Carbon Default Swap – Disentangling the Exposure to Carbon Risk Through CDS*†

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Abstract

Using Credit Default Swap spreads, we construct a forward-looking, market-implied carbon risk factor and show that carbon risk affects firms' credit spread. The effect is larger for European than North American firms and varies substantially across industries, suggesting the market recognizes where and which sectors are better positioned for a transition to a low-carbon economy. Moreover, lenders demand more credit protection for those borrowers perceived to be more exposed to carbon risk when market-wide concern about climate change risk is elevated. Lenders expect that adjustments in carbon regulations in Europe will cause relatively larger policy-related costs in the near future.

Keywords: Climate Change, Carbon Risk, Credit Risk, Credit Default Swap Spreads.

JEL classification codes: C21; C23; G12; G32; Q54.

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†Luca Taschini gratefully acknowledges funding from the Grantham Foundation for the Protection of the Environment, the UK Economic and Social Research Council (ESRC) through the Center for Climate Change Economics and Policy. We received helpful comments from participants at the CEFGroup, CEMA, CREDIT, DGF, EFI, EMCC, ICCF annual conferences in 2021 and 2022; and seminar participants at Bank of Italy, Citi, LSE, the universities of Berlin (HU), Edinburgh, Friedrichshafen, Munich (LMU, TUM) and Oslo. We would also like to thank Andrej Bajic, Simon Dikau, Marco Fanari, Enrico Foscolo, Glen Gostlow, Christoph Hambel, Martin Hellmich, Alexander Lauber, Bob Litterman, Christoph Meinerding, Pier Luigi Migliorati, Huyen Nguyen, Quyen Nguyen, Christina Nikitopoulos, Florentina Paraschiv, Tommaso Perez and Zacharias Sautner for valuable insights and conversations at different stages of this project.

1 Introduction

«There is no company whose business model won't be profoundly affected by the transition to a net-zero economy [...]. As the transition accelerates, companies with a well-articulated long-term strategy, and a clear plan to address the transition to net zero, will distinguish themselves with their stakeholders [...] by inspiring confidence that they can navigate this global transformation. But companies that are not quickly preparing themselves will see their businesses and valuations suffer, as these same stakeholders lose confidence that those companies can adapt their business models to the dramatic changes that are coming.»

— Larry Fink, Open letter to CEOs, January 26, 2021

The transformation of the economic structure required to achieve net-zero targets will be profound and could generate sizable costs for unprepared sectors and companies, as recognized by the chairman and CEO of multinational investment firm BlackRock in the quote above. Unquestionably, these costs could significantly affect firms' cash flows and valuations, undermining their ability to service and repay their debt, and eventually leading to higher probabilities of default and higher credit risks (Capasso et al., 2020; Kölbel et al., 2022; Aiello and Angelico, 2022; BIS, 2021; Carbone et al., 2021; Reznick and Viehs, 2018; Virgilio et al., 2022; Billio and Giacomelli, 2022; Caicedo, 2022). There is already some evidence that transition risk,[1] codified using firms' current carbon emissions data, influences credit risk (Ilhan et al., 2020; Duan et al., 2021; Zhang and Zhao, 2022). It is therefore important to understand how the scope and speed of the economic transformation, and the associated credit risk, varies across sectors, jurisdictions, and over time. Our study concentrates on the carbon component of transition risk – the "carbon risk" – recognizing the relative prominence of carbon among transition risks, and given its wide coverage across countries, markets, and sectors. Understanding the full impact of the transition, however, requires the measurement of entire carbon profiles, including firms' future emissions reduction plans (Kölbel et al., 2022; Carbone et al., 2021; ECB, 2022). To date, identifying an appropriate proxy for carbon risk has proven difficult. In this study, we construct a market-implied, high-frequency, and forward-looking proxy for carbon risk exposure and show that the exposure to carbon risk affects firms' credit spread – the difference between the interest rate on risky debt and the risk-free interest rate. We find that the magnitude of the exposure to carbon risk (i) is more prominent in Europe vs. North America, (ii) varies substantially across industries, (iii) is stronger during times of heightened attention to climate change news, and (iv) is particularly salient in Europe for shorter time horizons, confirming that lenders expect adjustments in carbon regulations in Europe to cause larger policy-related costs, relative to North America, in the near future.

While there has been increasing academic, private industry, and regulatory attention to the risks associated with this transition (e.g. Bolton et al., 2020; NZAM, 2022; NGFS,

[1]Climate change affects the economy through two main channels. The first involves physical risks, arising from damage to infrastructure, property, and business operations. The second, transition risk, results from changes in climate policy, technology, and consumer and market sentiment during the adjustment to a lower-carbon economy. As will be made clear later, exposures can vary significantly from region to region, and from industry to industry.

2019), there is no comprehensive theoretical framework linking the low-carbon transition to credit dynamics. Notwithstanding the complexity in precisely modeling specific risk drivers and transmission channels, markets are already recognizing that carbon policy, changing preferences and ongoing technological change are causing some parts of the economy to grow, while others decline in relative importance. This manifests in increased default risk or lower asset values for firms that are more exposed to transition risk.

At the same time, a number of the world's biggest companies have committed to decarbonizing their businesses, for example by setting emissions intensity targets or time limits for reaching net-zero emissions. Although not legally binding, non-compliance with self-imposed commitments carry reputational risks and can therefore become a credit risk. Equally, unambitious emissions reduction strategies might become a transition risk and therefore a credit risk. Markets recognize that firms may transition at different times and at different speeds (BIS, 2021; Carbone et al., 2021; Meinerding et al., 2020) and we argue that lenders take that into account in their firm valuations.

We begin our study by developing a theoretical argument about how carbon risk differently impacts the valuation of dissimilar firms, ultimately providing a theoretical foundation for a straightforward translation of carbon risk into credit risk. We use the Merton (1974) model to consider the effect of carbon costs on the credit spread, and to illustrate how exposure to higher carbon costs implies higher probabilities of default and, ultimately, higher credit spreads.

Motivated by this theoretical relationship, we utilize the information contained in the daily spreads of Credit Default Swap (CDS) contracts to construct a *market-implied, high-frequency* and *forward-looking* carbon risk factor. The construction of a carbon risk factor is our first main contribution. CDSs offer several advantages over other commonly used credit risk measures, such as corporate bonds (or ratings). First, CDSs respond more quickly to changes in market conditions than alternative financial debt and credit products, because CDS contracts are traded on standardized terms.[2] Second, CDSs are usually more liquid than corporate bonds (Longstaff et al., 2005; Ederington et al., 2015). The third crucial advantage is that, since there are CDS contracts with varying tenors up to 30 years, they allow us to incorporate lenders' collective forward-looking considerations.

The carbon risk factor is constructed as the difference between the daily median CDS spreads of high-emission-intensity (polluting) firms and low-emission-intensity (clean) firms. This difference is used to identify how the lenders market perceives the differential exposure of polluting and clean firms to carbon risk.[3] When policy events (e.g. announcement of tightening regulations) trigger a rise in carbon risk, lenders to more (less) exposed firms demand increased (decreased) protection, widening the CDS wedge, i.e. the distance between the price of default protection for polluting and clean companies. Conversely, if a loosening of

[2]Standard contractual characteristics include pre-specified maturity, default event, and debt seniority. Corporate bonds, for example, may be embellished with additional idiosyncrasies such as embedded options or specific guarantees. As such, CDSs are more reactive to new information arriving in the market (Blanco et al., 2005; Zhu, 2006; Norden and Weber, 2009).

