 | 4.45 | –1.53 | 1.29 | 3.24 | 13.65 |
| TSYIELD1 (%) | 59,958 | 1.35 | 1.61 | 0.19 | 0.50 | 2.06 | 5.16 |
| TSSLOPE (%) | 59,958 | 1.31 | 0.89 | 0.50 | 1.40 | 2.03 | 2.81 |
| VIX | 59,958 | 19.40 | 9.02 | 13.49 | 16.79 | 22.46 | 61.18 |

The mean and median firm-level bond short interest (*BONDSS*) across all firms and years are 1.65% and 0.84%, respectively, which are similar to those in Duong, Kalev, and Tian (2023) and Hendershott, Kozhan, and Raman (2020).

### 4.3 The relationship between bond short interest and CDS spread

This section provides evidence of the relationship between *CDS* spreads and bond short interest. We use the following general panel model specifications to test the relationship between the one-month ahead monthly 5-year *CDS* spread of a firm and the current month bond short interest:

$$CDS\_SPREAD_{i,t+1} = \beta_0 + \beta_{SS}BONDSS_{i,t} + \sum \beta_X X_{i,j,t} + \beta_Y Y_t + \varepsilon_{i,t+1}, \qquad (4.1)$$

where $t$ is a month from 2006 to 2020; $CDS\_SPREAD_{i,t}$ is the 5-year *CDS* spread of a sample firm $i$ at the end of month $t+1$; $BONDSS_{i,t}$ is the value-weighted average of the daily bond short interest scaled by the bond offering amount and aggregated for each firm $i$ in month $t$. $X_{i,t}$ represents vectors of firm-specific fundamental control variables. $Y_t$ controls for the macro-financial factors that may affect credit spreads over time. $\varepsilon_{i,t+1}$ represents i.i.d. standard normal errors. While we include all the possible determinants of CDS spreads, the model may omit unknown firm characteristics. To address this concern, we include the firm-fixed effect to control for the influence of time-invariant firm-specific factors. We also include time-fixed effects (year-month fixed effects) in our models to account for biases from time-varying unobservable factors across firms and control for entity-specific factors that remain constant over time. Finally, we cluster standard errors at the firm and the time level to account for cross-sectional and serial correlation in the error terms (Petersen, 2009).

Table 4-2 reports the main regression results examining the impact of bond short seller information on 5-year *CDS* spread. The first column shows the relationship between the firm bond short interest in month *t* and the 5-year CDS spread in month *t+1* without controlling for other determinants and with firm and time-fixed effects. The second column introduces several firm-level fundamental and macro-financial variables as controls. We include the time and industry fixed effects based on SIC2 codes for industry classification. In the third column, we include only the firm-fixed effects. Finally, we include all the firm- and time-fixed effects in column four, which we use as our main specification for subsequent analyses. When we use a model specification with time-fixed effects, macro-financial variables, which have identical values for all firms over time, are absorbed by the time-fixed effect. We find that coefficients on bond short interest are positive and significant at the 1% level across all the models. The results support our conjecture that a firm's *CDS* spreads reflect the information in its bond short interest, which are not transmitted to *CDS* spread through firm-level fundamental variables and macro-financial variables, as we explicitly control for all these factors in the models. [30]

Our results are also economically significant. We calculate the economic significance of our findings by estimating the expected change in *CDS* spread due to a one standard deviation change in the firm-level bond short interest. Based on the *BONDSS* estimate, a one percentage point increase in bond short interest raises the CDS spread by around 5.4%. Given that the average CDS spread of the sample firms is 156 basis points, a one standard deviation increase of *BONDSS* (about 2.28 percentage points, see Table 4-1) is associated with a 19.21 basis points (19.21 = 5.4% × 156 × 2.28) increase of CDS spread. This increase is around 12%

[30] When employing the Fama-Macbeth regression approach with Newey-West standard errors and incorporating three lags to address potential autocorrelation, our findings remain qualitatively consistent.

**Table 4-2: The Relationship between Bond Short Interest and 5–Year CDS Spread**

This table presents the results from the panel regression of the one-month-ahead 5-year CDS spread (*CDS5*) for firm *i* at the end of month *t*. *BONDSS* is the value-weighted average (the number of bonds shorted over the bond offering amount) of the daily short interest of all the bonds of firm *i* in month *t–1*. The sample period is from Feb 2006 to Dec 2020. We use firm fundamental variables (*SIZE; LEVERAGE; TANGIBILITY; CASH; ROA; MTB; TOBIN Q*) as the control variables, and b) macro-financial variables (*TSYIELD1, TSSLOPE, MKTRET and VIX*) as additional controls in estimations without the time fixed effects. We winsorise continuous variables at the 1st and 99th percentile. The standard errors are clustered by firm and by date. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels. The values in parentheses are the *t-statistics* of the estimated coefficients. Variable definitions are provided in Appendix 4.A.

| | CDS5<br>(1) | CDS5<br>(2) | CDS5<br>(3) | CDS5<br>(4) |
|---|---|---|---|---|
| *BONDSS* | 0.068*** | 0.103*** | 0.052*** | 0.054*** |
| | (4.24) | (4.98) | (2.99) | (3.19) |
| *SIZE* | | –0.003*** | –0.002** | –0.001 |
| | | (–7.79) | (–2.31) | (–1.33) |
| *LEVERAGE* | | 0.031*** | 0.021*** | 0.023*** |
| | | (9.20) | (5.05) | (5.32) |
| *TANGIBILITY* | | 0.005 | 0.016** | 0.020*** |
| | | (1.58) | (2.50) | (2.97) |
| *CASH* | | 0.004 | 0.001 | 0.002 |
| | | (1.60) | (0.35) | (0.99) |
| *ROA* | | –0.138*** | –0.104*** | –0.112*** |
| | | (–4.97) | (–5.87) | (–6.46) |
| *MTB* | | –0.000** | –0.000 | –0.000 |
| | | (–2.41) | (–0.57) | (–0.52) |
| *TOBIN Q* | | –0.003*** | –0.004*** | –0.003*** |
| | | (–5.24) | (–4.96) | (–3.64) |
| *CAPEX* | | –0.003 | 0.009 | –0.005 |
| | | (–0.31) | (1.11) | (–0.60) |
| *TURNOVER* | | 0.006 | 0.013*** | 0.010** |
| | | (1.37) | (2.71) | (2.20) |
| *IVOL* | | 0.117*** | 0.065*** | 0.065*** |
| | | (13.02) | (10.08) | (10.17) |
| *MktRET* | | | –0.020*** | |
| | | | (–3.86) | |
| *TSYield1* | | | –0.075** | |
| | | | (–2.09) | |
| *TSSlope* | | | 0.068 | |
| | | | (1.18) | |
| *VIX* | | | 0.0002*** | |
| | | | (4.21) | |
| *Firm FE* | Yes | No | Yes | Yes |
| *Industry FE* | No | Yes | No | No |
| *Time FE* | Yes | Yes | No | Yes |
| *Observations* | 59,935 | 45,111 | 45,099 | 45,099 |
| *Adj.$R^2$* | 0.670 | 0.536 | 0.735 | 0.750 |

(12% = 19.21 bps / 156 bps) of the mean of the CDS spread (or in dollar terms by about $123,000 for $1 million notional CDS contract). The coefficients on control variables are qualitatively similar to previous literature and coincide with expectations. For instance, we find that a firm's CDS spread is positively related to its leverage (*LEVERAGE*) and the volatility measures (*IVOL*) and negatively related to firm asset value (*SIZE*). The results are consistent with structural models of credit risk and associated theories (Ericsson, Jacobs, and Oviedo, 2009; Merton, 1974). The other firm-level determinants of CDS spread, such as profitability (*ROA*) and growth option, i.e. *TOBINQ,* show negative and statistically significant relationship with the CDS spread as established in previous work (Bai and Wu, 2016; Ericsson, Jacobs, and Oviedo, 2009). The explanatory powers of these regression tests range between 53% and 75%, which compares well with that of Augustin and Izhakian (2020) and Ericsson, Jacobs, and Oviedo (2009).

Overall, the results from the baseline model show that the bond short interest and CDS spread are positively associated. These findings suggest that CDS buyers perceive short bond interest as an indicator of significant risk associated with the underlying firm, and they consequently incorporate this information with higher CDS spreads.

## 4.4 Robustness Tests

### *4.4.1 Alternative Measures of CDS Spread and Bond Short Interest*

The results in the previous section suggest a positive relationship between bond short-interest and *CDS* spreads. We test the reliability of our results using alternative measures of CDS spread and bond short interest, as well as introducing additional control variables in the baseline regression equation (4.1). We use three sets of alternative measures for the main dependent (*CDS5*) and independent variable (*BONDSS*) in our baseline results of Table 4-2 and one set of tests with additional control variables. All the results are reported in Table 4-3. Panel A shows the baseline results with alternative measures of 5-year *CDS* spread as the dependent variables. Column 1 shows the baseline results with the natural logarithm of the 5-year CDS spread (*Ln(CDS5)*) as the dependent variable. In column 2, we use the monthly average of CDS spread (*CDS5_AVG*) as the dependent variable in the baseline regression. We find that the relationship between the *BONDSS* and the alternative measures of the 5-year *CDS* spread is positive and statistically significant at the 1% level. In columns 3 and 4, we use *CDS* spreads of other tenors as the dependent variable. We use *CDS* spreads of 3-year (*CDS3*) and 10-year tenors (*CDS10*), recorded at the end of the month *t+1,* as the alternative dependent variables. Similar to our baseline results, we observe a strong positive relationship between *BONDSS* in month *t* and the one-month ahead *CDS* spreads of 3-year and 10-year.

