Do Firms Benefit from Carbon Risk Management? Evidence from the Credit Default Swaps Market

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Abstract

This paper contributes to existing climate finance literature by examining how firms' proactive management of carbon risks affects market assessment of their credit risk. Using two quasi-exogenous events involving the 2015 Paris Climate Agreement and the staggered implementation of U.S. state climate adaptation plans, we find that stronger carbon risk management is associated with significantly lower credit default swap spreads. Our results are not driven by firm-level climate exposure, and social or governance risk. Firms with better carbon risk management also exhibit lower subsequent carbon emissions. Our paper highlights the importance of carbon risk management in mitigating credit risk.

Keywords: Carbon risk management; Credit risk; Credit default swap spread; Environmental, social, and governance; The Paris climate agreement; U.S. state climate adaptation plans.

JEL Classification: G00, G01, G10, G15

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)

1. Introduction

Investors are increasingly concerned about the climate risk exposure of financial asset prices. Such concerns have led investors, financial advisers, asset managers and regulators to exert significant pressure on carbon-intensive firms to curb their carbon emissions (Krueger et al., 2020; Azar et al., 2021).[1] 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.[2] While the implications of carbon emission risk for corporate performance are generally well understood (Bolton & Kacperczyk, 2021; Duan et al., 2023; Ilhan et al., 2020), there is little evidence of the benefits of firms' 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 favorably 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

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[1] A 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 U.S. Security Exchange Commission (SEC) has 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.

[2] 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).

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, 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 & 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 favorably 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 et al., 2017; Liang et al., 2022). Unsubstantiated claims of risk management or window-dressing efforts by overzealous firms can be counterproductive as financial market participants may penalize 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 favorably assessed in the Credit Default Swap (*CDS)* market. The U.S. credit market provides a plausible setting to investigate the impact of firms' carbon risk management given its robust size ($13.9 trillion in corporate debt outstanding as of the June quarter of 2024)[3] 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, which 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 et al., 2005). *CDS* instruments are less impacted by non-default components compared to corporate bonds, which are subject to high illiquidity (Zhang et al., 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 et al., 2009).[4] 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 et al., 2019).

We investigate the importance of carbon risk management for corporate *CDS* spreads over the period from August 2009 to May 2018. We rely on the Sustainalytics database on Environmental, Social, and Governance (*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

[3] Source: https://www.sifma.org/resources/research/us-corporate-bonds-statistics and FRED.
[4] 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 et al., 2015; Ericsson et al., 2009; Finnerty et al., 2013); and (iii) improved standardization in terms of maturities, debt seniority levels, and restructuring events (Norden & Weber, 2009).

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 favorably in managing carbon transition risk relative to its peers.

We examine the impact of *CRMS* primarily on the 5-year benchmark *CDS* spreads of firms, given their higher trading frequency compared to the *CDS* of other maturities (Augustin & Izhakian, 2020; Das et al., 2014; Ericsson et al., 2009; Galil et al., 2014). Our main analysis relies on the quasi-natural experiment of the Paris Agreement of December 2015. The Paris Agreement considered the most ambitious climate agreement ever signed (Capasso et al., 2020), serves as a significant exogenous shock as it drew increased attention from financial markets to firms' climate transition or carbon risks. Consequently, the Paris Agreement led to a substantial shift in perception regarding the materiality of climate change risk and the importance of risk management within the investor community.

We perform a difference-in-differences (DiD) analysis, matching treatment (high *CRMS*) firms with comparable control (low *CRMS*) firms based on propensity score matching. We control for firm-level carbon emissions in our analysis to assess the effect of CRMS on CDS spread relative to the carbon exposure of the firm. We observe that treatment firms have significantly lower subsequent credit spreads compared to control firms, and this effect is further accentuated after the Paris Agreement. These findings indicate that the credit markets favorably assess firms that demonstrate prudence in carbon risk management.

Next, we utilize the U.S. 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 increase carbon transition risk for firms with poor carbon risk management and highlight the associated cost of transition risk. Employing a stacked regression approach (Baker et al., 2022), we find that proactive carbon risk management is related to significantly lower credit spreads for firms headquartered in states where the government has implemented climate protection policies and plans.

We further investigate the possibility of alternative explanations and assess the robustness of our findings. First, the effect of CRMS may be influenced by underlying firm-level climate risks. To address this, we condition for firm-level climate change risk exposure measures of Sautner et al. (2023), which are extracted using textual analysis of firms' quarterly earnings conference calls. Our main results remain robust even after controlling for Sautner et al.'s measures. This finding suggests that *CRMS* conveys additional information not accounted for the firm-level climate change risk variables. Second, our results may be influenced by firms' governance risks or social policies and practices, given that well-governed firms invest more in environmental and social policies (Ferrell et al., 2016). We find that firms with higher *CRMS* experience reductions in *CDS* spread after the Paris Agreement, even after controlling for governance and social risk management risk scores. Additionally, we 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 the environmental pillar have gained prominence following the Paris Agreement and are associated with reduced subsequent credit risks for the firms under study.

In the final set of analyses, we show that a higher CRSM score is negatively related to the total carbon emissions, especially following the Paris Agreement. The decline in CDS spread in the post-Paris Agreement period for firms with higher *CRMS* is also more pronounced when firms have higher carbon emissions. We also assess the role of preparedness versus performance components of CRMS in managing carbon risk. We observe a stronger and more consistent effect of the performance component of *CRMS* in reducing CDS spread after the Paris Accord.

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, and hedging of climate change news in determining firm value or returns (Amiraslani et al., 2022; Bolton & Kacperczyk, 2021, 2023; Ehlers et al., 2022; Engle et al., 2020; Görgen et al., 2020; Huynh & Xia, 2020; Kölbel et al., 2022; Monasterolo & de Angelis, 2020; Wu & Tian, 2022). We incrementally contribute to the literature by emphasizing the role of *prudent carbon emission management* by a firm on its CDS spread.

Our paper is related to three studies on carbon emissions on CDS spread or bond credit spreads. Zhang and Zhao (2022) show that higher direct carbon emissions intensity is correlated with significantly higher CDS spreads, particularly for firms with higher financial constraints. Dumrose and Höck (2023) show that better carbon-risk performance and carbon management are associated with lower credit spreads, while a higher carbon exposure is related to larger bond credit spreads. While Zhang and Zhao (2022) and Dumrose and Höck (2023) study the association between carbon emissions (and /or carbon risk management) and CDS spreads or bond credit spreads, they do not attempt to provide causal estimation. In contrast, we focus on the effect of carbon risk management using causal estimation based on a DiD approach. While previous literature evaluates the role of carbon emission in determining financial risk, we examine the incremental role of carbon risk management after controlling for the effect of carbon emissions.

Seltzer et al. (2023) find that firms with lower environmental scores, higher carbon emissions or intensities tend to have lower credit ratings and higher bond yield spreads, particularly when their facilities are located in states with stricter regulatory enforcement. While Seltzer et al. (2023) emphasize how climate regulatory risk interacts with firm environmental profile or carbon exposure in explaining bond spreads, our contribution is the focus on the incremental effect of carbon risk management after controlling for carbon exposure in explaining CDS spreads. Similar to Seltzer et al. (2023), we use the Paris Accord as an exogenous event. We further supplement this test with the US state-level regulation based on State Climate Adaptation Plans- or SCAP- as a staggered policy setting to study the impact of carbon risk management. Furthermore, while Seltzer et al. (2023) consider the overall environmental profile of a firm, we show that the effect of subset of those environmental attributes related to CRMS on credit spread is much stronger than other environmental indicators. This impact is 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 in explaining the CDS spreads.

Second, our study contributes to the extant literature on risk management by specifically 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 & Rogers, 2002), (ii) decreasing cash flow and earnings volatility (Beatty et al., 2012; Giambona et al., 2018), (iii) lowering the costs of financial distress (Campello et al., 2011; Gilje & Taillard, 2017), (iv) decreasing the cost of capital (Smith & Stulz, 1985), (v) mitigating financial constraints (Froot et al., 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 & Taillard, 2017; Pérez-González & Yun, 2013). Risk management can also lower agency costs and tail risks (Ellul & Yerramilli, 2013; Kumar & Rabinovitch, 2013). Our study extends this strand of literature by emphasizing the effects of improved carbon risk management by firms. Firms with higher *CRMS* scores demonstrate superior preparedness and performance levels in reducing carbon emissions, thus implying lower transition risks, as reflected in favorable CDS spreads.

The remaining paper is structured as follows: Section 2 describes the data and key variables used in the study. Section 3 provides the empirical results on the association between *CRMS* and *CDS* spreads. In Section 4, we present various robustness tests and channel analyses. Finally, in Section 5, we offer our conclusions.

2. Data

2.1 Carbon Risk Management Score

We utilize the Sustainalytics database on *ESG* to assess data pertaining to the carbon risk management practices adopted by firms for the period of 2009 to 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 & Xia, 2020).[5]

To evaluate an individual firm's carbon risk management impact on the credit spread, 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 59 indicators of environmental risk management practices, with 13 of them being relevant to carbon risk management, which is the primary focus of this paper. Sustainalytics provides a firm level score for each of the carbon risk management indicators, which are 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

[5] 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 organization 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.

is future-ready and well-prepared to tackle the looming carbon transition risk. A higher value also indicates that the firm has performed better in managing carbon risk relative to other firms. The *CRMS* measure is exclusively centered 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 et al., 2022; Ehlers et al., 2021).

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 that are 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.[6] 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 is comprised of both quantitative and qualitative indicators which are capturing a firm's ability to manage its carbon risk. These indicators include the relative performance of the firm in reducing its carbon intensity vis-à-vis its peers, the percentage of energy use from clean energy sources, the revenue from clean technology or climate friendly products, and the carbon intensity of 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

[6] 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.

energy company or any other type of company. Appendix A1 provides details on such management practices which constitute our measure of a firm's carbon risk management.

2.2 Credit Risk Measure

We utilize the 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 the availability of the *CRMS* data from Sustainalytics. To maintain consistency with quarterly firm-level control variables, we employ daily CDS spreads which are then averaged over each quarter.

2.3 Control Variables

In order to isolate the impact of *CRMS* on the 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 are obtained from the Compustat-North America quarterly database. We also control for firm level carbon intensity measured as the natural log of firm's Carbon Intensity Scope 1 (tons CO_2e divided by firm's revenue), sourced from S & P Trucost.

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 et al. (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 sourced from the US Federal Reserve website. Further details and data sources for all variables are provided in Appendix A2.