[3]Emission intensity is a commonly used measure – it allows for a more accurate comparison of emissions between different industries and firms. In Appendix D.2, we consider several alternative specifications for the construction of the carbon risk factor, including absolute emissions.

regulation is expected, there is a narrowing of the wedge (or even a negative wedge). The carbon risk factor thereby represents changes in perceived exposure to carbon risk on a very granular level. By construction, the financial performance of this factor mimics the dynamics of a lending portfolio in which default protection is bought for a polluting firm and sold for a clean firm.

We then propose three hypotheses to study how, where, and when (respectively) carbon risk affects firms' creditworthiness by examining whether firms' exposure to carbon risk is reflected in the market prices of their CDS contracts. Specifically, using daily CDS data for more than 400 firms in Europe and North America for the period from 2013 to 2019, we investigate how firms' CDS spread returns change in response to variations in the carbon risk factor. Our findings are consistent with the hypothesis of a positive relationship between carbon risk and credit spread returns. We show that even under *ordinary* conditions (i.e. for *average* relative changes in CDS spreads), carbon risk is a determinant of credit risk. Specifically, since the carbon risk factor reflects the collective (market-wide) expectation of carbon risk, an increase in the carbon risk is accompanied by lenders demanding more credit protection. We use quantile regressions to examine the effect of credit risk when credit conditions are *extraordinary*, namely when firms experience large shifts in their credit spreads. The quantile regression describes the entire conditional distribution of the dependent variable and thus has the potential to uncover differences in the response of the dependent variable across different quantiles. We find that the effect of carbon risk is significantly amplified at the tails of the credit spread distribution. These findings are especially relevant for the regulatory framework of carbon risk. In particular, they highlight the relevance of assessing whether carbon risk is adequately accounted for in prudential standards.

We conduct further analyses to test for geographical and sectoral dependencies. While an increase in the perceived carbon risk exposure is generally associated with an increased cost of default protection, the size of this positive effect differs significantly across regions and industries. In Europe, where climate policies are more stringent, there is a very strong positive relationship, whereas the effect is comparatively weaker in North America, which has generally had more ambiguous climate policy signals in recent years. In Europe, the effect of carbon risk is economically significant: for example, considering the 5 years tenor, a one-standard-deviation increase in the carbon risk factor leads to a rise of 0.15 percentage points in the median CDS spread return. To fix ideas, this increment accounts for a remarkable 6.9% of the standard deviation of CDS spread returns, making our carbon risk factor the second most influential driver.[4] The effect approximately doubles in size when firms experience extreme positive CDS spread shocks – this corresponds to the ninth deciles. On a sectoral level, we find that carbon-intensive sectors (e.g. Energy) are more affected than less carbon-intensive industries (e.g. Healthcare). Limiting the attention to Europe and the median CDS spread return, a one-standard-deviation increase in the carbon risk factor leads to a rise of 0.19 percentage points and 0.65 percentage points for Basic Materials and Energy, respectively. Also, a one-standard-deviation increase in the carbon risk factor leads to a decrease of 0.13 percentage points and 0.05 percentage points for Industrials and Technology, respectively. This suggests that the market recognizes which sectors are better positioned for

[4]The Median Rated Index, that captures the perceived general economic climate is the first most influential driver.

a transition to a low-carbon economy.

We also find that the effect of carbon risk on CDS contracts is even stronger during times of heightened public attention to climate change. Lenders appear to be more sensitive to carbon risk when market-wide concern about climate change risk is elevated. However, the attention effect for North America is modest except for the very short tenor, 1 year. Conversely, in Europe, the attention effect for the 1-year tenor is nonexistent, suggesting that news about adjustments in European carbon regulations are irrelevant for short-term CDS contracts. Finally, we provide a comprehensive analysis of the temporal dimension of this effect, extending our understanding of when carbon risk affects firms' creditworthiness. Using information from the entire CDS spread curve, we show that a shift in the expected temporal materialization of carbon risk (the "carbon risk slope") positively affects the steepness of the CDS curve slope. In Europe, the effect on the CDS term structure is particularly salient for shorter time horizons, suggesting that the market perceives carbon risk to be a short- to medium-term risk. Specifically, the coefficient estimate for the 5-minus-1 year carbon risk slope is four times bigger than the coefficient estimate for the 30-minus-5 years carbon risk slope. This last result is of particular interest to central banks and speaks to the debate about the (horizon of the) carbon risk and the pertinence of monetary policy adjustments. Collateral in monetary policy operations is generally pledged for short periods only. If carbon risk is exclusively a long-horizon issue, central banks might be less concerned with carbon risk and associated consequences, such as stranded assets.

This paper contributes to the literature on the effect of climate policies on credit risk, and is related to the wider literature on climate finance and credit risk.

First, this paper studies the amplifying effect of a climate-related transition on credit risk. Undoubtedly, the changes induced by a transition to a net-zero economy will cause adjustments in firms' valuations which may contribute to the deterioration of firms' creditworthiness, ultimately translating to higher credit risk (BIS, 2021; Bingler and Senni, 2022).

Evaluation of firms' exposure to carbon risk involves quantifying the effort necessary to successfully transition to a low-carbon economy. Although different approaches exist, most of the recent literature has focused on carbon emissions, establishing that investors command higher returns and require a premium (Bolton and Kacperczyk, 2021; Cheema-Fox et al., 2020; Görgen et al., 2020; Hsu et al., 2022; Lioui, 2022), that the market demands changes in the capital structure (Nguyen and Phan, 2020; Kleimeier and Viehs, 2018), and that engagement effort concentrates on large firms with high carbon emissions (Azar et al., 2021). In other words, firms with an emissions-intensive business model have disproportionately higher transition costs than their low-carbon peers. Our findings are complementary, showing that carbon risk is concentrated in specific sectors, like construction materials, fossil fuels, and utilities. Our findings also suggest that businesses in sectors like industrial and commercial services, technology equipment, and healthcare are seen as capable of providing the innovation and technologies necessary to facilitate a low-carbon transformation.

There is a growing body of empirical work investigating the effects of transition risk on credit risk through the lens of the cost of debt (Kleimeier and Viehs, 2018; Jung et al., 2018; Delis et al., 2018), corporate bonds (Duan et al., 2021; Seltzer et al., 2022), distance-to-default (Capasso et al., 2020), options (Ilhan et al., 2020), and CDSs (Barth et al., 2022; Christ et al., 2022; Kölbel et al., 2022). This literature tends to find increased financing and protection costs for firms that are relatively more exposed to the low-carbon transition. Several of these studies document a strengthening of the effect after the Paris Agreement. Barth et al. (2022); Christ et al. (2022) and Kölbel et al. (2022) are the most closely related works in this literature. While Barth et al. (2022) and Christ et al. (2022) use environmental ratings, Kölbel et al. (2022) construct their proxy of carbon risks from a textual analysis of 10-K financial from filings of U.S. firms. Our paper extends the analysis by using firms' emissions to discipline the construction of a forward-looking and market-implied carbon risk factor.