In our second set of robustness tests in Panel B of Table 4-3, we employ various alternative measures of bond short interest in the baseline regression. *First*, we use a firm-level value-weighted average of the dollar value of the shorted bonds (*BONDSS_VALUE*) as the main independent variable (Column 1). *Second*, we use firm-level bond utilisation (*Utilisation*) as the main proxy for bond short selling. The utilisation measures the number of bonds lent out for short selling as a percentage of the total quantity available for bond lending. It incorporates the demand and supply side of the bond lending market. To determine the monthly firm-level measure of bond short interest utilisation, we aggregate the value-weighted bond level utilisation value of a firm's shorted bonds each month. The value weights are the offering amount of the shorted bond divided by the sum of the offering amounts of all the shorted bonds of the firm. Third, we use the bond short interest value (*BONDSS_Max)* of the bond that is shorted most among all the bonds issued by a firm each month. *Finally*, we use the equal-weighted bond short interest (*BONDSS_EW*) as the main independent variable. It is calculated as the average of the bond short interest (quantity of bond short interest scaled by the bond offering amount) of a firm's bonds in each month *t*. Overall, we find that our main results are robust to using the alternative measures of bond short interest.

#### *4.4.2 The Role of Equity Short Selling and Option Markets*

Debt and equity both represent claims on the same firm, but debt investors hold a priority in terms of claims. As suggested by Asquith et al. (2013), if investors possess negative information about the firm, they may choose to short-sell stocks instead of bonds due to the higher priority of claims for debt investors. Investors can also express negative views about the firm through put options trading, which is often seen as an alternative to short-selling underlying stocks (Danielsen and Sorescu, 2001; Figlewski and Webb, 1993; Grundy, Lim, and Verwijmeren, 2012). Hence, it is essential to investigate whether bond short sellers are merely substitutes for stock short sellers and put option investors. If bond short sellers are substitutes, they may only convey information from stock short sellers and put option investors to CDS pricing. Conversely, if bond short sellers possess additional information compared to stock short sellers and put option investors, it should significantly impact the CDS spreads.

Duong, Kalev, and Tian (2023) demonstrated that short selling in the corporate bond market provides an independent platform for investors to express their differing opinions regarding bond-specific news and information, not just a substitute for equity short selling and options trading. If bond short sellers possess credit market-relevant news and information, it will likely affect CDS spreads. In this section, we build on their research by investigating whether bond short sellers carry such additional news and whether their activity affects the

CDS spread independently of equity short sellers or put options traders. We address this question by running two baseline regression models after controlling for shorting in stocks of the firms and put options volume separately.

First, we import the stock short-selling data from the Compustat database. It provides information on stock short interest across the New York Stock Exchange, American Stock Exchange, and NASDAQ. The stock short-selling data are published on two dates in a month — the 15$^{th}$ of each month and at the end of the month. For each firm, we calculate the equity short interest as the number of short positions scaled by the total number of common shares outstanding from CRSP as of the end of the month. Our main measure of stock short selling is the average of the stock short interest data published in mid-month and scaled by the shares outstanding at the end of the month (*STOCK_SS*). The average *STOCK_SS* in the sample is 3.97%, with a median value of 2.14%, comparable to those reported by Engelberg, Reed, and Ringgenberg (2018).

We run the baseline regression with *STOCK_SS* as an additional control variable. Column 1 of Panel C in Table 4-3 shows that the relationship between the *CDS_SPREAD* and *BONDSS* holds strongly even after controlling for the stock short interest. This indicates that bond short sellers possess information that is additional to stock short sellers' information.[31] The stock short interest variable is also positively related to *CDS* spread, consistent with the results obtained by Griffin, Hong, and Kim (2016). One possible reason for this result may be

[31] For a robustness check, we also use the stock short interest at the end of the month scaled by shares outstanding for each firm in a month (*STOCK_SS_LAST*). The un-tabulated results are qualitatively similar to the main results. We also find that the results are strong and consistent across the full sample, investment grade and speculative grade subsamples.

that short sellers in both debt and equity markets express similar views about the underlying firm.

Next, we import the put options volume data from the OptionMetrics dataset. To match the main dataset with the OptionsMetrics dataset, we use the linking file between OptionsMetrics and CRSP provided by WRDS. The file links option SECID to CRSP_PERMNO, the main firm-level identifier in our main sample. We find that all 648 firms in our main sample have put options at some point in the time frame of the sample, except for 79 firms which do not have options at any point in time. Our main variable of interest is the average daily volume of put options of a firm in a month scaled by the total monthly traded volume of the underlying stocks obtained from the CRSP dataset following Roll, Schwartz, and Subrahmanyam (2010). The results in column (2) of Panel C of Table 4-3 show no evidence that the put options trading reduces the impact of bond short selling information on the *CDS* spread. The coefficient estimates for the firm-level bond short interest (*BONDSS*) over the full sample are significant at the 1% level. The coefficient of put options volume is also positive but statistically insignificant for the sample. [32]

Our results imply that firm-level bond short selling is not simply a substitute for equity short selling or put options trading. These findings are also consistent with Hendershott, Kozhan, and Raman (2020) who show that bond short sellers' information predicts bond returns independently of the informational role of short selling in stocks.

[32] We also use total volume of all the options, ratio of monthly call and put option volume, monthly open interest for put options as alternative control variables for put option volume in baseline regression. The (unreported) results are qualitatively similar to the one observed in column 2 of Panel C of Table 4-3.

#### *4.4.3 Persistence in CDS Spread*

The CDS spread could be quite "sticky", especially around the dates when the firm borrows loans (Demiroglu, James, and Velioglu, 2022). This may lead to biased estimates and incorrect statistical inferences. To allay concerns about the CDS spread stickiness impacting the CDS spread-*BONDSS* relationship, we use one-month and two-month lagged values of CDS spread denoted as *CDS_lag1* and *CDS_lag2*, respectively. Our results in Column 3 show that the relationship between the CDS spread and *BONDSS* remains strong even after controlling for the lagged values of CDS spreads.

#### *4.4.4 Bond and Stock Risk and Return Variables*

Finally, we include several variables to control for the firm's equity and bond pricing from CRSP and TRACE-FISD datasets, respectively. The vector of market pricing of stock variables includes average monthly stock returns in the previous 36 months (*Stock_Ret*), minimum monthly stock returns in the previous 36 months ($Stock\_Ret_{MIN}$), volatility (standard deviation) of monthly stock returns in the previous 36 months (*Stock_Volatility*). The bond pricing variables are first value-weighted using the weight as an individual bond offering amount scaled by the total offering amount of bonds issued by a firm each month. Then, these variables are aggregated for each firm in each period. The variables are firm-level bond returns in the previous 36 months (*Bond_Ret*), firm-level minimum monthly bond returns in the previous 36 months ($Bond\_Ret_{MIN}$) and firm-level bond returns volatility (standard deviation) of monthly firm-level bond returns in the previous 36 months (*Bond_Volatility*).

The coefficients of *Stock_Ret* and *Bond_Ret* are negatively and strongly related to CDS spread, consistent with the Merton Model suggesting a negative relationship between a firm's market value of equity and its probability of default. The coefficients of *Bond_Volatility* and

**Table 4-3: Robustness Checks**

This table presents three sets of robustness tests of the main results. Panel A presents the baseline regression of Table 4-2 using alternative measures of CDS spread. In Models 1 and 2, we use the natural logarithm of the 5-year CDS spread (ln(CDS5)) at the end of the month and the monthly average of the daily CDS spread (CDS5_Avg) as the dependent variable. Models 3 and 4 present the baseline regression results in Table 4-2 with the dependent variable as the end-of-month CDS spread of tenor 3 years (*CDS3*) and 10 years (*CDS10*). Panel B presents the baseline results of Table 4-2 with alternative measures of firm-level bond short interest as the main independent variable — model 1 uses the value-weighted average (the number of bonds shorted over the bond offering amount) of the daily dollar value of short interest (*BONDSS_VALUE*) of all the bonds of firm i at the end of month t-1; Model 2 uses the value-weighted average of the '*UTILISATION*', which measures the quantity of bond that is lent out for short-selling as a percentage of the total quantity available for bond lending; Model 3 uses the maximum value among all the shorted bonds of a firm in a month (BONDSS_Max); Model 4 uses the firm level equal-weighted bond short interest (BONDSS_EW). The results in Panel C present the baseline regression with additional controls. In Model 1, we include the *STOCKSS* variable, the short-selling position of a firm's stock at the end of the month *t-1*. Model 2 includes *PUTOPTIONS_Volume* as an additional control variable, which is the monthly traded volume of put options divided by the total trading volume of the underlying stock in a month. Model 3 includes the one-month (*CDS_lag1*) and two-month (*CDS_lag2*) lagged values of the 5-year CDS spreads. In Model 4, we include several control variables related to the return and volatility of stocks and bonds of the firms in the sample. These include average monthly bond (*Bond_Ret*) and stock (*Stock_Ret*) returns, the volatility (standard deviation) of monthly bond returns (*Bond_Volatility*) and stock returns (*Stock_Volatility*) in the previous 36 months, the minimum monthly bond returns ($Bond\_Ret_{MIN}$) and shares returns ($Stock\_Ret_{MIN}$) in the previous 36 months. We also include each firm's earnings volatility (Earning_*Volatility*), the standard deviation of quarterly earnings in the previous 5 years. The sample period is from Feb 2006 to Dec 2020. All the models include firm and time-fixed effects. We winsorise continuous variables at the 1st and 99th percentile. The standard errors are clustered by firm and by date. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively. The values in parentheses are the t-statistics of the estimated coefficients. Variable definitions are provided in Appendix 4.A.