2.4 Sample Construction

We follow prior studies (Bai & Wu, 2016; Ericsson et al., 2009; Griffin et al., 2016) to clean the *CDS* data as follows: (1) We exclude *CDS* which are denominated in currencies other than US dollars; (2) We retain only senior unsecured obligations, as they are the most liquid trading *CDS* contracts; (3) We include only those *CDS* contracts with a modified restructuring (MR) documentation clause before April 2009 ("CDS Big Bang") and no restructuring clause afterward; (4) We exclude *CDS* contracts which have a spread of more than 10,000 basis points (Bai & Wu, 2016) to minimize any measurement errors, as such contracts are mostly illiquid due to bilateral arrangements for up-front payments; (5) We exclude any *CDS* entries that do not have an observation for *CDS* spread for any of the tenors. The resulting *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 and firm-level control variables data from the Compustat database. For each firm, we calculate quarterly averages of *CRMS* 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.[7] We exclude 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 the impact of climate change risk ion *CDS* spreads (Kölbel et al., 2024). Finally, all continuous variables are winsorized at the 1st and 99th percentile to mitigate the effect of either data errors or outliers.

2.5 Descriptive Statistics

We present summary statistics on all main variables used in the analysis in Table 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 consistent with those reported in other recent papers focusing on credit spreads (Kaviani et al., 2020; Kölbel et al., 2024).

[INSERT Table 1 HERE]

Table 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 align quantitatively with those established in previous studies. 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.[8]

[7] 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.
[8] Our bivariate correlations are qualitatively similar to those observed by Ericsson, Jacobs, and Oviedo (2009) and Augustin and Izhakian (2019).

[INSERT Table 2 HERE]

3. Empirical Analysis

3.1 Carbon Risk Management and CDS Spread - The Impact of the Paris Agreement

We analyze how the carbon risk management practices of a firm affect its *CDS* spreads. Potential endogeneity issues can however arise, for example, as some unobservable variables correlated with carbon risk management may also be important for perceived credit risks. Alternatively, financially stronger firms may be more inclined to manage their carbon risk performance effectively. Therefore, we use the Paris Agreement of 2015 as a quasi-natural experiment to examine how *CDS* spreads change after a potentially exogenous shock to the value of *CRMS*.[9] The Paris Agreement has 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 the most significant event in climate finance history as it raised the awareness of risks tied to carbon emissions, and also the potential regulatory actions to curb carbon emissions (Bolton & Kacperczyk, 2021). Indeed, following the Paris Agreement, banks began to price carbon risk in their lending decisions (Delis et al., 2024), credit ratings decline while bond yield spreads increase for firms with worse environmental performance (Seltzer et al., 2023). There is also a highly significant and large carbon premium following the Paris Agreement, which was not evident before this event (Bolton & Kacperczyk, 2023).

The 2015 Paris Agreement, therefore, serves as a major exogenous shock to firms' exposure to climate risk, especially climate transition risk or carbon risk. This event also leads to a heightened awareness of the need to undertake actions to mitigate these risks (Borsuk et al., 2024). If the Paris Agreement strengthens the effect of carbon risk on a company's default risk and increases the awareness of the importance of mitigating carbon risk, following this

[9] 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.

event, firms with better and proactive carbon risk management practices should be viewed more positively by external stakeholders and in a better position to mitigate their credit spread risk. As such, the impact of carbon risk management on *CDS* spreads should be more pronounced after the Paris Agreement.

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:

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

where we compare changes in the *CDS* spread of firms with strong carbon risk management practices versus those with poor practices. To compare the credit spreads of firms with similar characteristics, we use propensity score matching (PSM) before performing the DiD analysis. We first classify firms into *treatment (TREAT)* 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 retain only firms that are 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 1) and use propensity scores to match to the nearest control sample.[10] The variables $X_{i,t}$ and Y_t are firm specific and macro-financial (i.e. yield curve level and slope, and market return) factors, respectively. Consistent with prior studies (Bai & Wu, 2016; Bharath & Shumway, 2008), we use the natural logarithm of *CDS* spreads to mitigate the impact of outliers. *POST* is a binary dummy variable

[10] We utilize 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%.

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 (1) is $\beta^{TREAT \times POST}$ for the DiD interaction term, which captures the incremental effect on *CDS* spread for high versus low CRMS firms post the Paris Agreement. A negative and significant coefficient estimate would indicate that effective carbon risk management plays a more pronounced role in mitigating credit risk following the Paris Agreement. We also control for firm level carbon risk exposure by including Scope 1 intensity.[11] Additionally, we include firm- and quarter- fixed effects to control for any firm level and time-specific factors that could affect credit spread. 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). As a robustness check, we also consider industry fixed effects, which are based on the industry classification provided by Sustainalytics; and accordingly, we double clustered standard errors at the industry and the quarter-year level.[12]

Table 3 presents the Model (1) baseline DiD regression results. Regressions (1) and (2) consist of firm- fixed effects, while regressions (3) and (4) include industry fixed effects. Regressions (2) and (4) include quarter effects, while (1) and (2) include macro-financial variables (in lieu of time fixed effects) as controls. Firm fixed effects absorb *Treated* variable in regressions (1) and (2). Since the dummy variable *POST* is highly correlated with the quarter fixed effect dummy variable, we exclude the *POST* variable from the regression (2) and (4).

Regressions (1) and (2) indicate that the coefficient estimates for the interaction term, $\beta^{TREAT \times POST}$, is negative and significant. This implies that firms with effective carbon risk

[11] Our results are robust to absolute Scope 1 measure, and both absolute and intensity total carbon emissions– untabulated for brevity and available upon request. The carbon emissions variables are sourced from S&P Trucost (see details in Appendix 2).
[12] Results are robust when we use industry classification based on the 2-digit Standard Industrial Classification (SIC2).

management practices have a significantly higher negative relationship with subsequent *CDS* spreads in the post - Paris Agreement period. The results suggest that the superior carbon risk management firms experience lower *CDS* spreads in the post-Paris Accord period. Both regressions (3) and (4) indicate treatment firms have a lower 5-year *CDS* spread compared to control firms. The coefficient estimates for the interaction term TREAT × *POST* is negative and significant in both models, with and without quarter fixed effects.

For economic significance, we present both mean (DiD coefficient ÷ mean of the CDS spread) and sigma (DiD coefficient ÷ standard deviation of the CDS spread) shock values.[13] The average (sigma) shock value demonstrates the effect of strong CRMS scores on the credit risk post-Paris Accord relative to the mean (standard deviation) of the CDS spread. In terms of economic significance, based on regression (1) and (2) values of $\beta^{TREAT \times POST}$, CDS spreads are lower for high CRMS firms post-Paris Accord by approximately 12.3% and 11.8%, respectively with respect to their corresponding means (and 11.6% and 11.1% respectively based on their standard deviations). Similarly, based on regression (3) and (4), treated firms experience about 17% and 15.6% (16% and 14.7%) decreases in their CDS spreads respectively with respect to their respective means (standard deviations).

[INSERT Table 3 HERE]

As a robustness test for clustering, we report two additional regressions (5) and (6) with industry and quarter-year fixed effects similar to regressions (3) and (4) respectively, but standard errors clustered at the industry- and quarter-year level; we find that our results remain robust. As an additional test for endogeneity, to better control for quarter effects specific for each industry, we further implement the baseline DiD model using industry × quarter fixed effects, with and without firm effects. The results presented in IA-Table 1 (in the Internet Appendix). We find that the baseline Table 3 results hold. We also consider a cross–sectional

[13] We follow the approach used in Berger, Roman and Sedunov (2023).

regression in which all variables are averaged across time at the firm level using the average time-series values of credit spreads, CRMS, and other control variables at the firm level. IA-Table 1 shows that the negative relation between CRMS and credit spreads still holds.

Overall, our results imply that the Paris Agreement has led *CDS* markets to view firms with high carbon risk management performance more positively. Firm level carbon risk management was favorably interpreted in the credit markets following the increased attention to climate risk from investors and regulators in the post-Paris Agreement era. Our results suggest that firms' credit risk management is viewed favorably by credit markets after Paris Accord.

3.2 Test for Change in CDS Spread Around the Paris Agreement

We next interact the dummy variable for *treatment* firms (*TREAT*) with dummy variables for pre- and post- the Paris Agreement, following the model below:

$$ln(CDS_{i,t+1}) = \sum_{n=-8}^{-1} \beta_n [\mathbb{1}(t = n) \times TREAT_i] + \sum_{n=1}^{8} \beta_n [\mathbb{1}(t = n) \times TREAT_i] + \beta^X X_{i,t} + \epsilon_{i,t+1}, \quad (2)$$

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 (1) and (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 1. As depicted in Figure 1, the coefficients of the interaction between TREAT and dummy variables for quarters after the Paris Agreement become increasingly negative in subsequent quarters following the Paris Agreement. This observation confirms that firms with high *CRMS* scores experience lower *CDS* spreads compared to firms with low *CRMS* scores after the Paris Climate Agreement.

3.3 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 a randomization 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 hypothesis of whether the sample realization of the treatment effect is consistent with the numerically inferred distribution (MacKinnon & Webb, 2020; White & Webb, 2021). Results are reported in Panel A of Table 4. 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 relation between the *CDS* spread and carbon risk management performance.

[INSERT Table 4 HERE]

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 the lax regulatory risk environment. A lenient carbon transition risk regime may dilute the impact of *CRMS* on *CDS* spreads. We first consider whether the election of President Trump in November 2016 played any role in the effect of *CRMS* on credit spreads - President Trump advocated for loosening environmental regulations and potential withdrawal of the US from the Paris Agreement during his presidency (January 20, 2017 until January 20, 2021). 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 the *CDS* spread. These events may alter market expectations regarding climate regulatory requirements, and potentially mitigate the effect of *CRMS* on the credit spread.

To test the effect of the President Trump's election and the actual announcement of US withdrawal from the Paris Agreement, we employ a DiD regression model similar to that in Model (1), 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 4, respectively, for the interaction term *Post Trump Election* × *CRMS* and *Post Paris Withdrawal Announcement* × *CRMS* are only weakly negative. Hence, we do not observe a reversal in the impact of *CRMS* on credit spread post President Trump's election or post formal announcement of the US withdrawal from the Paris Agreement. The weaker and insignificant results for the efects of these events compared to the impact of the Paris Agreement also suggest that, although regulatory risk can be reduced for firms with poor carbon risk management profiles, major curbs in CO_2 emissions are likely in the future (Bolton & Kacperczyk, 2021). Therefore, the companies that have been managing poorly their carbon emission risks would still be potentially affected by the regulatory restrictions.