Although carbon risk in general represents another layer of risk to the market, the magnitude of its effect can vary substantially across regions and industries, crucially depending on the stringency of local and sector-specific regulations (Huij et al., 2021). In a recent study, Deng et al. (2022) show that changes in the perception of carbon risk induced by the Russo-Ukrainian war differed vastly between North America and Europe. Different effects are also to be expected on a sectoral level. After all, decarbonizing the economy will involve large-scale structural changes, with some sectors having to rapidly expand their production and contribute to decarbonization goals, while other sectors have to entirely transform their technological basis or, alternatively, shrink and potentially disappear. A growing body of empirical literature on the matter shows that emissions-intensive industries, like the energy or cement and steel sectors, exhibit large effects (Dietz et al., 2020; Bouchet and Guenedal, 2020; Ilhan et al., 2020). In this paper, we construct a testable hypothesis to examine geographical and sectoral differences, explaining the underlying reasons for the varying magnitude across regions and industries.

Second, this paper contributes more broadly to the literature on the empirical determinants of credit risk spreads. It is important to understand the directional effects beyond regular credit phases and examine the effect of each credit risk driver during a firm's extraordinary, more extreme credit phases. Within the CDS literature, recent evidence indicates that the main drivers, such as stock return or volatility, do not act uniformly on CDS spreads, but that effects differ significantly across different parts of the distribution (Pires et al., 2015; Koutmos, 2019). While these observations are important for risk management purposes, only limited research has been conducted on this topic regarding carbon risk. The only exception is Barth et al. (2022) who establish a U-shaped effect pattern for ESG ratings on CDS spreads. However, there is still no comprehensive investigation on this matter and we attempt to fill this gap.

This paper also contributes to the understanding of how carbon risk perception continually changes as climate policies evolve. In a rapidly changing social and policy environment, as new information arrives in the market (e.g. conversations about tighter emissions constraints), lenders would be expected to update their expectations accordingly (Huynh and Xia, 2021; Ardia et al., 2022; Pastor et al., 2021). Using news and concern indexes related to carbon risks, we empirically test whether lenders demand more credit protection when attention to climate change increases, advancing our understanding of the effect of market awareness and carbon risk.

2 From carbon risk to credit risk

The transition to a low-carbon economy will be effected through a combination of changes in public regulation, technology and consumers' preferences, triggering changes in demand-related factors (TCFD, 2017; BIS, 2021). The risks related to this transition arise from uncertainties regarding the characteristics and nature of the low-carbon pathway – specifically the timing and speed of greenhouse gas emissions reductions, which will necessarily restructure the economy. Measurement of the associated transition risks is arduous though: since the transition path cannot be easily observed, it must be inferred. However, it is far from clear which proxies are appropriate, especially for representing technologies and consumer preferences. To date, the finance literature has universally focused on directly observable government policies and regulations to limit carbon emissions (hereafter *carbon policies*). This literature has approached the pricing of *carbon risk* by focusing on how various financial assets reflect market *concerns* about said carbon policies. To date, firms' exposure to carbon risk is most often codified using firms' actual emissions data, in spite of their limitation in reflecting firms' future emissions reduction plans. Recent work addresses this limitation by complementing carbon emissions data with information about firms' abatement commitments and strategies (Carbone et al., 2021; Bolton and Kacperczyk, 2022; ECB, 2022).[5] Yet, headline pledges are often ambiguous and emission reduction commitments are limited, raising achievable and credibility issues and demanding more fitting assessment of firms' efforts to align with the net-zero trajectory.

As with the transition more broadly, measuring the financial effects of carbon policies is intricate. Carbon policies can affect firms in multiple ways, both directly and indirectly. For example, because carbon emissions are tied to fossil fuels, carbon abatement regulations often translate into higher energy costs for firms. Higher energy prices translate into higher operating costs and, consequently, lower cash flows. Firms may moreover incur greater costs from emission control and abatement, through policy compliance and product modifications in response to changes in carbon restrictions and consumer preferences. Firms might increase their investment in research and development to reduce operating costs in the future, but this comes at the expense of lower cash flows in the present. Without question, these costs could significantly affect firms' cash flow, financial wealth and the value of their collateral, potentially undermining their capacity to generate enough income to service and repay their debt, and eventually leading to higher probabilities of default. This results in repricing – with more exposed firms' valuations being bid down and less exposed firms' valuations being bid up – in response to changing investor beliefs about firms' exposure to carbon risk. Crucially, firms may transition to a low-carbon business model at different times and at different speeds, reflecting the fact that carbon policies impose different costs on firms, depending on their size, sector, geographical footprint or other characteristics. In other words, superficially similar firms can face vastly different challenges, and carbon risk will affect them differently depending on how and where they do business. Further, firms' exposure may depend on where their operational footprint is concentrated. This means that differential valuations (Meinerding et al., 2020) do not depend exclusively on the sectors in which firms operate.

[5] We refer to Campiglio et al. (2022) for a review of the emerging literature that uses forward-looking methodologies to estimate the effect of transition risks on asset prices.

In fact, firms in the same industry or sector can face vastly different challenges, and carbon risk will affect them differently depending on how and where they do business.

To illustrate how carbon risk differentially impacts the valuation of dissimilar firms, we use the Merton (1974) model of credit risk. The model provides a convenient basis for intuition on the effect of costs associated with carbon regulations on the credit spread. Integrating carbon costs into the Merton (1974) model provides a theoretical foundation for a straightforward translation of carbon risk into credit risk. Consider a zero-coupon debt contract that matures in T years with a face value of F. The risk-free interest rate is r. As per convention, assume the value of the firm's assets is V_t and it follows a geometric Brownian motion with volatility σ. In the presence of carbon regulations, firms' cash flows are reduced – this reflects a possible combination of revenue reductions and operating expenditures due to restrictions on emissions. We call this the "carbon tax rate" and we label it δ.[6] Our working assumption is that each firm, depending on their exposure to carbon risk, pays δ per unit of time, where $0 < \delta < r$.[7] Adopting these parameters, the dynamics of the firm value are

$$\frac{\mathrm{d}V_t}{V_t} = (r - \delta)\mathrm{d}t + \sigma \mathrm{d}W_t,\ V(0) = V_0, \tag{1}$$

where W_t is a Brownian motion under an equivalent martingale measure $\mathbb{P}^*$.
At $t = 0$ the credit spread, defined as the difference between the yield on the firm's risky debt and the risk-free interest rate, is given by:

$$s(\delta) = -\frac{1}{T} \log \left\{ V_0 e^{-\delta T} \Phi(-d_1) + F e^{-rT} \Phi(d_2) \right\},$$

with $\Phi(\cdot)$ being the cumulative standard normal distribution function, and

$$d_1 = \frac{\log(V_0/F) + (r - \delta + \sigma^2/2)T}{\sigma\sqrt{T}},\ d_2 = d_1 - \sigma\sqrt{T}.$$

We can now express the conditional probability of default as a function of the carbon tax rate δ:

$$\mathrm{PD}(\delta) = \mathbb{P}^*(V_T(\delta) < F | \mathcal{F}_0) = \Phi(-d_2), \tag{2}$$

and observe that, when higher carbon-related costs materialize, firms may respond by increasing leverage, which can increase default risk. In fact,

$$\frac{\partial \mathrm{PD}(\delta)}{\partial \delta} = \frac{\phi(-d_2)\sqrt{T}}{\sigma} > 0.$$

Extant literature argues that high-emitting firms (*polluting* firms, hereafter labeled P) may incur greater costs compared to low-emitting firms (*clean* firms, hereafter labeled C). For an unspecified value of the continuous carbon tax rate δ for clean and polluting firms, respectively, we can calculate the default probabilities (under uncertainty) by taking the default

[6] The carbon tax rate is a random variable because the overall cost associated with carbon regulation is uncertain.