| Panel A: Alternative Measures of CDS Spread | | | | |
|---|---|---|---|---|
| | ln(CDS5) | CDS5_Avg | CDS3 | CDS10 |
| | (1) | (2) | (1) | (2) |
| *BONDSS* | 1.736*** | 0.055*** | 0.042** | 0.064*** |
| | (3.65) | (3.26) | (2.44) | (3.63) |
| *Firm Controls* | Yes | Yes | Yes | Yes |
| *Firm FE* | Yes | Yes | Yes | Yes |
| *Time FE* | Yes | Yes | Yes | Yes |
| *Observations* | 45,099 | 45,099 | 37,811 | 37,811 |
| *Adj.$R^2$* | 0.829 | 0.755 | 0.711 | 0.780 |

| Panel B: Alternative Measures of Bond Short Interest | | | | |
|---|---|---|---|---|
| | CDS5 | CDS5 | CDS5 | CDS5 |
| | (1) | (2) | (3) | (4) |
| *BONDSS_Value* | 0.036** | | | |
| | (2.29) | | | |
| *Utilisation* | | 0.026*** | | |
| | | (5.43) | | |
| *BONDSS_Max* | | | 0.022*** | |
| | | | (3.79) | |
| *BONDSS_EW* | | | | 0.053*** |
| | | | | (3.09) |
| *Firm Controls* | Yes | Yes | Yes | Yes |
| *Firm FE* | Yes | Yes | Yes | Yes |
| *Time FE* | Yes | Yes | Yes | Yes |
| *Observations* | 45,099 | 45,099 | 45,099 | 45,099 |
| *Adj.*$R^2$ | 0.749 | 0.755 | 0.757 | 0.750 |

| Panel C: Additional Controls | | | | |
|---|---|---|---|---|
| | CDS5 | CDS5 | CDS5 | CDS5 |
| | (1) | (2) | (3) | (4) |
| *BONDSS* | 0.040** | 0.056*** | 0.011** | 0.034** |
| | (2.41) | (3.27) | (2.20) | (2.36) |
| *STOCKSS* | 0.051*** | | | |
| | (5.33) | | | |
| *PUTOptions_Volume* | | 0.056 | | |
| | | (0.90) | | |
| *CDS_lag1* | | | 0.688*** | |
| | | | (21.43) | |
| *CDS_lag2* | | | 0.067*** | |
| | | | (3.16) | |
| *Bond_Ret* | | | | -0.481*** |
| | | | | (-4.73) |
| *Bond_Ret*$_{MIN}$ | | | | 0.006 |
| | | | | (0.65) |
| *Bond_Volatility* | | | | 0.201*** |
| | | | | (5.24) |
| *Stock_Ret* | | | | -0.253*** |
| | | | | (-8.24) |
| *Stock_Ret*$_{MIN}$ | | | | 0.000 |
| | | | | (0.07) |
| *Stock_Volatility* | | | | 0.081*** |
| | | | | (4.32) |
| *Firm Controls* | Yes | Yes | Yes | Yes |
| *Firm FE and Time FE* | Yes/Yes | Yes/Yes | Yes/Yes | Yes/Yes |
| *Observations* | 43,027 | 44,395 | 44,484 | 44,976 |
| *Adj.*$R^2$ | 0.760 | 0.750 | 0.940 | 0.787 |

*Stock_Volatility* are both positive and statistically significant. This is again consistent with the Merton (1974) model, which suggests that the higher asset volatility, proxied by stock and bond return volatility here, will lead to a greater probability of default or higher credit spread. Overall, the results in Panel C show that the relationship between CDS spread and bond short interest is robust even after including several additional control variables.

### 4.5 Endogeneity Tests

In sections 4.3 and 4.4 of our analysis, we observe a positive correlation between bond short interest and CDS spread after controlling for firm-specific and macro-financial variables, employing a one-month-ahead CDS spread, and incorporating firm and time-fixed effects. However, it is important to acknowledge that endogeneity may influence this relationship since the underlying credit risk of the firm primarily drives both strategies. Firstly, the actions undertaken by CDS investors may exert an influence on the observed relationship between bond short interest and CDS spreads. Secondly, common factors affecting both variables, such as overall market conditions or firm-specific characteristics, introduce the possibility of endogeneity. Thirdly, information asymmetry is an important consideration, as short interest in bonds may indicate private information that impacts both bond short interest and CDS spreads. Lastly, the market dynamics, including liquidity or market sentiment changes, may contribute to endogeneity concerns. Addressing these concerns necessitates adopting appropriate econometric techniques, such as instrumental variable approaches and panel regression methods, to mitigate endogeneity biases.

To address the endogeneity concerns, we employ two methods – matched sample analysis and the instrumental variable method developed by Lewbel (2012). In matched sample analysis, we test the CDS spread and bond short interest relationship only for the firms with similar characteristics, i.e. the matched sample. We use propensity score matching (PSM) to select firms with similar financial characteristics. The PSM approach helps to strengthen the validity of our findings and provides more robust evidence for drawing conclusions. We first classify the firms into two groups based on high and low firm-level bond short interest each month based on the median value of the bond short interest. We then estimate the probability of the firms being assigned under high- or low-bond short interest groups using a logit regression with all firm-level variables as specified in the baseline regression in equation 4.1 and use propensity scores to match the firms in the high-bond short interest group to the nearest firm in the low bond short interest group.[33] The firms that do not get any match in a month are removed from the sample. We are left with 23,498 observations in the matched sample, which consists only of firms with similar financial characteristics. We rerun our baseline regression for the matched sample. The results are shown in column 1 in Table 4-4. The relationship between the firm-level bond short interest and the CDS spread is also strong and positive for the matched sample.

Next, we utilise the instrumental variable (IV) approach introduced by Lewbel (2012) to address endogeneity concerns in our analysis. This methodology, employed in several recent finance research papers (Anderson and Core, 2018; Chen et al., 2021; Hasan, Lobo, and Qiu, 2021; Mavis et al., 2020), does not rely on external instruments. Instead, it leverages the heterogeneity in the error term of the first-stage regression to generate instruments from within the existing model. Our study applies this internal IV method to estimate the relationship

[33] We use the propensity score to perform one-to-one nearest-neighbor-matching method without replacement along with caliper matching using a caliper of 10%. This algorithm excludes all matches where the distance is above 10% by imposing a maximum propensity score distance of 10%.

between the instrumented *BONDSS* and the CDS spread. We find that the instrumented *BONDSS* using Lewbel (2012) estimation method continues to be positively and significantly associated with the CDS spread ($p < 0.01$), as shown in Column 2 of Table 4-4. In addition, we find that the *Cragg-Donald Wald F-statistic* (weak-identification test) yields a value of 3,108, which indicates a strong instrument relevance in our analysis.

**Table 4-4: Heteroskedasticity-based instrumental variable (IV) analysis and Matched Sample Analysis**

This table presents two sets of results to tackle the endogeneity issue. The results in Column 1 are based on the matched sample constructed using the propensity score matching method. The results in Column 2 are based on the instrumental variables (IV) estimation using heteroskedasticity-based instruments based on Lewbel (2012). The variable instrumented is the bond short interest (*BONDSS).* CDS5, the main dependent variable, is the 5-year CDS spread for firm *i* at the end of month *t*. The sample period for both the models is from Feb 2006 to Dec 2020. We use two sets of control variables: a) firm fundamental variables (*SIZE; LEVERAGE; TANGIBILITY; CASH; ROA; MTB; TOBIN Q*), and b) macro-financial variables (*TSYIELD1, TSSLOPE, MKTRET and VIX*) in estimations without the time fixed effects. We winsorise continuous variables at the 1st and 99th percentile. The standard errors are clustered by firm and by date. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels. The values in parentheses are the *t-statistics* of the estimated coefficients. Variable definitions are provided in Appendix 4.A.

| | Matched Sample | Lewbel (2012) IV Analysis |
|---|---|---|
| | CDS5 | CDS5 |
| | (2) | (2) |
| *BONDSS* | 0.032** | |
| | (2.57) | |
| *Instrumented BONDSS* | | 0.093*** |
| | | (2.83) |
| *Firm Controls* | Yes | Yes |
| *Macro-Financial Controls* | Yes | Yes |
| *Firm FE* | Yes | No |
| *Time FE* | Yes | No |
| *Observations* | 23,486 | 42,528 |
| *Adj.$R^2$* | 0.776 | 0.464 |
| *Under-identification Test:* | | |
| *Kleibergen-Paap rk LM statistic* | | 42.528 |
| *Weak instrument test:* | | |
| *Cragg-Donald Wald F statistic* | | 3,108 |
| *Stock-Yogo (2005) crit. Val* | | 21.18 |

### 4.6 Time-Series and Cross-Sectional Variations

Having documented a robust relationship between bond short selling and future CDS spreads in Sections 4.3-4.5, we examine this relationship's time series and cross-sectional variations.

#### *4.6.1 Impact of Natural Disasters on the CDS Spread and Bond Short Interest Relation*

In this section, our main focus is to examine the impact of natural disasters on the relationship between bond short interest and CDS spread. We anticipate that natural disasters will reduce the availability of bonds for shorting in the market. This reduction stems from a decrease in the supply of bonds for shorting, attributed to insurance companies recalling their bonds on loans and liquidating them to meet insurance claims following the disasters. Based on this premise, there may be two possibilities. The first possibility suggests that the diminished bond supply may lead to diminished information in the bond short-selling market, weakening information transmission for CDS investors. This effect is expected to be particularly pronounced during the periods following the disasters.

Additionally, we anticipate that the weakened information transmission will be more significant in states not directly affected by the disasters during the disaster periods. We test this hypothesis in two steps. The other possibility could be the opposite, wherein if the supply of bonds to be shorted reduces on account of natural disasters, only short sellers with really high conviction will continue shorting. Thus, a bond short could become more informative. Hence, the impact of natural disasters on the information content of a bond short is an open empirical question.

In the first step, we investigate whether natural disasters impact the demand for short-selling corporate bonds and the availability of bonds for short-selling from lenders or beneficial owners. Notably, insurance companies, which constituted approximately 28% of the total outstanding corporate bonds as of 2019, are one of the largest institutional investors in the corporate bond market (Foley-Fisher, Gissler, and Verani, 2019). Given their buy-and-hold investment strategy, insurance companies naturally serve as major lenders of corporate bond securities. However, natural disasters decrease corporate bond ownership by insurance companies as they sell off their holdings to fulfil insurance claims. The adverse effects of these disaster shocks often lead to fire-sale scenarios that can persist for several months (Butler, Gao, and Uzmanoglu, 2023; Massa and Zhang, 2021). As a result, the available supply of corporate bonds for short selling is expected to decrease due to the diminished ownership by insurance companies. Consequently, this reduction in bond supply can lead to declining demand for short selling.