3.4 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.[14] However, all SCAPs share a

[14] *SCAP* goals can be broadly divided into three categories: planning and capacity building; law and policy; and post-implementation monitoring (Ray & Grannis, 2015). The first category includes awareness campaigns and

common goal to combat climate change risk and make their respective state more resilient and better prepared to mitigate the disastrous effects of climate change. A total of 15 states finalized their first climate adaptation policies during our sample period, most of which adopted their first SCAP before 2015 but on staggered dates. Appendix A3 provides details on the dates when individual states of the firms in our sample adopted *SCAP*.

SCAPs can have wide-ranging direct and indirect material effects on local firms. The resulting new regulations and their post-implementation monitoring can have a direct effect on the cost of doing business in these states (see, for example, Ilhan, 2022; Heo, 2023). For example, SCAPs may increase the costs for local firms in the form of switching costs to green technology, or compliance costs with new regulations. The adoption of SCAPs also signals higher attention by state governments to climate-related issues and thus increases monitoring and climate-related regulatory risk for local firms.

The 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 risk (Seltzer et al., 2023) and associated costs. These potential regulatory risks and associated costs would be lower for firms with a higher level of CRMS. At the same time, by encouraging and facilitating prudent carbon risk management practices, a state's climate adaptation plans and initiatives also raise awareness about the importance of carbon risk performance for local firms. Ex-ante, we expect that while SCAPs may increase CDS spreads for local firms (due to higher regulatory risk and compliance costs), the mitigating impact of carbon risk management on CDS spreads would become stronger in states that have adopted a *SCAP*.

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.

To test this hypothesis, we use the stacked regression framework suggested by Baker et al. (2022). The stacked regression approach is an event-by-event analysis which estimates separate treatment effects for each of the events and addresses staggered treatment timing and treatment effect heterogeneity. It involves creating event-specific "clean 2×2" datasets, which include the outcome variable and controls for the treated cohort and other relevant variables. The datasets for each cohort are then "stacked" together, and a two-way fixed effect DiD regression is performed on the stacked dataset.[15]

Each event or cohort *d*-specific dataset consists of treated states and all other clean control states for a pre (post) 8 quarter panel with the SCAP adoption date at quarter $t = 0$. The control states are those which have never implemented SCAP in the whole sample. For each cohort *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:

$$\ln\left(CDS_{i,t+1}^{d}\right) = \alpha + \sigma_{ds}^{d} + \Theta_{dt}^{d} + \sum_{k=-8}^{-2} \mu_{l}^{d} D_{it}^{k} + \sum_{k=0}^{8} \mu_{l}^{d} D_{it}^{k} + \beta_{CRMS}^{d} HCRMS_{i,t}^{d} + \beta_{CRMS\times POSTSCAP}^{d} POSTSCAP_{t}^{d} \times HCRMS_{i,t}^{d} + \beta_{X}^{d} X_{i,t} + \epsilon_{i,t+1} \quad (3)$$

where, for every cohort *d*, σ_{ds}^{d} and Θ_{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. $D_{it}^{k} = \mathbb{I}[t - \mathrm{E_i} = k]$ here 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 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*

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

is the categorical variable which takes the value of one if the *CRMS* value of a firm is above the median in a quarter. As an alternative, we also construct *HCRMS* by sorting the *CRMS* by median 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.

We first show in Figure 2 that there is no clear pattern in quarters leading up to the SCAP implementation for the CDS spreads of firms located in states that adopt SCAP versus states that never adopt SCAP. In the post- SCAP implementation period, Figure 2 suggests that there is an increase in the CDS spreads for local firms. This finding is consistent with the argument that higher regulatory risk and compliance costs, as a result of SCAP implementation, leads to an increase in CDS spreads. The results in Table 5 further show that the 5-year CDS spreads are particularly sensitive to the carbon risk management performance of the firms headquartered in states where SCAP was implemented. The coefficients of the interaction variable HCRMS × POSTSCAP are negative and statistically significant, suggesting that the staggered adoption of climate plans by U.S. states enhances the importance of carbon risk management for credit risk assessment. That is, while firms with higher CRMS have lower CDS spreads, this finding is particularly stronger during the post-SCAP implementation period. Overall, the results indicate that credit markets have been sensitive to climate related interventions by state governments where firms operate.[16,17]

[INSERT Figure 2 & Table 5 HERE]

[16] 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.

[17] We further compare the characteristics of firms headquartered in treated and control groups post adoption. Results are presented in IA-Table 8. We find that post SCAP adoption, the treated firms have significantly higher CDS spreads, leverage, and size, but lower profitability (ROE), level (PPE) and growth (CAPEX) of long-term assets in comparison to the control firms. This finding implies that treated firms face higher credit stress and lower profitable opportunities. We also find that Post SCAP regulation, the carbon risk management significantly improves for firms domiciled in states that implemented the regulation (IA-Table 9).

4. Economic Channels, Alternative Explanations and Robustness Checks

4.1 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 provide a benchmark analysis by comparing it to 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 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 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. [18]

[18] We also conduct a univariate analysis to understand the relationship between CRMS and the climate measures used by Sautner et al. (2023) (see for details the Internet Appendix). We find that the CRMS variation across firms reflects differences in firm characteristics and firm-level risk exposures, and hence, better captures heterogeneity across firms than Sautner et al.'s risk exposure measures.

We consider the following fixed effects regression model where each type of firm-level climate change exposure ($CC_{i,t}$) is included as an additional regressor on *CRMS*:

$$CRMS_{i,t} = \alpha + \beta^{CC_{i,t}} CC_{i,t} + \beta^{X} X_{i,t} + \epsilon_{i,t} \;, \tag{4}$$

where $CRMS_{i,t}$ denotes firm *i*'s carbon risk management score in the current quarter. $CC_{i,t}$ represents three firm-level risk measures from Sautner et al. (2023), that is, *CCExposure*, $CCExposure^{Opp}$, and $CCExposure^{Reg}$, and $X_{i,t}$ is the firm specific common control vectors. We test empirically whether the firm-level climate risk exposure introduced by Sautner et al. (2023) is significantly related to the *CRMS* variable after conditioning for all controls that include firm- and quarter- fixed effects. The results are reported in Table 6. We find no relation between CRMS and climate risk exposures; only the physical risk exposure ($CCExposure^{phy}$) shows significance(at 10% level) to *CRMS* (Model 2). We carry out additional tests that are not tabulated for brevity. We conduct a principal component analysis of all the three sub-exposure variables ($CCExposure^{Opp}$, $CCExposure^{Reg}$, and $CCExposure^{Phy}$) and show that the first component (PC1), which captures the common variation in all three exposure measures, and find that PC1 is not related to the CRMS variable. We also consider two textual analytics measures, i.e., sentiment and risk-based firm-level climate change scores corresponding to the three climate risk exposure variables, thus providing six variables overall (that is, two textual analytics measures × three firm-level exposure variables), as reported by Sautner et al. (2023) 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 find no relation between these variables and the CRMS variable. Collectively our tests show that *CRMS* is not subsuming information from forward looking firm-level climate change exposure variables of Sautner et al. (2023); and confirm that information content of *CRMS* is not driven by climate risk perception.

[INSERT Table 6 HERE]

We also examine whether *climate risk variables* moderate the relation between *CRMS* and CDS spreads. We implement the baseline DiD specification in Model (1) by now including the climate risk exposures from Sautner et al. (2023). Results are tabulated in Table 7. Regressions (1), (2) and (3) show that DiD coefficient is still negative and significant after inclusion of overall, regulatory or opportunity risks respectively. Regression (4) examines the interaction effect of carbon management and climate risk exposures. We find from the *HighCCE* × *Post* interaction that high climate risk exposure firms have higher CDS spreads post-Paris Accord. However, the triple interaction effect (*TREAT* × *HighCCE* × *Post)* shows that high climate risk exposure firms with strong carbon risk management witness a significant reduction in CDS spreads post- Paris Accord. Our results, therefore, imply that the benefits of carbon risk management are most pronounced among firms that are most exposed to climate change post-Paris Accord and such firms would benefit most from signaling their commitment to better carbon risk management.

[INSERT Table 7 HERE]

4.2 Impact of Governance, Social, and other Environmental Risk Management Factors

Recall that the focus of our paper is to investigate the impact of climate change related risk management, or more precisely carbon risk management practices that aim to mitigate the credit spread of firms. However, it is plausible that our results are driven by firm-level corporate governance characteristics, as well-governed firms invest more in environmental and social policies (Ferrell et al., 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 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. The 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.

Additionally, we examine whether the *CRMS* effect holds after controlling for the rest of the environmental risk management measures from Sustainalytics. We define a new variable *E-CRMS* that pools the 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).[19]

Table 8 reports the regression results from baseline DiD model (1) augmented with additional governance, social and E-CRMS scores. We find that the DiD coefficient i.e. *TREAT* × *Post* remains significant even after we control for the governance, social, and *E-CRMS* variables. This implies that improved carbon risk management bears a strong negative relationship with CDS spreads post-Paris Agreement, even after controlling for governance, social, and remaining environmental risk management effects. Firms with better social scores

[19] E-CRMS variables include wider environmental indicators such as companies' 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 are correlated, the information content in CRMS is not captured in other Environmental risk management measures from Sustainalytics.

have lower credit spreads after controlling for firm or industry fixed effects. A better governance score lowers CDS spreads controlling for industry fixed effects. These results assure us 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-Paris Agreement period.

[INSERT Table 8 HERE]

4.3 Impact of Carbon Risk Management on CDS of Different Maturities

We continue the analysis by examining the term-structure effects of carbon risk management. We consider the effects of CRMS on CDS spreads at alternate (i.e., 1-year, 10-year, and 30-year) maturities, extending the baseline tests that were based on the 5-year maturity. We employ the baseline DiD model (1) from Table 3. Results tabulated in Table 9 show that after controlling for firm fixed effects, strong CRMS firms have significantly lower 10-year CDS spreads post-Paris accord. In terms of economic significance, treated firms experience 6.2% (7.1%) decrease in their CDS spreads with respect to their respective mean (standard deviation). The results hold for CDS for all the three maturities when only industry effects are considered. Our finding is consistent with the conjecture that carbon risk management has a beneficial effect on the long-term credit risks.[20]

[INSERT Table 9 HERE]

4.4 Signaling Effect of Carbon Risk Management

We also evaluate whether carbon risk management is an effective signaling mechanism for underlying firms by studying the relationship between CRMS and subsequent carbon emission

[20] We conduct additional robustness checks and present the results in the Internet Appendix (IA–Table 6). First, we use VIX as an additional market risk conditioning 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 the baseline DiD model augmented by *CDS* market liquidity (*CDS_Depth*) proxied by the number of contributors in the 5-year *CDS* market. Third, we include two-quarter lagged *CRMS* variable in Model (1) to control for possible persistence in *CRMS*. Finally, we include lagged CDS spread to consider possible persistence in the dependent variable. In all additional robustness tests, the previous finding that strong CRMS firms have significantly lower CDS spreads in the post-Paris Accord still holds.

levels. The signaling hypothesis implies that firms' commitment to carbon risk management would be associated with lower carbon emissions. We conduct a robustness test by studying the CRMS - CDS relationship for different carbon emission levels.