[7] The formulation is equivalent to the case where the firm pays a random dividend rate δ.

probability from Expression (2) and integrating it with respect to the relevant distribution of δ^C and δ^P:

$$\mathrm{PD}^C = \int_0^r \mathrm{PD}(\delta)\mathrm{d}F_C(\delta) \text{ and } \mathrm{PD}^P = \int_0^r \mathrm{PD}(\delta)\mathrm{d}F_P(\delta).$$

Naturally, $\delta^C \leq \delta^P$ and hence $F_P \geq F_C$. By stochastic dominance, we obtain $\mathrm{PD}^C \leq \mathrm{PD}^P$. Combining the relationship $\delta^C \leq \delta^P$ and the fact that the default probabilities have a monotonic relationship with the carbon tax rate, we retrieve a theoretically founded link between carbon risk exposure and the credit spread. Namely, depending on market's perception of how carbon regulation translates into carbon tax rate, changes in the credit spreads should respond to changes in (perceived) carbon risk exposure.

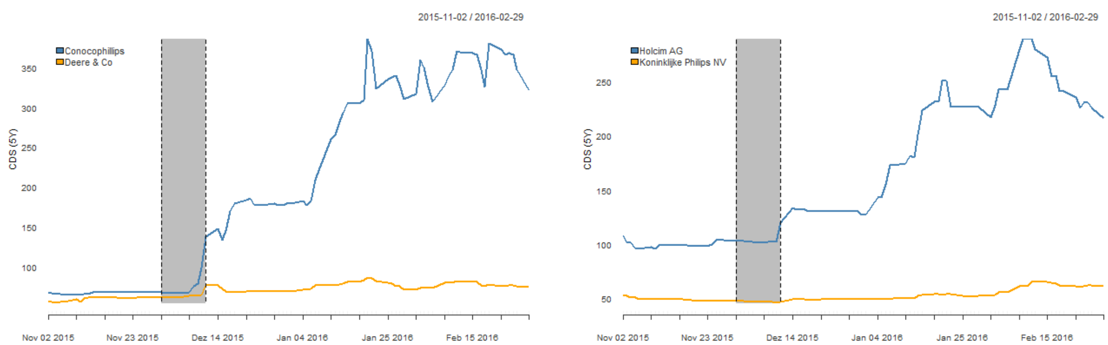
2.1 Measuring carbon risk

Examining how the market perceives firms' exposures to carbon risk requires a measurement of firms' carbon profiles. This is commonly proxied by firms' current emissions and emission intensity (Bolton and Kacperczyk, 2021; Azar et al., 2021; Görgen et al., 2020; Nguyen and Phan, 2020), although academics and practitioners recognize that this should be supplemented by firm-specific information on future emissions reduction targets (Carbone et al., 2021; ECB, 2022). This acknowledges firms' forward-looking plans, and their commitment and strategy to reduce carbon emissions.

Motivated by the theoretical relationship between carbon risk and credit spreads, our approach to measuring carbon risk relies on analyzing the changes in the credit spreads, which reflect the evolution in the market's perception of carbon risk. To do this, we utilize the information contained in the spreads of the CDS contracts. CDS contracts have three crucial advantages. They are typically traded on standardized terms, eliminating distortions due to differences in contractual arrangements or liquidity concerns (Longstaff et al., 2005). Furthermore, CDS spreads respond quickly to changes in credit and market (and arguably policy) conditions (Blanco et al., 2005; Zhu, 2006). Finally, since there are CDS contracts with varying tenors up to 30 years, they allow us to (i) incorporate the collective forward-looking considerations of lenders, and (ii) shed light on the expected degree of carbon risk within distinct time horizons. As such, CDS spreads provide a unique window for viewing the effect of carbon risk through the lens of lenders' perceptions of carbon risk. This is clearly illustrated in Figure 1, where we plot the evolution of the CDS spreads for two pairs of companies (with the same credit rating) before and after the Conference Of the Parties in Paris in 2015 (COP21), which culminated in the landmark Paris Agreement.[8]

[8] In this figure, we provide data on two exemplary polluting firms (ConocoPhillips and Holcim AG) and two exemplary clean firms (Deere & Company and Philips NV) in North America and Europe. Beginning with the North American examples, ConocoPhillips is a multinational corporation engaged in hydrocarbon exploration and production, and was ranked 21st among the World's Top 100 Polluters (CDP, 2017). Deere & Company, the world's largest agricultural equipment manufacturer, has demonstrated leading practice in controlling and reducing their emissions in recent years. For Europe, Holcim AG is a global manufacturer of construction materials, including emissions-intensive cement and concrete (IEA, 2021). Philips is a diversified global healthcare company that has effected emissions reductions through increased use of renewable energy.

Figure 1 illustrates that the difference in CDS spreads is approximately constant until the occurrence of a policy-relevant event. Post-Paris Agreement, however, the spreads diverge, which we interpret as the result of lenders expecting higher carbon impacts for high-emitting firms. They seek higher protection, demanding more of the CDSs of relatively more carbon-exposed firms (in this example, ConocoPhillips and Holcim), ultimately paying higher spreads.[9] Following this argument, we use the information contained in the CDS spreads themselves to construct a proxy that captures firms' evolving carbon risk, representing variation in lenders' concerns over time about transition-related aspects (especially climate regulations) that can impact firms' credit risk profiles.[10] Effectively, we compute a market-implied carbon risk factor, while also providing an instrument to discipline firms' abatement efforts in line with their net-zero strategies.



(a) North America (b) Europe

Figure 1: Evolution of the 5Y-CDS spreads of ConocoPhillips (blue) and Deere & Co (orange) on the left diagram, and Holcim AG (blue) and Koninklijke Philips NV (orange) on the right diagram. The time period spans from 02 November 2015 to 29 February 2016. The gray-shaded area indicates the time period of COP21 (30th Nov 2015 – 12th Dec 2015).

To date, the finance literature on climate change has approached the pricing of carbon risk by focusing on how various financial assets reflect investor concerns about carbon risk. In most studies, firms' exposure to carbon risk is codified using their emission intensity data[11] and argues that high-emitting firms may incur greater costs from changes in policy – through emissions abatement and the adoption of new technologies – and product changes in response to changes in consumer preferences. This literature asserts that the size of these costs and the consequent size of carbon risks are proportional to the size of firms' emissions, and to the rate of growth of these emissions (Bolton and Kacperczyk, 2021; Azar et al., 2021; Cheema-Fox et al., 2020; Görgen et al., 2020; Hsu et al., 2022; Nguyen and Phan, 2020).