We test this conjecture by running the panel regression analysis similar to equation (4.1) with bond short supply and the bond short interest as the main dependent variables and natural disaster period as the main independent variable. We utilise 12 natural disasters that led to the largest insured damages (please see Appendix 4.B) during our sample period as an exogenous shock to bond short supply and consequently to bond short interest. We define a *Disaster_Dummy* variable that equals 1 if the period of the sample is within 6 months after the start date of a disaster and 0 otherwise. The bond short supply (*BONDSS_Supply*) is measured as the aggregate of value-weighted (offering amount divided by the sum of the offering amounts of all the bonds by the firm in month $t$) bond inventory quantity (supply) of all the bonds of firm $i$ in month $t$. The bond inventory quantity is measured by the current inventory available from beneficial owners, specifically the bonds held by lenders that can be used for short selling. We include the state-fixed effects to account for any state-specific factors or characteristics that may influence the relationship being analysed. Given its high collinearity with time-fixed effect dummies, we do not include the time-fixed effects in this analysis as it absorbs the *Disaster_Dummy* variable.

The results of the first step are shown in Panel A of Table 4-5. The results in columns 1 and 2 are for the full sample. We find that the *Disaster_Dummy* is negatively related to both *BONDSS* (Column 1) and *BONDSS_Supply* (Column 2). Given the possibility of lower valuations of bonds issued by firms headquartered in disaster-affected states, it is plausible that investors exhibit reluctance to sell such bonds during the disaster period. Consequently, we anticipate a higher bond short-supply reduction for firms in these states. To investigate this, we replicate the analysis from columns 1 and 2 using a subsample of states unaffected by disasters in the past six months, and the results are presented in columns 3 and 4. We observe a substantially stronger relationship between bond short supply (Column 4) within this subsample. Overall, we find a reduction in the supply of the bonds available for shorting and, hence, a reduction in the bond short interest following natural disasters.

In the next step, we investigate the impact of the reduction in the bond short-selling market on CDS spread due to natural disasters. On the one hand, the overall reduction in the bond short selling can lead to reduced information amongst the bond short sellers and, hence, lower information transferred to the CDS market. On the other hand, the bond short sellers with high conviction may continue shorting, thus making them more informative for CDS investors. We run the baseline regression for two subsamples based on the natural disaster period and the impacted states to answer this open empirical question. The results are shown in Panel B of Table 4-5. In the first subsample analyses, we divide the sample based on disaster (*Disaster_Dummy =1*) and non-disaster periods (*Disaster_Dummy =0*). The coefficient of

*BONDSS* is weakly related to CDS spread for the subsample of the disaster period (Column 1). On the other hand, the coefficient of the *BONDSS* is quite strongly related to the CDS spread during the non-disaster period (Column 2).

There is a possibility that the CDS spreads of firms located in states affected by natural disasters may also be influenced during the disaster period. To obtain a subset of firms whose CDS spreads are less likely to have been affected by the natural disaster during the disaster

**Table 4-5: Bond Short Interest and CDS Spread: Natural Disaster vs. Non-Natural Disaster Periods**

This table presents the results from regressions that investigate the influence of large natural disasters (exogenous shocks to the bond short interest) on the bond short interest (*BONDSS*) and CDS spread (*CDS5*). We identify 12 large natural disasters between 2008 and 2020 based on their insured losses (please see Appendix 4.B for the list of disasters). *Disaster_Dummy*, a dummy constructed to proxy for the disaster periods, equals 1 if the sample period is within 6 months after the start date of a disaster and 0 otherwise. In the first step (Panel A), we investigate the impact of natural disasters on the supply of bonds available for shorting from the beneficial owners (*BONDSS_Supply*) and the *BONDSS*. Columns 1 and 2 present the results for the full sample, while Columns 3 and 4 focus on a subsample excluding observations from states affected by the disaster within the last 6 months. In the next step (Panel B), we assess the impact of natural disasters on the CDS spread and *BONDSS* relation. Column 1 provides results for the subsample when a natural disaster occurred within the last 6 months, while Column 2 pertains to the period without any recent natural disasters. In Column 3, we analyse a subsample that includes observations exclusively from states that experienced a disaster in the past 6 months. Finally, Column 4 presents results for a subsample of states unaffected by disasters in the past 6 months. The sample period is from Feb 2006 to Dec 2020. We use two sets of control variables: a) firm fundamental variables (*SIZE; LEVERAGE; TANGIBILITY; CASH; ROA; MTB; TOBIN Q*), and b) macro-financial variables (*TSYIELD1, TSSLOPE, MKTRET and VIX*) in estimations without the time fixed effects. All the models in Panel B include firm, state and time-fixed effects. We winsorise continuous variables at the 1st and 99th percentile. The standard errors are clustered by firm and by date. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels. The values in parentheses are the *t-statistics* of the estimated coefficients. Variable definitions are provided in Appendix 4.A.

| **Panel A: Impact of Natural Disasters on Demand and Supply of Bond Short Selling** | | | | |
|---|---|---|---|---|
| | Full Sample | | States unaffected by Disaster in last 6 months | |
| | BONDSS | BONDSS_Supply | BONDSS | BONDSS_Supply |
| | (1) | (2) | (3) | (4) |
| *Disaster_Dummy* | –0.002** | –0.008* | –0.002** | –0.010** |
| | (–2.41) | (–1.75) | (–2.49) | (–2.19) |
| *Firm Controls* | Yes | Yes | Yes | Yes |
| *Macro-Financial Controls* | Yes | Yes | Yes | Yes |
| *Firm FE* | Yes | Yes | Yes | Yes |
| *State FE* | Yes | Yes | Yes | Yes |
| *Time FE* | No | No | No | No |
| *Observations* | 45,099 | 45,099 | 42,251 | 42,251 |
| *Adj.$R^2$* | 0.442 | 0.604 | 0.449 | 0.602 |

| Panel B: Impact of Natural Disasters on relationship between CDS Spread and Bond Short Interest | | | | |
|---|---|---|---|---|
| | Disaster Period | Non-Disaster Period | States with Disaster in last 6 months | States with no Disaster in last 6 months |
| | CDS5 | CDS5 | CDS5 | CDS5 |
| | (1) | (2) | (3) | (4) |
| *BONDSS* | 0.052* | 0.054*** | –0.048 | 0.060*** |
| | (1.87) | (3.19) | (–0.94) | (3.30) |
| *Firm Controls* | Yes | Yes | Yes | Yes |
| *Firm FE* | Yes | Yes | Yes | Yes |
| *State FE* | Yes | Yes | Yes | Yes |
| *Time FE* | Yes | Yes | Yes | Yes |
| *Observations* | 12,326 | 32,768 | 1,062 | 42,251 |
| *Adj.*$R^2$ | 0.760 | 0.760 | 0.891 | 0.757 |

period, we partition the sample based on firms headquartered in the disaster-impacted states and firms unaffected by any natural disasters during the same period. We find that the coefficient of *BONDSS* is not associated with the CDS spread for the firms in the states that natural disasters have impacted in the last six months (Column 3). On the other hand, the coefficient of *BONDSS* has a strong positive relationship with the CDS spread for the firms in the states unaffected by the disasters in the last six months.[34]

Overall, this analysis shows that the exogenous shock of natural disasters lowers the informational value of the bond short interest, which eventually weakens the impact of bond short selling on CDS spread.

### *4.6.2 Impact of Bond Short Selling Fee on the CDS Spread-Bond Short Selling Relation*

In this section, we examine whether the impact of short selling on *CDS* spread is influenced by the borrowing cost (fee) of short selling. The borrowing cost can be an important economic channel through which CDS spread incorporates the impact of bond short interest.

[34] In another subsample analysis (unreported) focussed only on the states unaffected by the disasters in previous six months, we find that the *CDS-BONDSS* relationship is statistically stronger during the non-disaster period as compared to during the disaster period.

A higher borrowing fee results in higher constraints to short selling, making shorting more costly. Diamond and Verrecchia (1987) find that short selling becomes more informative when its constraints increase. Additionally, when short sellers are willing to invest in stocks despite the high short-selling fees, it reveals their confidence in the merit of their investments (Blocher, Reed, and Van Wesep, 2013; Cohen, Diether, and Malloy, 2007; Drechsler and Drechsler, 2014; Engelberg et al., 2022). Engelberg et al. (2022) find that equity loan fees are the most accurate predictors of stock market returns. This implies that equity short sellers have more information about a specific stock or company, having paid a relatively higher fee for it.

These findings from studies centred on equity markets suggest that the higher cost of short selling improves the informational value of short interest, as those willing to pay more anticipate greater benefits. We test these conclusions for the bond market and analyse whether the borrowing cost of short selling affects the impact of short selling on *CDS* spreads. Suppose short-selling information, reflected by higher fees, does not explain *CDS* spreads. In that case, we expect no significant change in the impact of bond short-selling on *CDS* spreads even when borrowing fees are higher, i.e., short-selling constraints are higher. Conversely, if *CDS* spreads respond to short selling due to its informational role, we expect to see a more pronounced effect of short selling on *CDS* spreads when borrowing fees, i.e., short selling constraints, are higher.

We use the daily cost of borrowing score (*DCBS*) to analyse the impact of the cost of borrowing on the *CDS* spread and bond short-selling relationship. DCBS, computed by Markit, is a normalised measure of the relative cost of borrowing for each bond, ranging from 1 (lowest cost) to 10 (highest cost). A DCBS value of 1 or 2 corresponds to bonds that are easiest to borrow, and the ones with a high score of 9 or 10 are most difficult to borrow. To arrive at the

**Table 4-6: Impact of Relative Borrowing Cost of Bond Shorting on CDS–Bond Short Selling**

This table presents the impact of the relative borrowing cost of bond short selling on the relationship between CDS spread (*CDS5*) and firm-level bond short selling (*BONDSS*). Markit computes a Daily Cost of Borrowing Score (*DCBS*) for each shorted bond, indicating the relative cost of borrowing a bond. We take the average DCBS value of a firm's shorted bonds monthly to determine the firm-level monthly relative borrowing cost indicator. Columns (1) and (2) show the baseline results of Table 4-2 for subsamples of the top (highest relative fee) and bottom DCBS (lowest relative fee) quartile firms, respectively. The results in column (3) show the baseline regression of Table 4-2 for the subsample having an average DCBS greater than 1 and column (4) with a subsample having a score equal to 1, respectively. The sample period is from Feb 2006 to Dec 2020. We use firm fundamental variables (*SIZE; LEVERAGE; TANGIBILITY; CASH; ROA; MTB; TOBIN Q*) as control variables. All the models include firm and time-fixed effects. We winsorise continuous variables at the 1st and 99th percentile. The standard errors are clustered by firm and by date. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels. The values in parentheses are the *t-statistics* of the estimated coefficients. Variable definitions are provided in Appendix 4.A.