We source the firm-level total carbon emission data, which combines Scope 1, Scope 2, and Scope 3 levels of carbon emissions, from S& P Trucost. We employ both absolute level and intensity of total carbon emissions in log form. The regression results in Table 10 show that the DiD interaction effect *CRMS* × *Post* is significantly negative implying that firms with strong carbon risk management experience significantly lower subsequent total carbon emission both in absolute levels and intensity in the post-Paris Agreement. This evidence is consistent with firms adopting stronger carbon risk management practices in the post-Paris Agreement period to credibly signal their ability to reduce their carbon emissions.

[INSERT Table 10 HERE]

Finally, we examine the relation between CRMS and credit risks based on firms' carbon emission levels. If risk reduction is possible through better carbon risk management, the signaling 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, high carbon emitters may indulge in "window-dressing" by inflating their CRMS scores and overstating 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 median groups based on their annual total carbon emission intensity. The above (below) median firms exhibit higher (lower) carbon emissions compared to other firms in each time period. Then, we implement the baseline DiD regression Model (1) separately for each of the high and low portfolios. Results are reported in Table 11. We find that the negative DiD effect after the Paris Agreement (*CRMS* × *Post*) is stronger and mainly evident for the high carbon emitting firms. 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.

[INSERT Table 11 HERE]

4.5 Individual impact of CRMS components

We next examine how the two components of CRMS (*preparedness* and *performance*) are related to the CDS spreads. As discussed under Section 2.1, the *preparedness* dimension reflects firm's policies, programs, and management systems that are designed to manage the material impact of carbon risk. Hence, *preparedness* dimension captures how well is better prepared and future ready to tackle the looming carbon transition risk and is forward looking. The *performance* dimension consists of quantitative and qualitative indicators capturing a firm's ability to manage its carbon risk. Therefore, *performance* measures how well a firm has performed better in managing the carbon risk relative to other firms and is backward looking. Firms' actions to improve carbon efficiency is captured by both components of CRMS measure, which is a combination of firm's past practices as well as salient efforts to improve its future performance.

The DiD regressions for both CRMS–preparedness and CRMS–performance components are presented in Table 12. The results show that improved carbon risk management in each CRMS component is related to significant reduction in credit spreads in the next period. Regression (1) and (2) show that higher CRMS *performance* is related to lower CDS spreads after controlling for industry effects. Regressions (3) and (4) show that the *CRMS–performance* component has a stronger risk-mitigating impact and holds even controlling for firm fixed effects. Given that the *CRMS–performance* component incorporates both carbon management actions and reporting of emissions, our results show that there is an implicit organizational dynamic, where firms exhibiting stronger carbon risk management performance are favorably evaluated by the credit markets.

[INSERT Table 12 HERE]

4.6 Alternative specifications of the CRMS-CDS relation

We also consider two additional specifications based on Li et al. (2024) and Kölbel et al. (2024) that include firm fixed effects as well as firm level carbon risk exposures. We follow Li et al (2024) and employ their firm fixed effect specification (see Table 8, Li et al.), and cluster the standard errors at the firm and quarter level. We regress changes in credit spreads on lagged changes in CRMS and lagged firm-level attributes, controlling for firm, industry × quarter fixed effects. This specification allows us to compare within-firm changes in climate risk management and CDS changes while addressing potential endogeneity issues. IA–Table 7, Internet appendix, presents the results. Regression (1) shows that improvements in CRMS significantly lower CDS spreads in the next period even after controlling for Scope 1 emission intensity. We also find robust results by using total emission intensity (untabulated).

In addition, we implement the Kölbel et al.'s (2024) panel first-difference specification by focusing on the effect of changes in the exogenous variables on changes in the endogenous variable. Taking first differences in each firm's time series helps control for any time-invariant, unobserved heterogeneous effect. Such a specification, as Kölbel et al. argue, helps address concerns related to correlated omitted variables and reverse causality. We therefore regress CDS changes on lagged changes in both CRMS and other firm- level and time series covariates. Regressions (2) to (3) in IA–Table 7 presents the results. We once again find that CRMS changes are significantly negatively related to subsequent CDS spreads after controlling for emission and other control variables. The main findings of DiD specification from Table 3 still hold and are robust to alternate specifications.

5. Conclusion

We examine whether firms prudently managing their carbon emissions are favorably assessed in the credit markets. Using data from Sustainalytics, we develop a firm-level measure of carbon risk management that capture firms' preparedness and performance in managing their carbon risk. Our main analysis is based on the changes in the relation between CRMS and CDS spread following the Paris Climate Agreement of December 2015. We find that the importance of carbon risk management has gained prominence following the Paris Accord. We also document 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 an enhanced regulatory regime can lead to lower subsequent credit risk assessment and lower cost of borrowing.

We find that high climate risk exposure firms with a strong carbon risk management witness a significant reduction in CDS spreads post-Paris Accord. 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. Firms with better carbon risk management have subsequent lower levels of carbon emission, particularly following the Paris Agreement. The relation between CRMS and credit spreads is also stronger among firms with higher carbon emissions. Finally, we compare the *performance* and *preparedness* components of CRMS, and find that the decline in CDS spread following the Paris Agreement is more pronounced for firms with better performance in managing their carbon risk.

Our study extends prior research by showing 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. 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.

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Appendix A1: Measurement of Carbon Risk Management Performance

This table lists 13 indicators which 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 paper. Sustainalytics provides a firm–level score for each of these indicators. The scores are industry adjusted weighted scores where the weights are proprietary and assigned to a sub–industry depending on its exposure to individual carbon risk indicators. Our Carbon Risk Management Score (*CRMS*) is the sum of the individual scores of the selected indicators. The

Carbon Risk Management Indicators

CRMS Indicators	**Indicator Classification**	**Key Criteria Used for Evaluation by Sustainalytics**
Formal Environmental Policy	Preparedness	This includes 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)	Preparedness	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	Preparedness	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)	Preparedness	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	Preparedness	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	Preparedness	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	Preparedness	Assesses the firm's commitment to transition its energy use in its operations to renewable energy. There must be formal programs within the firm to ensure such a transition.
Carbon Intensity	Performance	Assesses the relative performance of the firm compared to its peers on carbon intensity.
Carbon Intensity Trend	Performance	Evaluates carbon intensity trend of the firm over the past three years.
% Primary Energy Use from Renewables	Performance	Measures the percentage of total energy consumption from renewable energy.
Programs and Targets to Reduce GHG Emissions from Outsourced Logistics Services	Preparedness	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	Performance	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	Performance	An additional criterion that assesses the carbon intensity of the firm across its value chain and wider energy usage mix.

Appendix A2: 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 amortization (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: Firm Level Carbon Emission Variables	
ln_Scope1_Int	Natural log of firm's Carbon Intensity Scope 1 (tons CO_2e divided by firm's revenue)	S&P Trucost
ln_Scope1_Abs	Natural log of firm's Absolute Carbon Scope 1 emissions scaled by millions	S&P Trucost

lnCO2Tot_Int	Natural log of firm's total Carbon Intensity i.e. sum of Scope 1, Scope 2 and Scope 3 emission intensities (tons CO_2e divided by firm's revenue)	S&P Trucost
lnCO2Tot_Abs	Natural log of firm's total Absolute Carbon Emissions i.e. sum of Scope 1, Scope 2 and Scope 3 emission (scaled by millions)	S&P Trucost
Panel F: Governance and Social Variables		
Governance Score	Sum of the weighted scores of the governance risk management of a firm	Sustainalytics
Social Score	Sum of the weighted scores of the social risk management of a firm	Sustainalytics
Panel G: 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. Authors count the number of such bigrams and divide by the total number of bigrams in the transcripts.	Sautner et al. (2023)
$CCExposure^{Opp}$	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 summarized 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 summarized 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 A3: State Climate Adaptation Plan by the various states in the US

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 Finalized**
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

Table 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 A2. All continuous variables except *CRMS* are winsorized 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

Table 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 A2. 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 level, respectively.

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

Table 3: CDS–CRMS Relationship and Paris Climate Agreement

This table shows the results using the Paris Agreement of December–2015 as the exogeneous 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 results show difference–in–differences (DiD) analysis where the key variable in the models 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 (one year prior to Paris Accord), and zero otherwise. All firms which are not available in 2014 are dropped to create the TREAT dummy. Further, we use the 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. All variables are explained in detail in Appendix A2. The models (1) and (2) include the firm and quarter–year fixed effects and models (3) and (4) include industry fixed effect (Sustainalytics Industry Classification) and quarter–year fixed effects. The standard errors are clustered by firm and quarter–year. Models (5) and (6), are similar to (3) and (4) respectively, but standard errors are clustered by industry and 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	CDS5	CDS5
	(1)	(2)	(3)	(4)	(5)	(6)
TREAT			-0.125**	-0.117**	-0.125*	-0.117
			(0.057)	(0.057)	(0.071)	(0.071)
Post	–0.040		-0.088		-0.088	
	(0.082)		(0.095)		(0.089)	
TREAT × Post	–0.174**	-0.167**	-0.221***	-0.241***	-0.221**	-0.241***
	(0.077)	(0.079)	(0.075)	(0.079)	(0.091)	(0.085)
lnScope1_Int	–0.006	-0.018	0.040	0.039	0.040*	0.039*
	(0.033)	(0.037)	(0.025)	(0.026)	(0.021)	(0.019)
LEVERAGE	0.184	0.741***	1.245***	1.318***	1.245***	1.318***
	(0.283)	(0.280)	(0.261)	(0.263)	(0.333)	(0.326)
IVOL	35.471***	30.992***	62.813***	64.219***	62.813***	64.219***
	(4.010)	(4.386)	(4.482)	(4.249)	(3.342)	(3.826)
SIZE	–0.339***	-0.238**	-0.145***	-0.136***	-0.145***	-0.136***
	(0.117)	(0.096)	(0.034)	(0.034)	(0.045)	(0.045)
ROA	–5.696***	-6.142***	-7.645***	-7.734***	-7.645***	-7.734***
	(1.394)	(1.252)	(1.550)	(1.479)	(1.871)	(1.815)
CASH	–0.378	-0.567	0.410	0.309	0.410	0.309
	(0.463)	(0.419)	(0.353)	(0.345)	(0.412)	(0.435)
TURNOVER	–0.124	-0.210	0.178	0.150	0.178	0.150
	(0.394)	(0.420)	(0.180)	(0.174)	(0.160)	(0.153)
PPE	0.014	0.232	-0.617**	-0.669**	-0.617**	-0.669**
	(0.567)	(0.507)	(0.255)	(0.276)	(0.233)	(0.274)
CAPEX	–0.429	-0.515	-0.124	0.273	-0.124	0.273
	(0.905)	(0.733)	(0.942)	(0.928)	(0.648)	(0.757)
Yield1Yr	–3.864		-5.384		-5.384	
	(5.256)		(5.761)		(5.250)	
Yield_Curve	0.421		0.122		0.122	
	(5.648)		(6.319)		(3.327)	
MktRET	–0.442		-0.558		-0.558*	
	(0.719)		(0.717)		(0.291)	
Firm FE	Yes	Yes	No	No	No	No
Industry FE	No	No	Yes	Yes	Yes	Yes
Quarter–Year FE	No	Yes	No	Yes	No	Yes
Observations	2,333	2,332	2,357	2,356	2357	2356
Adj.R2	0.793	0.835	0.594	0.633	0.594	0.632