[9]Figure 4 in Appendix A illustrates that the same behavior can be observed for firms operating in the same industry.

[10]While factors constructed in the equity space (e.g. the 'Brown-Minus-Green' factor by Görgen et al. (2020) or the 'Pollutive-Minus-Clean' factor by Huij et al. (2021)) encapsulate many different types of risk, the consideration of the CDS market consent to concentrate on the credit risk component.

[11]The Greenhouse Gas Protocol distinguishes between three sources of emissions: Scope 1 emissions cover direct emissions from establishments that are owned or controlled by the company, including all emissions from fossil fuel used in production. Scope 2 emissions come from the generation of purchased heat, steam and electricity consumed by the company. Scope 3 emissions are caused by the operations and products of the company but are generated by sources not owned or controlled by the company.

As with this literature, we construct firms' carbon profiles using yearly emissions intensities (Scope 1 & 2 emissions normalized by revenue) from Refinitiv as our primary dataset.[12] Emissions are estimated where no actual emissions were reported. These data have been shown to be sufficiently consistent across different data providers (Busch et al., 2018). The emissions of firms in our CDS sample account for a significant fraction – approximately 30% – of the total emissions in the universe of companies represented in the Refinitiv database. We chose firms' emission because other prominent metrics (e.g. environmental ratings provided by Asset4, MSCI, etc.) have been shown to deliver mixed signals, seriously weakening their reliability in terms of constructing the carbon risk classification (Görgen et al., 2020; Berg et al., 2021; Berg et al., 2022; Dimson et al., 2020).

Our approach to constructing a carbon risk factor relies on tracking how firms' exposure to carbon risk changes – this change reflects one of two things: changes in lenders' expectations about the carbon exposure of different firms or changes in lenders perception of carbon risk for a specific firm over time. To that end, we follow the standard approach used in empirical asset pricing for factor construction (Fama and French, 1992). Specifically, we partition the universe of firms into different groups according to the emission intensity profile of each firm, and then subdivide firms into quintiles.[13] We use the groups to form portfolios meant to mimic the underlying risk factor in returns related to carbon.[14] In fact, this grouping allows us to capture the gradient of carbon intensity per unit of revenue while retaining a sufficient number of firms within each group. We then define firms below the first quintile as "clean" and gather their CDS spreads in the set $\mathcal{C}_t^m$. Analogously, we define firms above the last quintile as "polluting" and gather their CDS spreads in the set $\mathcal{P}_t^m$.

We then obtain the median cost of default protection of clean and polluting firms by calculating the median m-year CDS spread level for each tenor $m \in \{1, 3, 5, 10, 30\}$ at every time t:

$$\begin{aligned} \mathrm{C}_t^m &= \mathrm{Med}\left(\mathcal{C}_t^m\right), \\ \mathrm{P}_t^m &= \mathrm{Med}\left(\mathcal{P}_t^m\right). \end{aligned}$$

Finally, we calculate the difference between the median CDS spreads of polluting and clean firms.[15] This difference, or wedge, represents the differential credit risk exposure of polluting versus clean firms. We call this the *carbon risk* (CR) factor:

$$\mathrm{CR}_t^m = \mathrm{P}_t^m - \mathrm{C}_t^m$$

Essentially, CR mimics the dynamics of a portfolio in which default protection is bought for a representative (median) polluting company and sold for a representative (median) clean

[12]Refinitiv firm-level carbon emissions data follow the Greenhouse Gas Protocol, which sets the standards for measuring corporate emissions.

[13]We perform numerous robustness checks by extending the univariate portfolio sorts (based on emission characteristics) to bivariate sorts that also consider size, book-to-market ratio, and leverage. See Section D.2 for details.

[14]We refer to Fama and French (1992), Fama and French (1993) and Hou et al. (2017) for a detailed description of the construction of factors.

[15]Table 8 in Appendix B contains a comprehensive list of all firms entering the clean and polluting class (including median firms), respectively, during our sample period.

firm.[16] When policy events trigger a rise in carbon risk (e.g. expectation of a tighter future regulatory framework), the demand for protection of more (less) exposed firms increases (decreases), resulting in a widening of the wedge. Conversely, if the market expects a loosening of the regulatory framework, there is a narrowing of the wedge (or possibly even a negative wedge).[17] These changes in perceived exposure to carbon risk are aptly represented by the behavior of CR. As such, we consider CR to be an observable proxy for lenders' perception of carbon risk exposure.

To illustrate the relevance of CR, we examine its behavior in response to events that affect firms' exposure to carbon risk. Figure 2 displays the evolution of the CR over time, for tenors of 1, 5 and 30 years for the universe of CDS of firms listed in Europe (top panel) and North America (bottom panel), respectively.[18] In these graphs we also identify two events, identified in Meinerding et al. (2020), that oppositely affected market perceptions of carbon risk: the Paris Agreement and the election of Donald Trump in the US; these events are represented in Figure 2 with vertical solid dark green and brown lines, respectively.

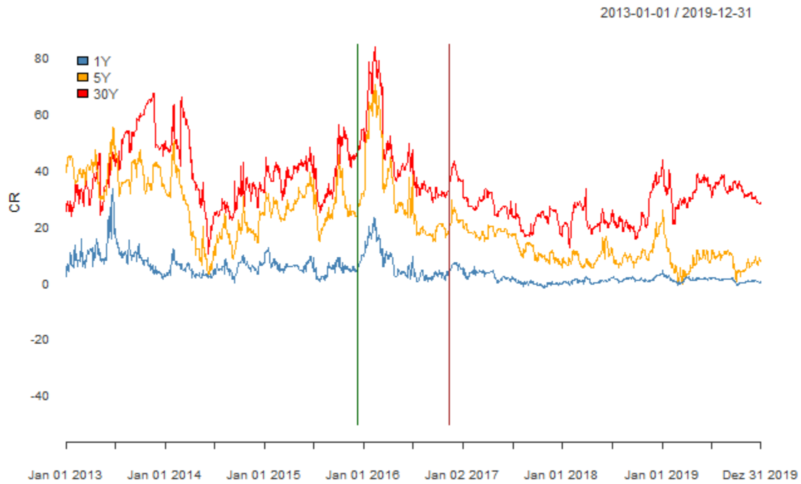
We first examine the European case, and observe that all CR time series (CRs) are non-negative. This is in stark contrast with CRs in North America, where all CRs (except 1Y tenor) continuously swing between positive and negative values, denoting a situation where lenders' perceptions of differential exposure are unclear and constantly evolving. Notwithstanding CRs irregularity (discussed below), lenders continually demand more (less) protection for European firms that are perceived to be more (less) exposed to carbon risk. In this case, a polluting-minus-clean credit protection portfolio, constructed using CR, would have delivered a positive premium. Second, the CR squarely reflects changes in lenders' demand for default protection in response to policy-relevant events, such as COP21, which called for more ambitious policies and plans to reduce emissions. It is reasonable to argue that policies following this event can increase expected costs for firms that are less prepared for a transition to a low-carbon economy, and benefit firms that are more adequately prepared. Nevertheless, the polluting-minus-clean outlook in North America was unclear until mid-2015. Only in the lead-up to COP21 did CRs turn positive, indicating a surge in perceived exposure to carbon risk. However, this trend reverts almost immediately after the election of Donald Trump – a notorious climate change denier – indicating that this event is associated with a decline in carbon risk. The impact of this election was geographically limited, however, reflecting the limited effect of US climate policy on European firms. In summary, we observe that, conditional on the relevance of the event, lenders will demand *more* or *less* protection according to their perception of a firm's ability to absorb the costs associated with carbon regulations, resulting in a continuous adjustment of the CDS spread wedge.[19] Essentially, this is what

[16] A long-short portfolio is similarly constructed in Meinerding et al. (2020) by sorting firms on their carbon footprints. Combined with a climate news index, Meinerding et al. (2020) use these portfolios to identify the differential effect of carbon risk. Essentially, portfolios are used to identify shocks that affect clean and polluting firms differently.