| | High Fee (Top DCBS Quartile) | Low Fee (Bottom DCBS Quartile) | High Fee (DCBS >1) | Low Fee (DCBS <=1) |
|---|---|---|---|---|
| | CDS5 | CDS5 | CDS5 | CDS5 |
| | (1) | (2) | (3) | (4) |
| *BONDSS* | 0.089*** | -0.032 | 0.083*** | 0.021* |
| | (3.28) | (-1.50) | (3.01) | (1.76) |
| *SIZE* | -0.004 | 0.002 | -0.003 | -0.000 |
| | (-1.53) | (0.98) | (-1.38) | (-0.10) |
| *LEVERAGE* | 0.031*** | 0.047*** | 0.028*** | 0.019*** |
| | (3.41) | (4.66) | (3.30) | (5.20) |
| *TANGIBILITY* | 0.024** | 0.038** | 0.019* | 0.013** |
| | (2.28) | (2.73) | (1.90) | (2.47) |
| *CASH* | 0.003 | 0.009* | 0.002 | 0.002 |
| | (0.56) | (1.73) | (0.58) | (1.22) |
| *ROA* | -0.139*** | -0.098 | -0.129*** | -0.084*** |
| | (-4.45) | (-1.66) | (-4.37) | (-5.37) |
| *MTB* | -0.000 | 0.000 | -0.000 | 0.000 |
| | (-0.55) | (0.13) | (-0.43) | (0.73) |
| *TOBIN Q* | -0.009*** | -0.001 | -0.007*** | -0.002*** |
| | (-4.42) | (-0.54) | (-3.72) | (-3.94) |
| *CAPEX* | -0.001 | -0.003 | 0.003 | -0.002 |
| | (-0.07) | (-0.24) | (0.20) | (-0.33) |
| *TURNOVER* | 0.003 | 0.007 | 0.004 | 0.008** |
| | (0.22) | (0.60) | (0.35) | (2.08) |
| *IVOL* | 0.076*** | 0.002 | 0.068*** | 0.045*** |
| | (7.88) | (0.12) | (7.54) | (8.52) |
| *Firm FE* | Yes | Yes | Yes | Yes |
| *Time FE* | Yes | Yes | Yes | Yes |
| *Observations* | 8,305 | 2,059 | 10,314 | 30,164 |
| *Adj.$R^2$* | 0.803 | 0.765 | 0.814 | 0.766 |

firm-level DCBS measure, we take the mean of DCBS value for each of the shorted bonds issued by a firm in each time period.[35]

We divide the sample based on the top and bottom quartiles of *DCBS.* We ran our baseline regression based on their DCBS values for the top-quartile and bottom-most quartile firms separately. As shown in columns 1 and 2 of Table 4-6, the *CDS5-BONDSS* relationship is present only in the high fee subsample. Furthermore, the median DCBS score in the sample is 1, meaning most bonds have the lowest possible score and are easy to borrow. Therefore, as an alternative way to classify the sample, we assign it as a high fee sample if the average firm-level DCBS score is greater than 1 or classified as a low fee subsample. As shown in columns 3, the coefficient of *BONDSS* is strongly positive for the high fee subsample while weakly positive for the low fee subsample (Column 4). These results show that high-fee shorted bonds contain more information, which is eventually reflected in the corresponding *CDS* spreads of such firms.

### *4.6.3 Impact of CDS Liquidity*

In this section, we repeat the baseline regression presented in Table 4-2, but this time, we differentiate between *CDS* with low and high liquidity. We examine whether the higher credit spread of a *CDS* on account of higher bond short interest is simply a reflection of illiquidity in the *CDS* market.

Our analysis considers two contrasting scenarios. Firstly, we anticipate that in a more liquid CDS market, information conveyed by bond short sellers is more promptly incorporated

[35] There were around 10,000 missing values (26% of the total sample). We imputed the missing values with the average DCBS score which is the mean of DCBS score of a firm in that year leading to only around 2500 missing values in the sample.

into subsequent CDS spreads. This assumption stems from the notion that increased liquidity facilitates smoother and more efficient trading, thereby allowing for swifter incorporation of new information. Conversely, it's also plausible to argue that in less liquid CDS markets, bond short interest may exhibit stronger predictive power for CDS spreads. This hypothesis posits that in such markets, the impact of information from bond short sellers might be more enduring or pronounced due to slower information dissemination and trading activity. Hence, this seems to be an open empirical question.

The liquidity measurement is evaluated using Markit's composite depth score, based on quotes from a minimum of two distinct contributors for composite spread calculation for a 5-year *CDS* spread. The higher the depth score, the higher will be the liquidity of the *CDS*. We record the composite depth score of a *CDS* contract at the end of each month. We employ two measures of sorting the sample based on the depth score of CDS contracts.

First, we sort the sample based on each month's CDS liquidity value quartiles. The *CDS* in the top quartile have the highest liquidity, and the ones in the bottom have the lowest liquidity. We run the baseline regressions of Table 4-2 separately for a subsample of the firms with the highest *CDS* liquidity (TOP Quartile) and those with the lowest *CDS* liquidity (BOTTOM Quartile). The results in Columns (1) and (2) of Table 4-7 show that bond short sellers' information impact the CDS spread of CDS with high liquidity values.

Alternatively, we use Griffin, Hong, and Kim (2016) measure of dividing the sample into high and low CDS liquidity based on Markit's CDS depth score. If the depth score is less than or equal to three in a month, it is classified as the low CDS liquidity sample. On the other hand, if the depth score is higher than three, the sample is classified as the high liquidity sample in a month. The results of the regression analysis run for the two subsamples are shown in

**Table 4-7: Impact of CDS Liquidity on the CDS Spread–Bond Short Selling Relation**

This table presents the impact of CDS liquidity on the relationship between CDS spread and firm-level bond short interest. The liquidity of CDS is the month-end Markit's composite depth score for the CDS in the sample. *CDS5,* the main dependent variable, is the 5-year CDS spread for firm *i* at the end of month *t*. *BONDSS* is the value-weighted average (the number of bonds shorted over the bond offering amount) of the daily short interest of all the bonds of firm *i* in month *t-1*. Columns (1) and (2) present the baseline regression results of Table 4-2 for the top and bottom quartile subsamples based on CDS liquidity in each month, respectively. The results in column (3) show the baseline regression of Table 4-2 for the subsample having the '*CDS_Depth Score*' greater than three and the column (4) with the subsample having a score less than or equal to 3, respectively. The sample period is from Feb 2006 to Dec 2020. We use firm fundamental variables (*SIZE; LEVERAGE; TANGIBILITY; CASH; ROA; MTB; TOBIN Q*) as control variables. All the models include firm and time-fixed effects. We winsorise continuous variables at the 1st and 99th percentile. The standard errors are clustered by firm and by date. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels. The values in parentheses are the *t-statistics* of the estimated coefficients. Variable definitions are provided in Appendix 4.A.

| | High CDS Liquidity (Top CDS Depth Score Quartile) | Low CDS Liquidity (Bottom CDS Depth Score Quartile) | CDS_Depth Score > 3 | CDS_Depth Score <= 3 |
|---|---|---|---|---|
| | CDS5 | CDS5 | CDS5 | CDS5 |
| | (1) | (2) | (3) | (4) |
| *BONDSS* | 0.041** | 0.035 | 0.057*** | 0.047* |
| | (2.10) | (1.33) | (3.09) | (1.81) |
| *SIZE* | 0.000 | –0.002 | –0.001 | –0.002 |
| | (0.04) | (–1.19) | (–0.80) | (–1.31) |
| *LEVERAGE* | 0.024*** | 0.009 | 0.025*** | 0.015** |
| | (5.19) | (1.35) | (5.06) | (2.23) |
| *TANGIBILITY* | 0.020** | 0.008 | 0.022*** | 0.011 |
| | (2.55) | (0.74) | (3.35) | (0.88) |
| *CASH* | 0.001 | –0.002 | 0.002 | –0.000 |
| | (0.35) | (–0.58) | (0.92) | (–0.08) |
| *ROA* | –0.124*** | –0.044 | –0.132*** | –0.064** |
| | (–5.74) | (–1.54) | (–6.87) | (–2.27) |
| *MTB* | 0.000 | –0.000 | –0.000 | –0.000 |
| | (0.32) | (–1.64) | (–0.14) | (–1.56) |
| *TOBIN Q* | –0.004*** | –0.001 | –0.004*** | –0.002* |
| | (–4.26) | (–1.60) | (–3.81) | (–1.80) |
| *CAPEX* | 0.002 | 0.001 | –0.007 | –0.005 |
| | (0.18) | (0.08) | (–0.87) | (–0.47) |
| *TURNOVER* | 0.016*** | 0.003 | 0.012** | 0.008 |
| | (2.70) | (0.38) | (2.10) | (0.87) |
| *IVOL* | 0.085*** | 0.038*** | 0.078*** | 0.036*** |
| | (7.75) | (4.88) | (10.38) | (4.92) |
| *Firm FE* | Yes | Yes | Yes | Yes |
| *Time FE* | Yes | Yes | Yes | Yes |
| *Observations* | 11,957 | 10,283 | 31,622 | 13,442 |
| *Adj.R2* | 0.746 | 0.786 | 0.746 | 0.784 |

columns 3 and 4 of Table 4-7. Like the results in the previous two columns, the bond short interest impacts the CDS spread and bond short interest relationship for the CDSs with high liquidity.

Overall, these results show that bond short interest have a greater impact on the CDS with higher liquidity.

## 4.7 Bond Short Selling, Future Firm Performance, and Financing Costs

### *4.7.1 Firm Performance*

This section examines what firm-level information these short sellers base their trading decisions on. We try to observe possible channels that can induce the relationship between firm-level bond short interest and *CDS* spread. Specifically, we test whether the bond short sellers can predictively explain the key financial variables. We consider model specification similar to equation 4.1, with the dependent variable being defined as one of the firm-level financial variables. Dependent variables represent one quarter ahead of financial variables, and the independent variable is the firm-level bond short interest in the previous quarter. We use several financial variables such as the one-quarter-ahead leverage (*F_LEVERAGE*), value of growth options (*F_TOBINQ*), return on assets (*F_ROA*), and idiosyncratic volatility measure (*F_IVOL*).