Table 4: Placebo Test for the CRMS–CDS Spread relation

Panel A presents the results of the placebo test using randomization inference method to ascertain the impact of the Paris Agreement of December 2015. In Table 4, '*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 realization of the test statistic in the data; '*c*' is the count of under how many of the re–sampled iterations, the realization of the test–statistic was more extreme than '*T(obs)*'; '*n*' is the total count of re–samplings; '*p=c/n*' is the actual randomized 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 using the Table 3 specifications. We use the dummy variable *Post_Trump* 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. The results in column 1 and 2 show difference–in–differences (DiD) analysis where the key variable is *TREAT_Trump×Post_Trump*. *TREAT_Trump* takes the value of one if a firm's *CRMS* is above the median *CRMS* value in the year 2015 (one year prior to Trump getting elected as President), and zero otherwise. All firms which are not available in 2015 are dropped to create the *TREAT_Trump* dummy. Columns 3 and 4 replicate the results of column 1 and 2 with *TREAT_PW* × *Post_PW* as the key variable of interest. The dummy variable *Post_PW* 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. The indicator variable *TREAT_PW* takes the value of one if a firm's *CRMS* is above the median *CRMS* value in the year 2016 (one year prior to the US government's formal withdrawal from Paris accord), and zero otherwise. The samples are constructed using the PSM method as used in Table 3. All the variables including control variables (financial, macro–financial and firm–level emissions) are explained in detail in Appendix A2. The model includes the firm or 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 (1)	CDS5 (2)	CDS5 (3)	CDS5 (4)
TREAT_Trump		–0.178*** (0.060)		
Post_Trump				
TREAT_Trump× Post_Trump	–0.009 (0.070)	–0.098 (0.076)		
TREAT_PW				–0.202*** (0.070)
Post_PW				
TREAT_PW × Post_PW			–0.128 (0.097)	–0.157 (0.113)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No
Industry FE	No	Yes	No	Yes
Quarter–Year FE	Yes	Yes	Yes	Yes
Observations	2,359	2,382	2,058	2,087
Adj. R^2	0.847	0.639	0.851	0.630

Table 5: Impact of State Climate Adaptation Plans on the CRMS–CDS spread Relation – Stacked Regression Approach

Using the stacked analysis, this table assesses the relation between firms' carbon risk management (*CRMS*) performance and *CDS* spreads exploiting the impact of State Climate Adaptation Plans (*SCAPs*) adopted by 15 states in the U.S. 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 that are headquartered in the states which have adopted *SCAP* (treated firms) as well as the firms that are headquartered in states that 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, the interaction variable '*HCRMS × POSTSCAP*' 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 at the top top median *CRMS* values (assigned the value 1) and those at the bottom median (assigned the value 0). We use two different ways to calculate *HCRMS*: one based on the median values of *CRMS* within each quarter ($HCRMS_{Qtr}$), shown in Column 1 and the other based on the median of *CRMS* values within each state ($HCRMS_{State}$), shown in Column 2. The dependent variable is the natural logarithm of the daily average of 5–year CDS spread level (CDS5) in a quarter. All variables (financial, macro–financial and firm–level emissions) are explained in detail in Appendix A2. Furthermore, the model includes fixed effect based on the interaction of cohort indicator with the industry fixed effect and quarter–year fixed effect and state fixed effects (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 (1)	CDS5 (2)
$HCRMS_{Qtr}$	–0.071***	
	(0.010)	
$HCRMS_{State}$		–0.053***
		(0.008)
$HCRMS_{Qtr}$ × *POST_SCAP*	–0.052**	
	(0.022)	
$HCRMS_{State}$ × *POST_SCAP*		–0.064***
		(0.023)
lnScope1_Int	0.012***	0.010***
	(0.003)	(0.003)
Pre–SCAP Quarter–Year Dummies	Yes	Yes
Post–SCAP Quarter–Year Dummies	Yes	Yes
Control Variables	Yes	Yes
Cohort × Industry FE	Yes	Yes
Cohort × Quarter–Year FE	Yes	Yes
State FE	Yes	Yes
Observations	25,188	25,188
Adj.R2	0.710	0.710

Table 6: CRMS and the Firm–level Climate Change Exposure Measures Constructed by Sautner et al. (2023)

This table shows the effect of various climate change exposure scores constructed by Sautner et al. (2023) on carbon risk management (*CRMS*) practices of a firm using the model: $CRMS_{i,t} = \alpha + \beta^{CC_{i,t}} CC_{i,t} + \beta^{X} X_{i,t} + \epsilon_{i,t+1}$ where $CC_{i,t}$ is one of the general scores constructed by Sautner et al. (2023). This includes *CCExposure*, $CCExposure^{Opp}$, $CCExposure^{Reg}$ and $CCExposure^{Phy}$. *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 (financial, macro–financial and firm–level emissions) are explained in detail in Appendix A2. All models include the firm fixed effect 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.

	CRMS	*CRMS*	*CRMS*	*CRMS*
	(1)	(2)	(3)	(4)
CCExposure	0.013			
	(0.021)			
$CCExposure^{Opp}$		0.035		
		(0.034)		
$CCExposure^{Reg}$			–0.060	
			(0.065)	
$CCExposure^{Phy}$				0.382**
				(0.143)
Control Variables	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Quarter–Year FE	Yes	Yes	Yes	Yes
Observations	6,484	6,484	6,484	6,484
Adj .R^2	0.842	0.842	0.842	0.842

Table 7: Impact of Firm Level Climate Change Exposure (Sautner et al., 2023) on CDS and CRMS Relation

The results in Column 1, 2 and 3 shows the baseline results of Table 3 after controlling for various climate change exposure scores constructed by Sautner et al. (2023) – *CCExposure*, $CCExposure^{Reg}$, and $CCExposure^{Opp}$. In Column 4, the results show the relation between CDS spread and high CRMS score (*TREAT*) for the firms which are highly exposed to climate change risk and in the period after the Paris Agreement. The key variable in the Column 4 is triple interaction variable – *TREAT*×*HighCCE* × *Post*. The indicator variable *HighCCE* takes the value of 1 if a firm's aggregate climate change exposure score i.e. *CCExposure*, constructed by Sautner et al. (2023), is more than the median score of all the firms' *CCExposure* in a time period, else it takes 0. All variables (financial, macro–financial and firm–level emissions) are explained in detail in Appendix A2. All models include the firm fixed effect 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)
TREAT × *Post*	–0.169*	–0.164*	–0.168*	0.161
	(0.093)	(0.092)	(0.093)	(0.235)
CCExposure	0.006			
	(0.006)			
$CCExposure^{Reg}$		–0.028		
		(0.031)		
$CCExposure^{Opp}$			0.008	
			(0.011)	
HighCCE × *Post*				0.231*
				(0.127)
TREAT × *HighCCE*				0.142*
				(0.077)
TREAT×*HighCCE* × *Post*				–0.620**
				(0.267)
High_CCE				–0.066
				(0.073)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Quarter–Year FE	Yes	Yes	Yes	Yes
Observations	1,715	1,715	1,715	599
Adj .R^2	0.802	0.802	0.802	0.783

Table 8: The Relation between CRMS and 5–Year CDS Spread, Controlling for Governance, Social and other Environmental Risk Management Scores

This table shows the baseline results of Table 3 after controlling for the governance (*Governance Score*), social (*Social* Score) and remaining environmental risk management variables (*E–CRMS*). All variables (financial, macro–financial and firm–level emissions) are explained in detail in Appendix A2. All the models include the firm or 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.

	CDS5 (1)	CDS5 (2)	CDS5 (3)	CDS5 (4)	CDS5 (5)	CDS5 (6)	CDS5 (7)	CDS5 (8)
TREAT × Post	–0.157**	–0.168**	–0.169**	–0.168**	–0.314***	–0.286***	–0.314***	–0.273***
	(0.077)	(0.077)	(0.080)	(0.078)	(0.088)	(0.089)	(0.089)	(0.092)
Governance Score	–0.005			–0.004	–0.008**			–0.004
	(0.004)			(0.004)	(0.003)			(0.003)
Social Score		–0.006**		–0.007**		–0.009***		–0.009***
		(0.003)		(0.003)		(0.002)		(0.003)
E–CRMS			0.002	0.012			–0.010	0.008
			(0.010)	(0.010)			(0.011)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	No	No	No	No
Industry FE	No	No	No	No	Yes	Yes	Yes	Yes
Quarter–Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,332	2,332	2,273	2,273	2,356	2,356	2,297	2,297
Adj. R^2	0.836	0.837	0.833	0.836	0.633	0.638	0.629	0.639

Table *9*: Robustness Checks using CDS Spreads of Different Maturities

This table replicates the results of Table 3 but the main dependent variables are *CDS* spreads over different time periods after controlling for governance and social factors. The dependent variables are the natural logarithm of the daily average of *CDS* spreads of 1–year, 10–year and 30–year maturities in a quarter. All variables (financial, macro–financial and firm–level emissions) are explained in detail in Appendix A2. All models include the firm or 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.