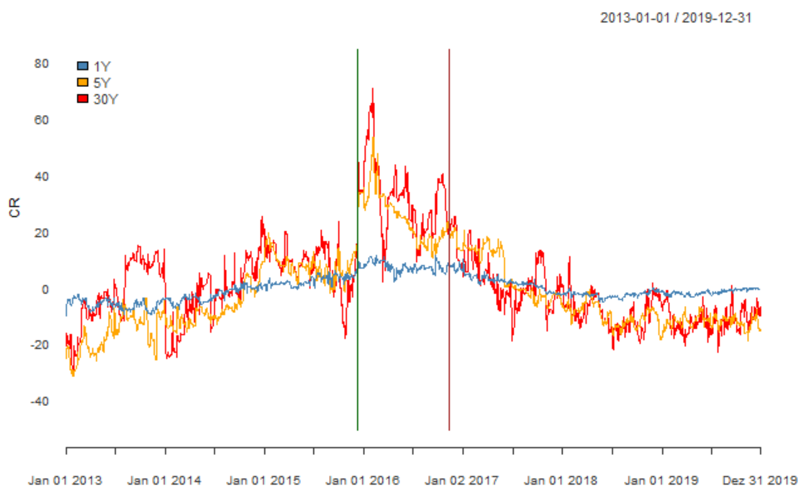
[17] This case corresponds to the situation where expected profits of actively compliant firms are hampered by a policy reversal. The increased costs associated with earlier tighter regulation are perceived as unnecessary expenditure.

[18] We relegate to the Appendix C Figure 5 that plots all available tenors (including 3Y and 10Y).

[19] Demonstrating how firms are prepared to operate in a low-carbon economy is at the center of carbon risk mitigation strategies, as evidenced in the opening quote from BlackRock's Chairman and CEO, Larry



(a) Europe



(b) North America

Figure 2: Evolution of the CR over time for maturities 1Y (blue), 5Y (orange) and 30Y (red) for Europe (top) and North America (bottom). The vertical solid lines refer to the Paris Agreement (dark green) and Trump election (brown), respectively.

makes CR an observable and market-implied proxy for carbon risk exposure.

Furthermore, we can extract valuable information about carbon risk over a specific time horizon by considering the difference between a long- and a short-tenor CR. This difference constitutes the slope of the CR factor,[20] which is constructed as

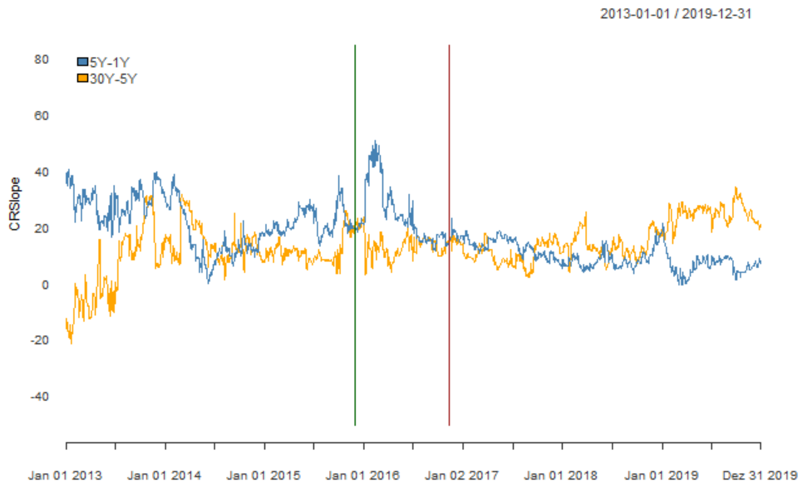
$$\text{CRSlope}_t^{mn} = \text{CR}_t^m - \text{CR}_t^n,$$

where the relationship between tenors is $m > n$. Conceptually, starting from a carbon risk exposure over the next n years, CRSlope_t^{mn} provides valuable information by describing how the exposure to carbon risk is perceived over the remaining $m - n$ years. CRSlope_t^{mn} can

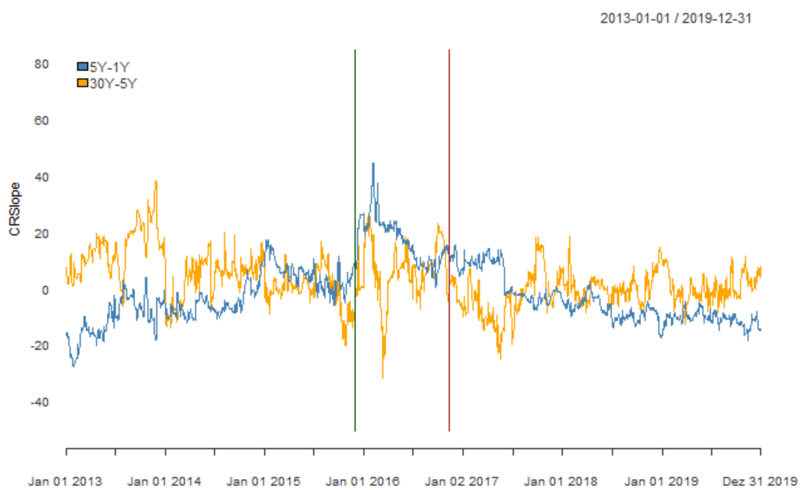
Fink's open letter to CEOs.

[20]Later in the analysis, we examine the effect of said information on the entire CDS spread curve.

take positive and negative values, depending on how the market's perception of carbon risk evolves. Compared to the next n years, a positive (negative) CR slope reflects expectations of an increasingly tighter (looser) carbon regulatory framework in the later $m-n$ years.



(a) Europe



(b) North America

Figure 3: Evolution of the CR slope over time for 5Y-1Y (blue) and 30Y-5Y (orange) for Europe (top) and North America (bottom). The vertical solid lines refer to the Paris Agreement (dark green) and Trump election (brown), respectively.

This is illustrated in Figure 3, where the plots again suggest distinct conditions for Europe and North America. The CR slope is uninterruptedly positive in Europe, indicating a collective perception of continuously, albeit erratic, growing exposure to carbon risk. In other words, the longer the time horizon, the larger the perceived exposure to carbon risk in Europe. Conversely, the perceived future exposure to carbon risk in North America varies continuously and is less clear-cut. For example, contrasting the 5Y-1Y vs 30Y-5Y CR slopes, and focusing on the period immediately following COP21, the CR slopes show that the market anticipated a surge in exposure to carbon risk in the four subsequent years, as opposed to the successive

25 years. This indicates that lenders in North America expected most of the risks associated with COP21 to materialize between 2017 and 2021.