We present the results in Table 4-8. We only report the coefficient of bond short interest variable for brevity. Firstly, a strong negative relationship exists between bond short interest and the firm's value of growth options (*F_TOBINQ*). Secondly, we find a robust and positive association between firm-level bond short interest and the idiosyncratic volatility of the firm (*F_IVOL*). Additionally, we observe a weak positive correlation between bond short interest and leverage one quarter ahead (*F_LEVERAGE*).[36] These results collectively indicate the ability of bond short sellers to predict the heightened credit risk through various financial channels.

**Table 4-8: Financial Channels Inducing the relationship between Bond Short Sell and CDS spreads**

This table presents the results to identify financial channels inducing the relationship between Bond Short Interest and CDS spreads. The regression outputs are similar to that reported in Table 4-2 with the dependent variable being one of the financial variables used as control. All the models use one quarter ahead of financial variables. *BONDSS* is the value-weighted average (the number of bonds shorted over the bond offering amount) of the daily short interest of all the bonds of firm i in month t-1. Only the *BONDSS* is presented for brevity. We show only those financial variables as independent variables, which show statistically significant association with the BONDSS for brevity. The sample period is from Feb 2006 to Dec 2020. We use firm fundamental variables (*SIZE; LEVERAGE; TANGIBILITY; CASH; ROA; MTB; TOBIN Q*) as control variables. All the models include firm- and time-fixed effects. We winsorise continuous variables at the 1st and 99th percentile. The standard errors are clustered by firm and by date. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 levels. The values in parentheses are the *t-statistics* of the estimated coefficients. Variable definitions are provided in Appendix 4.A.

| | F_TOBINQ | F_IVOL | F_LEVERAGE |
|---|---|---|---|
| *BONDSS* | –1.771*** | 0.127*** | 0.152* |
| | (-3.65) | (2.88) | (1.69) |
| *Firm Controls* | Yes | Yes | Yes |
| *Firm FE* | Yes | Yes | Yes |
| *Time FE* | Yes | Yes | Yes |
| *Observations* | 13,057 | 13,034 | 13,102 |
| *Adj.R2* | 0.818 | 0.537 | 0.807 |

### *4.7.2 Financing Costs*

We have so far examined the impact of bond short-seller information on the *CDS* spreads of the underlying firms, which is a secondary market credit instrument. In this section, we try to understand if the short sellers in the bond market provide valuable information to investors in the primary bond market and the lenders in the bank loan market. While previous studies have shown that the short sellers in the equity market provide valuable information to

[36] Our results are qualitatively similar when we run the analysis for the sample using monthly frequency data.

investors in the bond market (Kecskés, Mansi, and Zhang, 2013) and the bank loan market (Ho, Lin, and Lin, 2021; Rhee, Duong, and Vu, 2023), no such studies have been done to understand the role of bond short sellers in influencing the primary debt issuance cost of underlying firms. Kecskés, Mansi, and Zhang (2013), using a sample of publicly traded bond data over a period from 1988 to 2011, find that firms with high stock short interest have high bond yield spreads, lower credit ratings, and are more prone to credit rating downgrades. Similarly, Ho, Lin, and Lin (2021), using a difference-in-difference approach and exploiting the 2004 Securities Exchange Commission's new regulation called Regulation SHO, find that the loan spreads of the firms whose stocks are shorted under no-price-test constraints enjoy an 8.68 reduction in basis point loan spread compared to the firms whose stocks are shorted under the price-test constraint.

We first assess the impact of the bond short-seller information on the loan spread of the firm issuing those bonds. We obtained the bank loan data for our analysis from Reuters' DealScan database. The database provides data on loan characteristics, which include loan spread, loan maturity, loan size, and purpose and type of loan. We merge the loan data with firm-level bond short-selling data and firm-level accounting data from Compustat. Our final sample includes 6,753 bank loan contracts at the loan-deal level from 1,072 individual firms between Jan 2006 and July 2020. Our main dependent variable is the loan spread (*LOAN_SPREAD*), measured as the natural log of the all-in spread drawn (*ALLINDRAWN*) variable in the DealScan dataset. *ALLINDRAWN* is the amount a borrower pays in terms of basis points over LIBOR or LIBOR equivalent for each dollar drawn. We include several control variables in the panel regression, which include firm and loan-level variables. The firm-level control variables include *SIZE*, *LEVERAGE*, *TANGIBILITY*, *CASH*, *ROA*, *MTB*, *SALE_GROWTH* (growth rate of sales from two quarters before the quarter immediately before the loan inception date), *EARN_VOL* (earnings volatility which is calculated as the standard deviation of quarterly earnings in the previous five years), and *Z_SCORE*. The vector of loan characteristics includes *LN_LOANSIZE* (natural logarithm of amount of loan in US$ million), *LN_MATURITY* (natural logarithm of loan maturity in months), *DSYN* (a dummy variable which equals to one if the loan obtained by a firm in a year *t* is syndicated and zero otherwise). We use panel regression with firm-level bond short interest (*BONDSS*) as the main independent variable, vector of loan and firm characteristics as control variables and industry and year fixed effects. The firm-level bond short interest (*BONDSS*) is the main independent variable recorded in the period before but not more than one year before the loan facility start date.

Column (1) and (2) of Table 4-9 presents the results of the panel regression with all the fixed effects and firm-clustered, heteroskedasticity-robust standard errors (White 1980, Petersen 2009). We adjust standard errors for within-firm clustering because firms can obtain multiple facilities in the same loan package in a given contract year, leading to potential correlation in loan terms of the same firm. The coefficient on bond short interest at firm level (*BONDSS*) is positive and significant at 1% level without (Column 1) and with firm controls (Column 2).[37] These results show that short sellers in the bond market provide valuable information to banks thus impacting the cost of the firm's private debt. These results warrant further research on what additional information these short sellers in the bond market have, which is not privy to even banks.

[37] The results remain qualitatively similar if we exclude financial and utility companies (SIC codes in the 6000s or 4900–4999) from the sample.

Next, we examine whether the short sellers in the bond market provide valuable information to investors in the bond market. We match our firm-level bond short sample with the Fixed Income Securities Database (FISD) and firm-level characteristics from Compustat. The FISD database provides detailed information on corporate bond variables such as offering amount, offering yield, maturity date, coupon rate, treasury spread and bond credit rating. Our final sample includes 9,211 unique bond issues from 1,052 individual firms between Jan 2006 and Sep 2021. Our main dependent variable to proxy for the cost of the primary bond issuance is the *BOND_SPREAD,* measured as the natural logarithm of the difference between the yield of the benchmark treasury issue and the issue's offering yield. We include all the usual firm-level characteristics in the panel regressions as well as three bond-level control variables – *LN_BONDAMT* (natural logarithm of Bond Issuance Size in thousand US$), *LN_MATURITY* (natural logarithm of bond maturity in months) and bond rating (provided by Moody's of S&P with Aaa/AAA = 1, C/C = 21 and anything below the rating C or missing rating = 22). The firm-level bond short interest (*BONDSS*) is the main independent variable recorded in the period before but not more than one year before the bond offering date.

Columns (3) and (4) of Table 4-9 present the results of the panel regression with all the industry and time-fixed effects and firm-clustered, heteroskedasticity-robust standard errors (White 1980, Petersen 2009). The coefficient on bond short interest at firm level (*BONDSS*) is positive and significant at 1% level without (Column 1) and with firm controls (Column 2).[38] These results show that short sellers in the bond market are sophisticated investors and provide valuable information to the bond issuers.

[38] The results remain qualitatively similar if we exclude financial and utility companies (SIC codes in the 6000s or 4900–4999) from the sample.

**Table 4-9: Bond Short Selling and the Cost of New Loan and Bond Issuance**

This table presents the results of the relationship between bond short interest and the cost of new bond issues. In Models 1 and 2, the dependent variable is the natural logarithm of the loan spread. In Model 3, the dependent variable is the natural logarithm of the bond spread, which is the difference between the yield of the benchmark treasury issue and the issue's offering yield expressed in basis points. The main independent variable in all models is *BONDSS* (the value-weighted average of the daily bond short interest divided by the bond offering amount in the fiscal year before the offering date of the new bond issue). We winsorise continuous variables at the 1st and 99th percentile. All models include year and industry effects (based on SIC2 codes). Standard errors are clustered at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% levels. Variable definitions are provided in Appendix 4.A.

| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| *BONDSS* | 3.447*** | 1.909*** | 5.838*** | 2.947*** |
| | (0.687) | (0.675) | (0.845) | (0.816) |
| *LN_LOANSIZE* | | –0.039*** | | |
| | | (0.013) | | |
| *LN_LOANMATURITY* | | 0.050*** | | |
| | | (0.018) | | |
| *LN_BONDAMT* | | | | 0.158*** |
| | | | | (0.019) |
| *LN_BONDMATURITY* | | | | 0.240*** |
| | | | | (0.012) |
| *SIZE* | | –0.167*** | | –0.087*** |
| | | (0.015) | | (0.018) |
| *LEVERAGE* | | 0.718*** | | 0.081 |
| | | (0.091) | | (0.102) |
| *TANGIBILITY* | | 0.073 | | 0.249** |
| | | (0.099) | | (0.107) |
| *CASH* | | 0.039 | | 0.208*** |
| | | (0.093) | | (0.071) |
| *ROA* | | –2.345*** | | –1.042*** |
| | | (0.306) | | (0.247) |
| *MTB* | | –0.003 | | –0.003*** |
| | | (0.004) | | (0.001) |
| *Z* | | –0.009 | | –0.001 |
| | | (0.015) | | (0.011) |
| *SALE_GROWTH* | | 0.057 | | 0.046 |
| | | (0.043) | | (0.051) |
| *EARN_VOL* | | 0.031*** | | 0.014** |
| | | (0.007) | | (0.006) |
| *DSYN* | | 0.119** | | |
| | | (0.050) | | |
| *BOND_RATING* | | | | 0.118*** |
| | | | | (0.011) |
| *Industry FE* | Yes | Yes | Yes | Yes |
| *Year FE* | Yes | Yes | Yes | Yes |
| *Observations* | 6,752 | 5,229 | 6,715 | 4,200 |
| *Adj.$R^2$* | 0.305 | 0.489 | 0.357 | 0.677 |

Overall, these results provide evidence that short sellers in the bond market can influence the primary debt markets, impacting the loan offering and bond offering cost.