	CDS1	CDS1	CDS10	CDS10	CDS30	CDS30
	(1)	(2)	(3)	(4)	(5)	(6)
TREAT		0.024		–0.067		–0.068
		(0.096)		(0.058)		(0.056)
Post						
TREAT × Post	–0.142	–0.255**	–0.110*	–0.164**	–0.084	–0.142**
	(0.091)	(0.104)	(0.060)	(0.064)	(0.055)	(0.059)
lnScope1_Int	–0.024	0.030	–0.009	0.046**	0.003	0.043**
	(0.046)	(0.033)	(0.030)	(0.022)	(0.027)	(0.021)
Governance Score	–0.004	–0.008	–0.003	–0.002	–0.002	–0.002
	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.002)
Social Score	–0.005	–0.016***	–0.004*	–0.005*	–0.004*	–0.005*
	(0.004)	(0.005)	(0.002)	(0.003)	(0.002)	(0.002)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No	Yes	No
Industry FE	No	Yes	No	Yes	No	Yes
Quarter–Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,332	2,356	2,332	2,356	2,332	2,356
Adj. R^2	0.847	0.620	0.849	0.638	0.842	0.627

Table 10: 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 exogeneous 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). 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 (financial, macro–financial and firm–level emissions) are explained in detail in Appendix A2. The sample includes 405 firms located in the US from August 2009 to May 2018. All the models include the firm or 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.

	lnCO2Tot_Abs	lnCO2Tot_Abs	lnCO2Tot_Int	lnCO2Tot_Int
	(1)	(2)	(3)	(4)
CRMS	0.013**	0.011	–0.002	–0.011
	(0.006)	(0.015)	(0.004)	(0.013)
Post				
CRMS × *Post*	–0.018***	–0.028**	–0.011**	–0.023**
	(0.006)	(0.011)	(0.005)	(0.009)
LEVERAGE	–0.161	–0.287	–0.035	–0.172
	(0.134)	(0.251)	(0.103)	(0.194)
IVOL	–3.976**	–11.359**	0.394	–4.429
	(1.661)	(4.459)	(1.178)	(3.519)
SIZE	0.572***	0.916***	–0.126***	0.041
	(0.064)	(0.044)	(0.043)	(0.031)
ROA	–0.307	–1.958*	0.070	–1.583*
	(0.389)	(1.123)	(0.201)	(0.940)
CASH	–0.071	1.024***	0.168*	0.717***
	(0.136)	(0.311)	(0.093)	(0.256)
TURNOVER	1.234***	3.054***	–0.221	–0.117
	(0.265)	(0.310)	(0.143)	(0.247)
PPE	–0.426	2.438***	–0.097	2.324***
	(0.264)	(0.337)	(0.155)	(0.288)
CAPEX	0.042	–4.187***	–0.526*	–3.954***
	(0.307)	(1.251)	(0.279)	(1.112)
Yield1Yr				
Yield_Curve				
MktRET				
Firm FE	Yes	No	Yes	No
Industry FE	No	Yes	No	Yes
Quarter–Year FE	Yes	Yes	Yes	Yes
Observations	8,089	8,104	8,089	8,104
Adj. R^2	0.982	0.831	0.983	0.808

Table 11. CRMS–CDS Relationship for subsamples based on High and Low Carbon Emissions of Firms

This table presents the results for the CRMS–CDS relationship in Table 3 separately for firms in the top and bottom quartiles of carbon emission measures sorted within each period and conditioned upon Paris Climate Agreement. Columns 1 and 2 show the relationship of CDS and *TREAT* × *Post* for the bottom (*LowTotCO2Int*) and top (*HighTotCO2Int*) subsample based on median of natural log of total carbon emission intensity in each time period, respectively. Similarly, columns 3 and 4 show the relationship of CDS and *TREAT* × *Post* for the bottom (*LowScope1_Int*) and top (*HighScope1_Int*) subsample based on median of natural log of Scope 1 carbon emission intensity in each time period, respectively. All variables (financial, macro–financial and firm–level emissions) are explained in detail in Appendix A2. All models include the firm fixed effect 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.

	LowTotCO2_Int	HighTotCO2_Int	LowScope1_Int	HighScope1_Int
	CDS5	CDS5	CDS5	CDS5
	(1)	(2)	(3)	(4)
TREAT × *Post*	–0.150*	–0.242**	–0.101	–0.206*
	(0.085)	(0.120)	(0.088)	(0.123)
LEVERAGE	0.422	1.340***	0.572	1.215***
	(0.384)	(0.416)	(0.440)	(0.423)
IVOL	30.418***	30.178***	28.052***	31.842***
	(5.715)	(6.285)	(5.590)	(6.204)
SIZE	–0.221	–0.323***	–0.172	–0.258**
	(0.139)	(0.117)	(0.152)	(0.112)
ROA	–5.694***	–5.920***	–5.427***	–6.669***
	(1.297)	(1.847)	(1.436)	(1.880)
CASH	–0.644	–0.434	–0.862*	0.349
	(0.546)	(0.571)	(0.464)	(0.773)
TURNOVER	–0.174	–0.024	0.075	–0.102
	(0.458)	(0.676)	(0.503)	(0.535)
PPE	–0.645	0.550	–0.532	0.555
	(0.691)	(0.660)	(0.776)	(0.652)
CAPEX	–1.073	–0.391	–1.057	–0.567
	(0.994)	(0.866)	(1.070)	(0.844)
Yield1Yr				
Yield_Curve				
MktRET				
Firm FE	Yes	Yes	Yes	Yes
Quarter–Year FE	Yes	Yes	Yes	Yes
Observations	1,127	1,185	1,128	1,185
Adj. R^2	0.848	0.817	0.845	0.823

Table 12: Impact of CRMS Components on CDS Spread and Paris Climate Agreement

This table replicates the results using of Table 3 but separately for components of CRMS – Preparedness and Performance components. 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 results show difference–in–differences (DiD) analysis where the key variable in the models 1 and 2 is *TREAT_Prep* × *POST* which is an interaction term of *TREAT_Prep* and *Post. TREAT_Prep* takes the value of one if the aggregated score of preparedness indicators of a firm is above the median preparedness score in the year 2014 (one year prior to Paris Accord), and zero otherwise. All firms which are not available in 2014 are dropped to create the *TREAT_Prep* dummy. Similarly, the key variable in the models 3 and 4 is *TREAT_Perf* × *Post* which is an interaction term of *TREAT_Perf* and *Post. TREAT_Perf* takes the value of one if the aggregated score of performance indicators of a firm is above the median performance score in the year 2014 (one year prior to Paris Accord), and zero otherwise. All firms which are not available in 2014 are dropped to create the *TREAT_Prep* dummy. Further, we use the 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 for all the models. All variables (financial, macro–financial and firm–level emissions) are explained in detail in Appendix A2. The models (1 and 2) include the firm and quarter–year fixed effects and models (3 and 4) include 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 (1)	CDS5 (2)	CDS5 (3)	CDS5 (4)
TREAT_Prep		–0.103		
		(0.075)		
TREAT_Perf				–0.062
				(0.071)
Post				
TREAT_Prep × *Post*	0.013	–0.142*		
	(0.065)	(0.075)		
TREAT_Perf × *Post*			–0.209**	–0.186**
			(0.090)	(0.085)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No
Industry FE	No	Yes	No	Yes
Quarter–Year FE	Yes	Yes	Yes	Yes
Observations	2,175	2,192	1,938	1,958
Adj. R^2	0.861	0.656	0.823	0.581

Figure 1: CDS Spreads Around the Paris Climate Agreement

This figure plots the β_n coefficient from the equation:

$$CDS_{i,t+1} = \sum_{n=-8}^{-1} \beta_n [\mathbb{1}(t = n) \times TREAT_i] + \sum_{n=1}^{8} \beta_n [\mathbb{1}(t = n) \times TREAT_i] + \beta^X X_{i,t} + \epsilon_{i,t+1} \quad (2)$$

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 β_n can be interpreted as the effect of being a firm with high carbon risk.

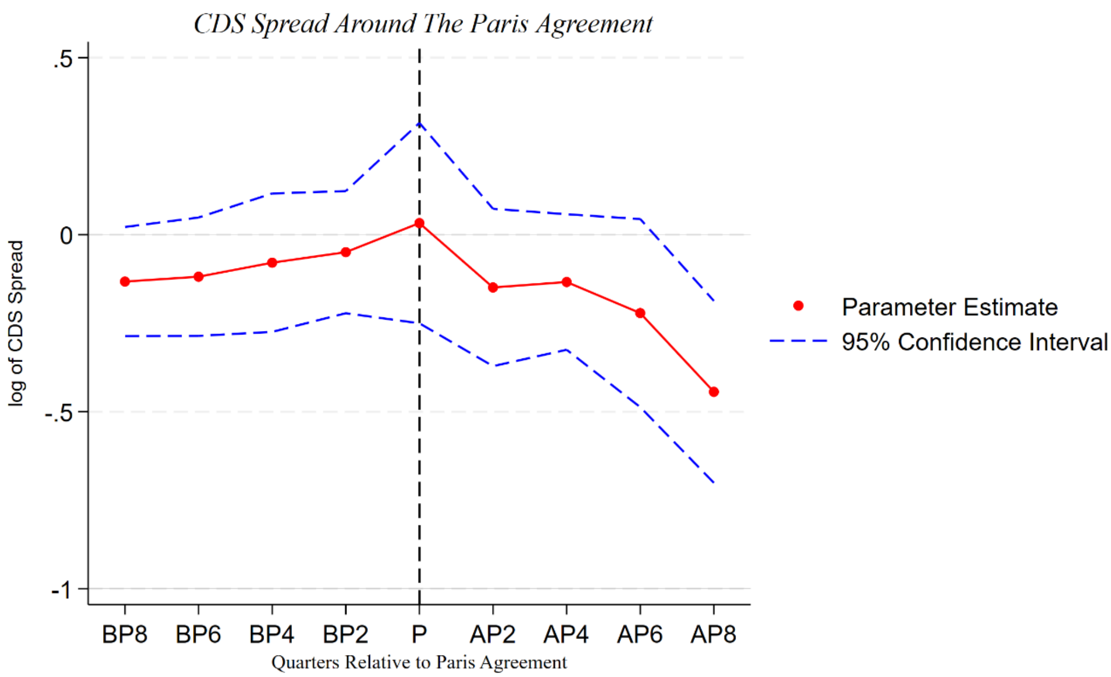

Figure 2: CDS Spreads Around the State Climate Action Plan (SCAP) regulation

This figure plots the μ_l^d coefficients from the equation:

$$\ln\left(CDS_{i,t+1}^{d}\right) = \alpha + \sigma_{ds}^{d} + \Theta_{dt}^{d} + \sum_{k=-8}^{-2} \mu_l^d D_{it}^{k} + \sum_{k=0}^{8} \mu_l^d D_{it}^{k} + \beta_{CRMS}^{d} HCRMS_{i,t}^{d} + \beta_{CRMS\times POSTSCAP}^{d} POSTSCAP_t^d \times HCRMS_{i,t}^{d} + \beta_X^d X_{i,t} + \epsilon_{i,t+1} \quad (3)$$

where, for every cohort d, σ_{ds}^{d} and Θ_{dt}^{d} are the interaction of d, an identifier for each of the cohort-specific datasets, with either the industry fixed effects and quarter-year fixed effects respectively. $D_{it}^{k} = \mathbb{I}[t - \mathrm{E_i} = k]$ here 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 captures the quarters leading up to the *SCAP* implementation ('leads') and the second summation captures the quarters after *SCAP* implementation. The regression coefficient μ_l^d can be interpreted as the effect of being a firm located in SCAP regulation state on the credit default swap spreads in each period relative to the SCAP regulation onset date.