2.2 Hypothesis development

In the next section, we empirically test several predictions based on the structural credit risk model, conditioned on known variables and the CR factor in particular. Our empirical examination employs data on CDS spreads and their reaction to changes in carbon risk exposure. Hence, compared to existing empirical studies, our examination has two distinct advantages: it uses a frequently observable and market-implied proxy for carbon risk exposure, and is based on a theory-motivated series of testable hypotheses.

In the previous section, we argued that CR represents the general perception of carbon risk exposure, such that a higher CR corresponds to a higher perceived carbon risk. We also noted that, according to Merton (1974) model, a firm with high exposure to carbon risk can see a decline in its valuation, a higher probability of default and, therefore, a higher CDS spread. Within Merton (1974), higher costs are represented by an increase in δ, the carbon tax rate. We thus propose the first sensible hypothesis:

Hypothesis 1a. *There is a positive relationship between carbon risk and CDS spread returns.*

Recent studies suggest that carbon risk differs across regions due to the varying degrees of ambition of environmental regulations and diverse restrictions on carbon emissions (Huij et al., 2021).[21] While Europe has generally been considered a global forerunner in the implementation of stringent carbon policies, North American countries – in particular the US – consistently fall short in their efforts to regulate and reduce carbon emissions. Consequently, one would expect firms in Europe to face a stronger prospect of higher costs associated with policy compliance – in the form of emissions abatement costs and costly adoption of new technologies. As such, the prospect of carbon risks materializing is stronger in Europe than in North America. Applying this to the Merton model, we assume that $\delta_{\text{EU}} > \delta_{\text{NA}}$, yielding higher expected CDS spreads for firms located and operating predominantly in Europe vs North America. This is already reflected in Figures 2 and 3, which indicate a decidedly larger response to policy-relevant events in Europe vs North America. We thus propose the second hypothesis, as follows:

Hypothesis 1b. *The effect of carbon risk on CDS spread returns is stronger in Europe than in North America.*

Climate policies continually evolve within a rapidly changing social and policy environment, as attested to by frequent revisions to national climate policies around the world (Aiello and Angelico, 2021). The inherent uncertainty of climate and carbon regulations may cause a vacillating perception of the associated carbon risk. As new information arrives in the market (e.g. conversations about tighter emissions constraints), lenders update their expectations

[21] There are currently 68 carbon pricing instruments in operation today (36 carbon taxes and 32 Emissions Trading Systems), spanning a broad range of carbon tax rates and carbon caps (Aiello and Angelico, 2021).

accordingly. Specifically, when concerns about carbon risks increase during times of heightened attention to climate change in the news, lenders will demand more credit protection, thus increasing CDS spreads. Thus, we state the next hypothesis, as follows:

Hypothesis 2. *The effect of carbon risk on CDS spread returns is stronger during times of heightened attention to climate change.*

Last, we examine whether carbon risk also depends on the speed at which a transition to a low-carbon economy is expected to occur. Essentially, carbon risk depends on both the stringency and the deadline of the policy. For example, if a new carbon regulation with a more pressing deadline is introduced, one would expect the costs associated with transitioning to be higher in the short-term than in the long-term. This should be noticeable in the term structure of the CDS. The relative adjustment in the spread of the CDS with shorter tenor would be higher (steeper sloped) than in the spread of the CDS with longer tenor. We therefore propose the following testable hypothesis:

Hypothesis 3. *There is a positive relationship between the term structure of carbon risk and CDS spread slopes.*

3 Data and methodological framework

We first describe the CDS data, then the variables to control for the effects of known determinants of CDS spread returns, and we report some summary statistics. Last, we introduce our methodological framework.

3.1 Credit default swap (CDS) spreads

We obtain CDS spread data from Refinitiv for the period January 1, 2013 to December 31, 2020. The dataset covers single-name CDS spreads across tenors of 1, 3, 5, 10 and 30 years for publicly listed European[22] and North American (US & Canada) entities. Each CDS is denominated in US dollars and refers to senior-unsecured debt. For Europe we use CDSs with the "modified modified restructuring" clause (MM), whereas North American CDSs contain the "no restructuring" clause (XR).[23] We exclude all firms that defaulted during the sample period or that exhibit illiquid CDSs, but in general retain firms with large CDS spreads.[24] To account for possible distorting effects from the COVID-19 pandemic, we exclude the year

[22]The European countries included in the sample are: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Luxembourg, Netherlands, Norway, Poland, Portugal, Russia, Spain, Sweden, Switzerland and the UK.

[23]MM and XR represent the standard clauses within their respective region and as such provide the best coverage of CDSs.

[24]Illiquid CDSs are those contracts where no spread movement is recorded for a minimum of 245 consecutive trading days. We acknowledge that this condition is rather lax, but we still use it to ensure a significant number of entities in our samples. Appendix D.1 applies a much more stringent filtering condition, and shows that for both Europe and North America, the results remain unchanged with respect to the baseline findings reported in the Results section. Some studies also exclude firms with CDS spreads exceeding specific thresholds (Zhang et al., 2009; Kölbel et al., 2022; Barth et al., 2022). Our robust modeling approach allows us to dispense with this exclusionary criterion by eliminating exclusively illiquid CDSs.

2020 from our sample. Additionally, we exclude financial firms from the sample because of their special business models (Hasan et al., 2016). In total, our sample contains 229,036 and 447,640 CDS spreads-day observations for an unbalanced panel covering 137 European firms and 281 North American firms, respectively.

The emerging consensus in the literature is that (log) CDS spread *levels* tend to be non-stationary (Collin-Dufresne et al., 2001; Avramov et al., 2007; Ericsson et al., 2009; Galil et al., 2014; Huang, 2019; Koutmos, 2019). In line with the majority of previous studies, we find that log CDS spread series are not level-stationary and so we analyze first-differences. Following Koutmos (2019), we thus calculate the daily CDS spread log returns as:

$$s_{i,t}^m = \log(\text{CDS}_{i,t}^m) - \log(\text{CDS}_{i,t-1}^m),$$

where $\text{CDS}_{i,t}^m$ is the m-year CDS spread of firm i at day t. $s_{i,t}^m$ quantifies the daily *relative* change in a firm's CDS spread. The relative change consents a straightforward comparison of credit improvement (or credit deterioration, respectively) across all firms.

When investigating the term structure of CDS spreads, we proceed in a similar fashion to the construction of the CR slope. Namely, we first calculate the CDS slope as the difference between two CDS spreads of differing maturities $m \neq n$

$$\text{CDSSlope}_{i,t}^{mn} = \text{CDS}_{i,t}^m - \text{CDS}_{i,t}^n.$$

Second, due to the nonstationarity of the CDS slope time series, we calculate the change in the CDS slope as

$$\Delta\text{CDSSlope}_{i,t}^{mn} = \text{CDSSlope}_{i,t}^{mn} - \text{CDSSlope}_{i,t-1}^{mn}.$$

Note that log transformation of the time series is not possible. Although the CDS curve is typically upward-sloping, and consequently the CDS slopes are positive, we occasionally observe hump-shaped term structures denoting negative slopes.