### 4.8 Conclusion

While extant literature provides evidence on the information role of the CDS market for price formation in corporate bonds, we provide novel evidence that short-selling corporate bonds significantly impacts the underlying firms' CDS spreads. Notably, utilizing comprehensive data on bond short selling spanning the 2006-2020 period, we demonstrate that bond short sellers possess information pertinent to participants in the credit derivative market. We specifically examine the impact of the bond short-selling activity on the subsequent level of spread of a 5-year CDS contract. We find that the bond short interest, calculated as the value-weighted bond short interest of all the bonds issued by a firm each month, has an economically and statistically significant positive relationship with the one-month-ahead CDS spread.

We analyse two primary channels that may contribute to this relationship: the borrowing fee associated with bond short interest and the short sellers' ability to predict the underlying firm's key credit risk-related financial variables. First, to assess the borrowing fee channel, we utilise the relative cost of borrowing a bond, as measured by Markit's daily cost of borrowing scores (DCBS). Our results demonstrate that bonds with high DCBS contain relatively more information and exhibit a significant and positive relationship between bond short interest and CDS spread. Second, we find that CDS spread and bond short interest become weaker during the period following the large natural disasters. Third, the bond short sellers can predict certain financial variables, such as a firm's leverage, volatility, and future growth options. Specifically, we observe that firms exhibiting higher bond short-selling activities are associated with higher idiosyncratic volatility and leverage, and lower TOBIN Q and ROA, indicating elevated credit risk profiles for such firms, which ultimately manifest in the CDS spread of the shorted firms.

The findings of this study have several implications for market participants and regulators. For market participants trading in the CDS market, the results suggest that monitoring bond short selling activity could provide valuable information to improve assessments of corporate credit risk and pricing of CDS contracts. For regulators, the predictive power of bond short selling on subsequent CDS spreads raises questions about whether greater transparency is needed in either the bond or CDS markets. More disclosure of short positions could help ensure credit risk assessments are informed by all available information. However, regulators would also need to balance transparency with concerns about front-running by other market participants. The study's implications also extend to financial firms involved in risk management and product design. For example, institutions relying on CDS spreads as an input to valuation models could potentially improve accuracy by incorporating insights from bond short selling trends. Regulators may also want to consider whether oversight of derivatives that reference CDS spreads as an underlying asset need to account for information flows between bond and CDS markets. Overall, the findings suggest multiple avenues for both market participants and policymakers to gain from increased understanding of cross-market information dynamics.

## Appendix 4.A. Variable Description

| Variables | Definitions | Source |
|---|---|---|
| | **CDS Variables** | |
| $CDS\_SPREAD_{i,t}$ | CDS spread for firm *i* at the end of month *t*. | Markit |
| | **Bond Short Selling Variables** | |
| $BONDSS_{i,t-1}$ | The aggregate of value-weighted (offering amount divided by the sum of offering amount of all the bonds by the firm in month t-1) bond short interest of all the bonds of firm i in month t-1. Bond Short Interest is proxied as the Total Demand Quantity, equal to the Total quantity of borrowed/loaned securities net of double counting. | Markit |
| DCBS | DCBS is Markit Securities Finance Daily Cost of Borrow Score; a number from 1 to 10 indicating the rebate/fee charged by the agent lender based on Data Explorer's proprietary benchmark rate, where 1 is the cheapest and 10 is the most expensive. Our proxy for the relative cost of bond shorting at the firm level is the average of DCBS of each shorted bond of a firm *i* at time *t-1*. | Markit |
| | **Stock Short Selling Variables** | |
| $STOCK\_SS_{i,t-1}$ | The average of the short selling position (the number of shares shorted over the number of shares outstanding) for firm i held on mid and end of the month t-1 | Compustat and CRSP |
| | **Firm Level Variables** | |
| SIZE | The natural logarithm of total assets is computed as ln(*atq*). This variable is measured in the quarter before the CDS spread, or loan facility start date, or bond offering date. | Compustat – North America Quarterly |
| LEVERAGE | Firm leverage, computed as (*dlttq* + *dlcq*)/*atq*. This variable is measured in the quarter before the CDS spread or loan facility start date, or bond offering date. | Compustat – North America Quarterly |
| TANGIBILITY | Fixed asset, computed as the ratio of plant, property, and equipment over total asset *ppenqt*/*atq*. This variable is measured in the quarter before the CDS spread, or loan facility start date, or bond offering date. | Compustat – North America Quarterly |
| CASH | Cash holding, computed as *cheq*/*atq*. This variable is measured in the quarter before the CDS spread or loan facility start date or bond offering date. | Compustat – North America Quarterly |
| ROA | Return on asset, computed as *oibdpq* / *atq*. This variable is measured in the quarter before the CDS spread or loan facility start date or bond offering date. | Compustat – North America Quarterly |
| MTB | Market to book ratio, computed as (*prccqxcshoq* + *dlttq* + *dlcq*)/*atq*. This variable is measured in the quarter before the CDS spread or loan facility start date or bond offering date. | Compustat – North America Quarterly |
| IVOL | Idiosyncratic Volatility is computed as the standard deviation of the difference between a firm's stock return and the CRSP value-weighted return over the past 180 days | CRSP |
| EARN_VOL | Earnings Volatility: Standard deviation of quarterly earnings (*epspiq*) in the previous 5 years. | Compustat – North America Quarterly |

| | | |
|---|---|---|
| Z_SCORE | Z score, computed as [(3.3x*piq* + *saleq* + 1.4x*req* + 1.2x(*actq* - *lctq*)]/*atq*. This variable is measured in the quarter before the CDS spread or loan facility start date or bond offering date. | Compustat – North America Quarterly |
| SALE_GROWTH | The growth rate of sales (SALEQ) from two quarters prior to the quarter immediately before the loan inception date. | Compustat – North America Quarterly |
| **Firm Credit Rating Variable** | | |
| FIRM_RATING | Average of bond level credit rating on each date for a firm. The bond level rating is Moody's bond rating. If Moody's rating is absent, we use the S&P bond rating. If both ratings are absent, then we assign a rating. The highest rating is coded as '1', and the lowest or missing rating is coded as '22'. | FISD |
| **Bond Return Variables (averaged at firm level)** | | |
| BOND_RET | The firm-level aggregate of value-weighted (offering amount divided by the sum of the offering amounts of all the bonds by the firm in month *t-1*) average monthly bond returns in the previous 36 months | TRACE/FISD |
| $BOND\_RET_{MIN}$ | The firm-level aggregate of value-weighted minimum monthly bond returns in the previous 36 months | TRACE/FISD |
| BOND_VOL | The firm-level aggregate of value-weighted volatility (standard deviation) of monthly bond returns in the previous 36 months | TRACE/FISD |
| **Stock Return Variables** | | |
| STOCK_RET | The average monthly stock returns in the previous 36 months | CRSP |
| $STOCK\_RET_{MIN}$ | The minimum monthly stock returns in the previous 36 months | CRSP |
| STOCK_VOL | The volatility (standard deviation) of monthly stock returns in the previous 36 months | CRSP |
| **Macro-Financial Variables** | | |
| MKTRET | Difference between market return and risk-free rate | Kenneth French data library |
| TSYIELD1 | 1-year constant-maturity Treasury yield | US Federal Reserve website |
| TSSLOPE | Government treasury yield Slope - difference between ten-year and two-year constant-maturity US treasury rate/yields | US Federal Reserve website |
| VIX | CBOE S&P500 Volatility Index - Close | CBOE |
| **Loan and Bond (Primary Debt Market) Variables** | | |
| LOAN_SPREAD | Natural logarithm of all-in spread drawn (ALLINDRAWN). All-in spread drawn is the amount the borrower pays in basis points over the London Interbank Borrowing Rate (LIBOR) or LIBOR equivalent for each dollar drawn down. | DealScan |
| LN_LOANSIZE | The natural logarithm of the total loan amount. | DealScan |
| LN_LOANMATURITY | The natural logarithm of the loan time to maturity (in months) | DealScan |
| DSYN | A dummy variable for syndicated loans | DealScan |

| | | |
|---|---|---|
| BOND_SPREAD | Natural logarithm of the difference between the yield of the benchmark treasury issue and the issue's offering yield | TRACE/FISD |
| LN_BONDAMT | The natural logarithm of the total bond offering amount | TRACE/FISD |
| LN_BONDMATURITY | The natural logarithm of the time to maturity (in months) for a bond | TRACE/FISD |
| BOND_RATING | Categorical variables ranging from one (AAA rating) to 21 (missing rating). We use the borrower's S&P long-term issuer rating. A smaller number indicates a higher rating. | TRACE/FISD |

## Appendix 4.B.    Natural Disasters

The information on natural disasters is sourced from the Emergency Events Database (EM-DAT), a global dataset on natural and technological disasters. In this table, we provide the list of the large natural disasters, their start dates, affected states and the amount (in billion US dollars) of insured damages. (Source: "EM-DAT, CRED / UCLouvain, Brussels, Belgium – www.emdat.be)"

| Disaster Name | Start Date | States Affected | Insured Damage (bn USD) |
|---|---|---|---|
| Hurricane Gustav | 01-Sep-2008 | Alabama, Louisiana, Mississippi, Texas | 4.76 |
| Hurricane Ike | 12-Sep-2008 | Arkansas, Illinois, Indiana, Kentucky, Louisiana, Michigan, Missouri, Ohio, Pennsylvania, Tennessee | 20.39 |
| Super Outbreak | 27-Apr-2011 | Georgia, North Carolina | 8.00 |
| Hurricane Irene | 26-Aug-2011 | North Carolina | 6.00 |
| Hurricane Sandy | 28-Oct-2012 | Connecticut, Delaware, Maine, Maryland, Massachusetts, New Hampshire, New Jersey, New York, North Carolina, Ohio, Pennsylvania, Rhode Island, Vermont, Virginia, West Virginia | 30.00 |
| Hurricane Matthew | 08-Oct-2016 | Florida, Georgia, North Carolina, South Carolina, Virginia | 6.10 |
| Hurricane Harvey | 25-Aug-2017 | Louisiana, Texas | 35.82 |
| Hurricane Irma | 10-Sep-2017 | Florida, Georgia, South Carolina | 34.62 |
| Hurricane Florence | 12-Sep-2018 | North Carolina, South Carolina, Virginia | 5.83 |
| Hurricane Michael | 10-Oct-2018 | Alabama, Florida, Georgia, Maryland, North Carolina, Virginia | 11.65 |
| Hurricane Laura | 27-Aug-2020 | Arkansas, Louisiana, Mississippi, Texas | 11.31 |
| Hurricane Sally | 11-Sep-2020 | Alabama, Florida | 3.96 |

# Chapter 5: Conclusion

This chapter outlines the four key questions this thesis addresses and the conclusions it draws for each question.