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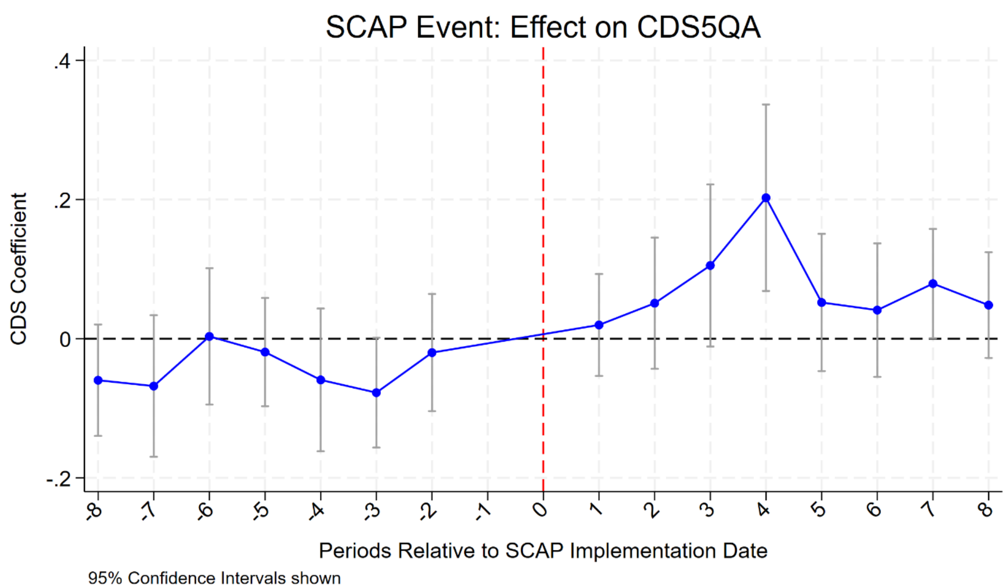

Internet Appendix

"Do Firms Benefit from Carbon Risk Management: Evidence from the Credit Default Swaps Market"

Contents

IA- A: Discussion of Univariate Tests

We analyze the correlations between CRMS and different firm-level climate exposure variables. We find that CRMS has a lower correlation with other measures of firm-level climate change exposure from Sautner et al. (2023) than CDS spreads, with correlations ranging from 5.2% to 13.6% (tabulated in IA-Table 3 in the Internet Appendix), 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 Sautner et al. (2023), that is *CCExposure*, $CCExposure^{Opp}$, and $CCExposure^{Reg}$. In IA-Table 4 in the Internet Appendix, we find that firms with weak carbon risk management scores (low CRMS) have significantly higher risks, that is: higher 5-year CDS spreads (CDS5), idiosyncratic volatility (IVOL), and lower cash holdings (CASH) and poor revenue (TURNOVER). 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 Sautner et al. (2023) yields no such clear and monotonic correspondence. Only the opportunity risk exposure ($CCExposure^{Opp}$) shows a direct relation to CRMS and an inverse relation to physical assets (firm-level risk and cash). Variations across other risk exposures show no material variation across financial variables. Our results, therefore, imply that the CRMS better captures heterogeneity across firms in comparison to risk exposure measures.

We further perform double sorting into 4×3 portfolios based on CRMS and climate change opportunity risk exposure ($CCExposure^{Opp}$), with the corresponding mean CDS spreads in IA-Table 5 in the Internet Appendix. We find that CRMS partitioning provides a clear monotonic increase of CDS spreads for lower CRMS portfolios. No such monotonic trends in CDS spreads are observed across opportunity risk exposure portfolios.

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

IA-Table 1: Cross-Sectional Regression and Baseline Regression with Alternative Fixed Effects

This table presents the results of Table 3 with alternative fixed effect specification (Column 1 and 2) and results for the cross–sectional regression in which all variables are averaged across time at the firm level (Column 3). Column 1 presents the baseline regression of Table 3 with industry × quarter–year fixed effects and Column 2 includes an additional fixed effect i.e. firm fixed effect. The Column 3 shows the OLS regression where *CRMS_CS* is the main independent variable (cross–sectional average of CRMS) and *CDS5_CS* (cross–sectional average of 5–year CDS spread) is the main dependent variable. All the control variables (*Controls_CS*) in Column 3 are similarly averaged across time at the firm level. All variables (financial, macro–financial and firm–level emissions) are explained in detail in Appendix A2. 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 (1)	CDS5 (2)	CDS5_CS (3)
TREAT × Post	–0.290**	–0.226**	
	(0.114)	(0.103)	
CRMS_CS			–0.036***
			(0.010)
Controls	Yes	Yes	No
Controls_CS	No	No	Yes
Industry FE × Quarter–Year FE	Yes	Yes	No
Firm FE	No	Yes	No
Observations	1,852	1,820	365
Adj. R^2	0.611	0.849	0.675

IA-Table 2: Summary of other Climate Risk Measures used in the Prior Literature

Climate Change Risk Measure	Papers	Source/Database
Corporate Carbon Emission (Scope 1, Scope 2, and Scope 3 emissions)	• Bolton and Kacperczyk (2021) • Bolton and Kacperczyk (2023) • Azar et al. (2021) • Capasso et al. (2020)	S&P Trucost, Thomson Reuter's Asset 4
Carbon Intensity (total carbon emission divided by company revenue)	• Bolton and Kacperczyk (2021) • Bolton and Kacperczyk (2023) • Ilhan et al. (2020) • Capasso et al. (2020) • Duan et al. (2023)	S&P 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 Regulatory Risk	• Kölbel et al. (2024)	Constructed by authors using Google's BERT for Textual Analytics techniques on firms' disclosure in their SEC 10-K filings
Climate Change Exposure Measure	• Sautner et al. (2023)	Constructed by authors using Textual Analytics techniques on quarterly earning calls of the firms
Climate Change News Index	• Engle et al. (2020)	Constructed by authors using Textual Analytics techniques on news related to climate change issues
Climate Physical Risk Measures (sea level rise, drought, etc.)	• Alok et al. (2020) • Bernstein et al. (2019) • Huynh et al. (2020) • Painter (2020)	Spatial Hazard and Loss Database for the United States (SHELDUS), Palmer Drought Severity Index (PDSI), Geographic Mapping Software for sea-level rise

IA-Table 3: Correlation Matrix for CRMS and Different Firm-level Exposure Variables

This table shows the pooled Pearson correlation coefficients 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. All variables are explained in detail in Appendix A2. ***, ** 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

IA-Table 4: 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), CCExposure^{Reg} (Panel D), and CCExposure^{Phy} (Panel E). The variables showing a monotonic trend are shaded in grey. 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 A2. ***, ** and * indicate statistical significance at the 0.01, 0.05, and 0.10 level, respectively.

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

CRMS	CDS *(bps)*	*LEVERAGE*	*IVOL(%)*	*SIZE*	*ROA*	*CASH*	*TURNOVER*	*CAPEX*	*PPE*	*CCExposure*	*CCExposure^{Opp}*	*CCExposure^{Reg}*	*CCExposure^{Phy}*
Low CRMS	194.8	0.35	1.50	9.38	0.01	0.07	0.14	0.02	0.27	0.47	0.16	0.02	0.01
1	138.5	0.29	1.36	10.02	0.01	0.08	0.16	0.03	0.35	1.24	0.44	0.11	0.01
2	101.5	0.31	1.27	10.24	0.01	0.1	0.19	0.02	0.32	1.26	0.51	0.08	0.01
High CRMS	109.9	0.3	1.23	10.2	0.01	0.11	0.19	0.03	0.29	1.84	0.81	0.12	0.02
t–test (High–Low)	0.667***	0.0455***	0.2***	–0.767***	–0.007***	–0.04^{4***}	–0.053***	–0.006***	–0.016	–1.230***	–0.585***	–0.092***	–0.013***
t–stat	–26.65	–7.68	–8.5	(-20.28)	(-15.05)	(-15.51)	(-11.65)	(-5.88)	(-1.77)	(-12.44)	(-11.36)	(-9.16)	(-3.73)

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

CCExposure	*CRMS*	*CDS (bps)*	*LEVERAGE*	*IVOL(%)*	*SIZE*	*ROA*	*CASH*	*TURNOVER*	*CAPEX*	*PPE*	*CCExposure^{Opp}*	*CCExposure^{Reg}*	*CCExposure^{Phy}*
Low CCExposure	3.19	146.97	0.31	1.37	9.92	0.01	0.1	0.18	0.02	0.22	0.05	0	0
1	3.76	113.77	0.29	1.32	10.26	0.01	0.1	0.17	0.02	0.25	0.09	0.01	0.01
2	3.62	140.41	0.3	1.37	9.87	0.01	0.09	0.18	0.03	0.3	0.15	0.02	0.01
High CCExposure	4.35	123.1	0.33	1.27	9.99	0.01	0.07	0.15	0.04	0.47	1.66	0.31	0.03
t–test (High–Low)	0.127***	–0.0145**	0.001***	-0.1	0.001	0.035***	0.028***	–0.016***	–0.242***	0.173***	–1.608***	–0.303***	–0.034***
t–stat	–5.51	(-2.98)	–4.54	(-1.81)	–1.52	–14.05	–6.35	(-16.74)	(-31.69)	–8.01	(-31.83)	(-22.34)	(-11.19)

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

CCExposure^{Opp}	*CRMS*	*CDS (bps)*	*LEVERAGE*	*IVOL(%)*	*SIZE*	*ROA*	*CASH*	*TURNOVER*	*CAPEX*	*PPE*	*CCExposure*	*CCExposure^{Reg}*	*CCExposure^{Phy}*
Low CCExposure^{Opp}	3.34	142.9	0.3	1.37	9.92	0.01	0.1	0.17	0.02	0.26	0.31	0.02	0.01
2	4.16	111.27	0.29	1.30	10.14	0.01	0.09	0.18	0.02	0.3	0.7	0.05	0.01
High CCExposure^{Opp}	4.26	127.06	0.33	1.27	9.99	0.01	0.07	0.15	0.03	0.44	3.73	0.26	0.02
t–test (High–Low)	–0.926***	0.058**	–0.027***	0.1***	–0.069*	0.001*	0.029***	0.026***	–0.010***	–0.177***	–3.420***	–0.244***	–0.011***
t–stat	(-13.21)	–2.72	(-5.85)	–5.41	(-1.98)	–2	–12.11	–6.42	(-11.28)	(-23.80)	(-43.06)	(-23.52)	(-4.33)

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

CCExposure^{Reg}	*CRMS*	*CDS (bps)*	*LEVERAGE*	*IVOL(%)*	*SIZE*	*ROA*	*CASH*	*TURNOVER*	*CAPEX*	*PPE*	*CCExposure*	*CCExposure^{Opp}*	*CCExposure^{Phy}*
Low CCExposure^{Reg}	3.53	136.12	0.31	1.35	9.94	0.01	0.1	0.17	0.02	0.28	0.66	0.27	0.01
High CCExposure^{Reg}	4.66	134.97	0.31	1.27	10.12	0.01	0.05	0.13	0.04	0.53	6.15	2.36	0.04
t–test (High–Low)	–1.214***	0.044	–0.011	0.1**	–0.197***	0.002***	0.046***	0.042***	–0.013***	–0.259***	–5.922***	–2.304***	–0.036***
t–stat	(-11.58)	–1.4	(-1.63)	–2.94	(-3.81)	–3.82	–12.94	–6.9	(-9.74)	(-23.77)	(-52.61)	(-38.87)	(-9.54)

Panel E: Univariate sorting based on Sautner's Climate Change Physical Exposure Measure (aggregate) quartiles

CCExposure^{Phy}	*CRMS*	*CDS (bps)*	*LEVERAGE*	*IVOL(%)*	*SIZE*	*ROA*	*CASH*	*TURNOVER*	*CAPEX*	*PPE*	*CCExposure*	*CCExposure^{Opp}*	*CCExposure^{Reg}*
Low CCExposure^{Phy}	3.63	136.41	0.31	1.34	9.96	0.01	0.09	0.17	0.03	0.31	1.14	0.47	0.07
High CCExposure^{Phy}	4.25	122.22	0.3	1.20	9.89	0.01	0.07	0.15	0.02	0.39	3.32	0.86	0.39
t–test (High–Low)	–0.604**	0.005	0.015	0.1*	0.113	–0.001	0.022***	0.015	0.002	–0.089***	–2.215***	–0.436***	–0.308***
t–stat	(-3.17)	–0.08	–1.19	–2.48	–1.2	(-0.89)	–3.37	–1.36	–0.91	(-4.24)	(-9.26)	(-3.70)	(-10.74)

IA-Table 5: Bivariate Sorting of 5-year CDS Spreads based on CRMS and Climate Change Opportunity Exposure Measure of Sautner et al. (2023)

The table reports the results of bivariate sorting of 5-year *CDS* spreads into quartile portfolios based on *CRMS* and climate change opportunity exposure measure $CCExposure^{Opp}$ variables. Initially, we sort firms by *CRMS* into quartiles each quarter and then further sort each *CRMS* quartile into terciles based on $CCExposure^{Opp}$ of the underlying firms. We report the average value of *CDS* spreads for each of the 4 × 3 bins. The last row and columns report the differences between High and Low values for each bin. All variables are explained in detail in Appendix A2.

	$CCExposure^{Opp}$			
	Lowest $CCExposure^{Opp}$	2	Highest $CCExposure^{Opp}$	*High-Low*
		CDS Spread 5Yr		
Lowest *CRMS*	189.38	.	183.71	*–5.67*
2	131.05	109.85	132.00	*0.95*
3	101.77	100.24	101.42	*–0.35*
Highest *CRMS*	112.59	102.04	96.69	*–15.90*
High-Low	*76.79*		*87.02*	

IA–Table 6: Baseline Regression with VIX, CDS Liquidity, Lagged CRMS, and Lagged CDS Variables

This table presents the results of baseline results of Table 3 with *VIX* as a measure of market expectation of volatility in Column 1 and 2, *CDS_Depth* as a measure of *CDS* liquidity in Column 3 and 4, two quarter lagged *CRMS* variable in Column 5 and 6 and one quarter lagged *CDS* variable (*lag_CDS5*) in Column 7 and 8 with respect to 5–year *CDS* spread (*CDS5*) as additional control variables, as the main independent variable. All variables (financial, macro–financial and firm–level emissions) are explained in detail in Appendix A2. The sample matched firms located in the US from August 2009 to May 2018. All models include the firm or industry fixed effect (based on Sustainalytics Industry Classification) and quarter–year fixed effects except in Column 1 and 2. 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 (1)	CDS5 (2)	CDS5 (3)	CDS5 (4)	CDS5 (5)	CDS5 (6)	CDS5 (7)	CDS5 (8)
TREAT × Post	–0.156**	–0.332***	–0.164**	–0.335***	–0.168**	–0.297***	–0.067**	–0.063**
	(0.073)	(0.076)	(0.078)	(0.079)	(0.076)	(0.096)	(0.029)	(0.024)
VIX_Avg	0.019***	0.012***						
	(0.004)	(0.005)						
CDS_Depth			–0.012	–0.038***				
			(0.008)	(0.011)				
lag_CRMS					0.016	–0.017		
					(0.012)	(0.014)		
lag_CDS5							0.757***	0.891***
							(0.024)	(0.016)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Quarter–Year FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,333	2,357	2,295	2,320	2,170	2,181	2,170	2,181
Adj. R^2	0.806	0.596	0.838	0.641	0.843	0.638	0.937	0.927

IA–Table 7: CRMS–CDS Relationship Using Alternative Specifications

This table present the relationship between 5–year CDS spread and CRMS using alternative specifications following Li et al. (2024) in Column 1 and Kölbel et al. (2024) in Columns 2 and 3. The key dependent and independent variables in all the models is the differenced CDS spread (Δ*CDS5*) and differenced CRMS (Δ*CRMS*) i.e. difference between the corresponding values in the current and previous quarter. In column (1) , only the key dependent and independent variables are differenced and uses *Industry FE × Quarter–Year* and firm fixed effects. The Columns 2 follows the panel first difference regression where all coefficients are estimated by performing pooled OLS using the difference. Column 3 is similar to Column 2 but it uses the absolute value of natural log of Scope1 carbon emission intensity rather than the differenced value. All variables (financial, macro–financial and firm–level emissions) are explained in detail in Appendix A2. The standard errors are clustered by firm and by quarter–year in Column 1 and on industry level (based on Sustainalytics Industry Classification) for Column 2 and 3. ***, ** 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.

	ΔCDS5	ΔCDS5	ΔCDS5
	(1)	(2)	(3)
Δ*CRMS*	–0.033***	–0.019***	–0.019***
	(0.011)	(0.007)	(0.007)
lnScope1Int	–0.002		–0.001
	(0.011)		(0.001)
Δ*lnScope1Int*		–0.026	
		(0.020)	
Controls	Yes	No	No
Δ *Controls*	No	Yes	Yes
Industry FE × Quarter–Year FE	Yes	No	No
Firm FE	Yes	No	No
Quarter–Year FE	No	No	No
Industry FE	No	No	No
Observations	7,111	7,588	7,588
Adj. R^2	0.174	0.258	0.257

IA–Table 8: Firm Characteristics Under SCAP and Non–SCAP States

This table provides the general comparison of treated (POSTSCAP = 1) and control group (POSTSCAP = 0) firms' characteristics using pooled t–test i.e. the difference between firms headquartered in treated and control groups post adoption of State Climate Adaptation Plan proxied by POSTSCAP indicator.

		POSTSCAP				
Firm Variables		0	1	Difference	t–Value (pooled)	p–Value
CDS5	N	5,885	2,866			
	Mean	(4.58)	(4.71)	0.13	6.81	0.000
CRMS	N	5,885	2,866			
	Mean	3.76	3.81	(0.05)	(0.81)	0.416
LEVERAGE	N	5,585	2,755			
	Mean	0.30	0.33	(0.03)	(7.29)	0.000
IVOL	N	5,885	2,866			
	Mean	0.01	0.01	(0.00)	(1.07)	0.286
SIZE	N	5,885	2,866			
	Mean	9.90	10.04	(0.14)	(4.89)	0.000
ROA	N	5,881	2,866			
	Mean	0.01	0.01	0.00	5.38	0.000
CASH	N	5,885	2,866			
	Mean	0.09	0.10	(0.01)	(4.11)	0.000
TURNOVER	N	5,865	2,838			
	Mean	0.21	0.18	0.02	6.27	0.000
PPE	N	5,523	2,721			
	Mean	0.31	0.29	0.02	3.44	0.001
CAPEX	N	5,876	2,866			
	Mean	0.03	0.02	0.00	3.74	0.000

IA–Table 9: CRMS Validation Test Around Paris Climate Agreement and State Climate Adaptation Plans

This table shows the validation test for *CRMS* variable around the Post Paris Climate Agreement and State Level Climate Adaptation Plans (SCAP). The Columns 1 and 2 shows the impact of *Post*, which takes value of one for the period after December 2015 and zero otherwise, on *CRMS*. The results in Columns 3 and 4 shows the impact of *POST_SCAP*, which takes the value of 1 if a state has adopted the state climate action plan and zero otherwise, on *CRMS* using stacked regression specification used in Table 5. All variables (financial, macro–financial and firm–level emissions) are explained in detail in Appendix A2. The standard errors are clustered by firm and by quarter–year in Column 1 and 2. The standard errors for columns 3 and 4 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.

	CRMS	CRMS	CRMS	CRMS
	(1)	(2)	(3)	(4)
Post_Paris	–0.244	–0.217		
	(0.167)	(0.177)		
POST_SCAP			0.669***	0.293***
			(0.080)	(0.085)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	No	No	No
Industry FE	No	Yes	No	No
Quarter–Year FE	No	No	No	No
Cohort × Industry FE	No	No	Yes	No
Cohort × State FE	No	No	No	Yes
Cohort × Quarter–Year FE	No	No	Yes	Yes
Observations	8,079	8,095	25,189	25,187
Adj. R^2	0.835	0.445	0.478	0.354