1. Does a firm's carbon risk management contain information not captured by various climate change risk indicators?
2. Does the proactive carbon risk management of firms get rewarded in the credit derivative markets?
3. How do changes in climate change regulations or investor awareness impact the relationship between a firm's carbon risk management score and its CDS spread?
4. Could CDS investors obtain value-relevant information from short selling in the bond market?

This chapter also discusses avenues for future research.

## 5.1 Does a firm's carbon risk management contain information not captured by various climate change risk indicators?

To answer this question, we assess the association of firms' carbon risk management score, i.e., CRMS, with various indicators of climate change exposure and risk available in the public domain. In particular, we use various climate change exposure measures constructed by Sautner et al. (2023) from quarterly earnings calls and the transition risk measure constructed by Kölbel et al. (2024) from their 10-K filing reports. We find that the CRMS captures incremental information not captured by the climate risk exposure measure. Furthermore, CRMS is statistically and negatively associated with the total carbon emission measure of the firms. Combining these analyses underscores the relevance and effectiveness of the carbon risk management score as a measure of climate change risk management.

Chapter 2 provides insights for investors seeking leaders in climate transition risk management by examining key risk management metrics centred on carbon risk. Previous research mostly focussed on climate risk at the firm level, missing a full picture of portfolio decarbonisation. Looking only at carbon exposures could generate an overly negative view without spotlighting proactive carbon risk managers. The little association between carbon risk management practices and climate change exposure measures indicates the possibility of valuable risk management information captured by the *CRMS* variable. It equips investors with a holistic view of transition opportunities due to climate change risk. Understanding risk and its management allows investors to identify winners amongst targets as companies serious about transitioning to low-carbon business models.

## 5.2 Does the proactive carbon risk management of firms get rewarded in the credit derivative markets?

In Chapter 3, we examine the influence of firms' carbon risk management practices on market assessment of their credit risk. Our conjecture stems from Merton (1974) framework, which implies that high carbon emissions risk could impact the credit risk of the underlying firm through multiple channels. First, disproportionate carbon emissions expose firms to regulatory risks, increasing costs and reducing cash flows. The volatility prevailing in fossil fuel prices leads to uncertainty, amplifying cash flow volatility. Second, dependency on fossil fuels significantly exposes firms to technological risk. Clean technology advancements can rapidly render carbon-intensive assets worthless or stranded. This compounds costs and risks bankruptcy, diminishing firm value. Potential consequences involve carbon taxes or early plant retirement mandates. High emissions intrinsically elevate credit risk through cash flow and asset risk factors. This suggests firms proactively addressing stated climate transition risks, mainly from carbon emissions, should see rewards in credit risk assessments.

We examine how carbon risk management impacted US firm CDS spreads from 2009 to 2018. Using Sustainalytics' proprietary data, we assessed 405 companies' practices and performance via a carbon risk management score, i.e. CRMS. CRMS incorporated 13 carbon risk preparedness and performance indicators, with higher scores denoting better management relative to peers. We find that firms with better CRMS have significantly lower future 5-year CDS spreads, the most frequently traded credit default swap. Results were also economically significant - a one standard deviation higher CRMS reduced the 5-year CDS spread by 10.31 basis points, equivalent to a 7.26% reduction in average CDS spread value.

Our findings show that stronger carbon risk management is associated with significantly lower CDS spreads. This suggests that proactive management of carbon emission risk can mitigate credit risk. The results were robust and not driven by firm-level climate exposures, leverage, or other risk factors. Furthermore, firms with better carbon risk management demonstrated lower subsequent carbon emissions, highlighting the importance of sustainable practices.

### 5.3 How do changes in climate change regulations or investor awareness impact the relationship between a firm's carbon risk management score and its CDS spread?

We examine the impact of climate change regulations and heightened investor awareness on the relationship between a firm's carbon risk management score and its CDS spread (Chapter 3). We utilise two key events - the Paris Climate Agreement and staggered US state-level climate adaptation plan, i.e., the SCAP - as quasi-natural experiments. To help address potential endogeneity in the relationship between CRMS and CDS spreads and examine the influence of climate regulation and changing risk perception, we leverage the two events as quasi-natural experiments.

Our findings indicate that CRMS has a more pronounced impact on credit spreads post-Paris Agreement. Treatment firms (high CRMS firms) exhibit significantly lower credit spreads than control firms (low CRMS firms), especially after the Paris Agreement. This finding suggests that credit markets favour firms demonstrating prudence in carbon risk management.

Similarly, we examined the impact of the staggered adoption of SCAP by 15 states on the relationship between CRMS and CDS spread. This staggered SCAP implementation heightens transition risks for firms lacking robust carbon risk management, highlighting associated costs. Employing a stacked regression approach, we find that proactive carbon risk management significantly reduces credit spreads for firms headquartered in states with formalised SCAPs. This implies that credit markets view favourably the climate change implications for firms in states with comprehensive government policies and protective plans.

### 5.4 Could CDS investors obtain value-relevant information from short selling in the bond market?

This is a pertinent question, especially considering previous research indicating that the CDS market often leads other financial markets to provide crucial information for corporate bond investors. Despite the challenges and costs associated with bond short selling, the active presence of short sellers in this market suggests compelling motives behind their behaviour. The higher expenses associated with shorting a bond directly, as opposed to purchasing a CDS, imply that short sellers may possess additional insights into the creditworthiness of underlying bonds or firms. Therefore, investors in related asset classes, such as CDS investors, may find information regarding bond short interest pertinent to their investment decisions. Under this assumption, we examined the link between bond short-selling activity and subsequent CDS spreads (Chapter 4). We find that firm-level bond short interest positively relates to one-month-ahead 5-year CDS spreads even when adjusting for various firm characteristics and macro-financial variables.

Moreover, this relationship holds economic significance - a one standard deviation increase in firm-level bond short interest results in a 19.21 basis point rise in the 5-year CDS spread, equivalent to 12% of its mean value. This underscores the informational value that bond short sellers offer to cross-market assets like CDS. Furthermore, the relationship between bond short interest and CDS spreads is present primarily in firms with higher short-selling fees and more liquid firm-level CDS contracts. Additionally, we ascertain that the impact of firm-level bond short selling on the CDS spread operates independently of the effects of equity short interest and put options volume of the underlying firms. These fundamental outcomes persist even after accounting for factors like CDS spread persistence, return, and risk variables of stocks and bonds. Overall, the findings in this chapter represent the first piece of evidence within the corporate bond short-selling literature emphasizing the value relevance of bond short-selling for cross-market assets.

### 5.5 Future Research Directions

The second chapter sets the stage for future research avenues in carbon risk management. Moving forward, it is imperative to delve into the impact of emerging green technologies and green patents across the energy value chain on carbon risk management strategies. Understanding how these innovations intersect with existing frameworks and their potential to mitigate carbon risk will be essential. Additionally, exploring the influence of investor pressure on driving improvements in carbon risk management practices presents a compelling direction for further inquiry. Analysing the mechanisms through which investors prioritize carbon risk management factors within the broader ESG factors and its translation into tangible outcomes can provide valuable insights. Furthermore, investigating the evolving regulatory landscape and its implications for carbon risk management is crucial. By assessing the effectiveness of existing regulations and identifying regulatory gaps, one can contribute to the development of more robust carbon risk management frameworks.

Next, greenwashing poses a significant challenge for regulators and investors focused on sustainability. While Chapter 3 presents evidence supporting the signalling role of carbon risk management practices, the chapter also notes the lack of a direct method for detecting greenwashing at the firm level. The absence of robust ESG regulations and standardised green taxonomies in key markets like the US exacerbates this challenge. However, future research can explore several promising avenues. One such avenue is integrating big data science and advanced machine learning techniques to detect firm greenwashing instances. The application of these methods could be instrumental in the identification and assessment of greenwashing practices. Furthermore, investigating the impact of emerging ESG regulations on firms' greenwashing behaviour and their subsequent impact on their financial performance offers an intriguing line of inquiry. Understanding how regulatory frameworks influence corporate conduct in climate transition risk management could provide valuable insights for policymakers and stakeholders.

Regarding bond short selling, Chapter 4 provides new insights into the valuable information bond short sellers possess and its potential influence in the CDS market. However, several areas warrant further research in the field of bond short selling. First, there is a need to investigate the effectiveness of bond short-selling regulations and their impact on the bond market and CDS spreads. This could involve studying the effects of regulatory measures such as short sale restrictions, disclosure requirements, or changes in margin requirements on market dynamics and price discovery. Second, a cross-market analysis is warranted to explore the interplay between bond short selling, CDS spreads, and other related markets, such as equity or options. Understanding the information transmission and trading strategies across these markets will contribute to a comprehensive understanding of overall market efficiency. Third, exploring the relationship between bond short selling and credit rating agencies' assessments is essential. This research can shed light on whether bond short sellers' information and trading activities influence credit ratings and how credit rating agencies incorporate such information into their assessments. Furthermore, investigating the behavioural aspects of bond short selling, such as the motivations and biases of short sellers, can provide a deeper understanding of their decision-making processes and influence on market outcomes. These potential areas for future research will further enhance our understanding of the informational role of bond short selling and its impact on other asset classes.

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