3.2 Other control variables

To isolate the impact of carbon risk on CDS spreads, we employ a comprehensive list of firm-specific and market-specific variables that have commonly been identified in the literature as determinants of CDS spreads. Following structural credit risk models, particularly Merton (1974), firm-specific measures include stock return and stock volatility. Market-specific measures include general market conditions, interest rates and the term structure of interest rates. These have been shown to adequately account for the general behavior of CDS spreads, largely outperforming alternative models that consider the inclusion of further firm-level fundamental determinants (Galil et al., 2014; Han and Zhou, 2015; Koutmos, 2019).[25] By controlling for these variables, we can isolate the effect of carbon risk on the probability of default.

Stock return (Return) is calculated as the difference of the natural log of daily stock prices; $r_{i,t} = \log(S_{i,t}) - \log(S_{i,t-1})$ where $S_{i,t}$ denotes the stock price of firm i at time t (obtained

[25] Additionally, the construction of a daily carbon factor, as well as our quantile regression approach (which requires a lot of data), automatically excludes all variables that are not reported on a daily basis.

from Refinitiv). By measuring the relative change in a firm's market value of equity, the stock return is considered to be one of the main explanatory variables of a firm's probability of default (Galil et al., 2014; Koutmos, 2019). Model-based expectations indicate that default probability decreases with the firm's past stock returns. Consequently, we expect a negative relationship between CDS spread and stock return $r_{i,t}$. Additionally, we include the stock volatility (Vol) measured as the annualized variance of a firm's returns (estimated on a 245-day rolling window). The volatility of a firm's assets captures the general business risk of a firm and provides crucial information about the firm's probability of default. Theoretical results indicate that default probability increases with stock return volatility, and hence we expect a positive relationship between CDS spread and changes in stock volatility $\Delta\sigma_{i,t}$.

We also include information capturing the current state of the CDS market. Specifically, we include a market condition variable, the Median Rated Index (MRI), that captures the perceived general economic climate. The general assumption is that improvements in market-wide conditions decrease firms' probability of default and automatically lead to lower credit spreads. We follow Galil et al. (2014) and measure the current business climate using the change in the MRI $\Delta\text{MRI}^{m}_{i,t}$. The MRI is defined as the median CDS spread of all firms in the S&P rating supercategories "AAA/AA", "A", "BBB" and "BB+ or lower". It has been documented that the MRI has a positive relationship with CDS spreads (Galil et al., 2014).

Moving beyond CDS spreads, we consider the term structure of CDS spreads that reflects the shape of the conditional default probability over different time horizons (Han and Zhou, 2015). Following Collin-Dufresne et al. (2001) and Han and Zhou (2015), we include the risk-free interest rate (IR). Specifically, we measure the change in the 10-year constant maturity Treasury yield (ΔIR_t) using data collected from the St Louis Federal Reserve (FRED). Our starting observation is that an increase in the IR reduces risk-adjusted default probabilities, and hence the CDS spread falls. Therefore, we expect a negative relationship between the slope of the CDS spreads and the IR.

Finally, following Han and Zhou (2015), we include the market's view on the future interest rate proxied by the change in the difference between short- and long-term risk-free interest rates. We calculate the change of the slope of the risk-free yield curve ΔTerm_t as the difference between the 10-year and 1-year constant maturity Treasury yields. An upward-sloping curve reflects the market's expectation of lower future interest rates. Consequently, an increase in the change of ΔTerm_t increases default probabilities, and hence CDS spreads rise. We therefore expect a positive relationship between the slope of the CDS spreads and the risk-free yield curve.

3.3 Descriptive statistics

To gain more intuition about the data under investigation, Table 1 presents descriptive statistics for all dependent and independent variables under consideration in both regions.[26] Average CDS spread returns fluctuate below zero and slightly increase toward longer maturities. The corresponding standard deviations indicate a relatively large dispersion with

[26]We omit descriptive statistics for the variables used in term structure models (e.g. $\text{CDSSlope}^{m,n}_{i,t}$, IR_t, etc.). They resemble the statistics shown here and are available upon request.

numbers varying between 1.6% to 7.3%. CDS spread returns exhibit large outliers with maximum (minimum) returns from 85% (-67%) to 300% (-220%), and even the shortest maturity of 1 year reaching maximum (minimum) returns of over 550% (-550%) and 370% (-310%), for Europe and North America respectively. The CDS spread return distributions are slightly right-skewed and characterized by heavy tails (with a kurtosis ranging from 47 to more than 1,000). These extreme CDS spread statistics are in line with those reported in the existing literature and illustrate the unconventional characteristics of CDS data (Pires et al., 2015).[27]

3.4 Panel quantile regression

While linear regression has served as the standard workhorse in empirical finance, several scholars have identified its limitations in only focusing on the center of a dependent variable's conditional distribution (Barnes and Hughes, 2002; Baur et al., 2012). Moreover, in the CDS literature, various analyses reveal ambiguous results concerning fundamental drivers, hinting at heterogeneous effects across the conditional distribution of CDS spreads (Collin-Dufresne et al., 2001; Pereira et al., 2018; Kölbel et al., 2022). As such, a standard linear conditional mean regression framework would not adequately describe the full distributional relationship between CDS spread returns and firms' carbon exposure. In particular, distributionally varying signs and magnitudes of explanatory variables may remain concealed within the data. For this reason, we use a quantile regression (QR) approach, which allows us to (i) provide a more complete description of how carbon risk is linked to the entire conditional distribution of CDS spread returns, and (ii) capture the marginal impact of carbon risk above and beyond known determinants. Introduced by Koenker and Bassett (1978), QR extends the classical conditional mean model to a series of models for different conditional quantile functions, allowing us to dissect and test the effect of different variables on the conditional distribution of the dependent variable. This is especially relevant for credit risk, where understanding the effects on the tails of the distribution is essential.

Additionally, QR can mitigate some of the typical empirical problems frequently encountered in the CDS literature (e.g. the presence of outliers, non-normality) and which also apply to our data. In particular, the descriptive measures in Table 1 illustrate that CDS returns tend to be interspersed by occasional influential outliers and their distributions are extremely heavy-tailed, making the normality assumption very problematic. While these empirical features would pose a threat to the validity of Ordinary Least Squared (OLS) estimates and their standard errors, QR is robust to these data characteristics and thus a viable option.

The use of QR is rather scant in the credit risk literature, although Pires et al. (2015) and Koutmos (2019) are notable exceptions. Since several scholars report that the presumed explanatory variables actually have varying degrees of explanatory power on the center of the distribution of CDS spreads and CDS spread changes, both these studies adopt a QR framework documenting a varying degree of sensitivity on parts of the CDS spread distribution. In particular, Pires et al. (2015) shows that the impacts of the explanatory variables on CDS spreads vary according to whether firms have conditionally high or low credit risk. Koutmos

[27] Compared to previous literature, these descriptive measures are even smaller in magnitude by some margin. Also, due to the financial crisis, the data of Han and Zhou (2015) (for example) are interspersed with many more outliers and move on a relatively larger scale in general.

Variable	Mean	Q25	Median	Q75	SD	Min	Max	Skew	Kurt
Europe									
Dependent variables									
$s^1_{i,t}$ (%)	-0.05	-1.02	0.00	0.24	7.31	-555.00	554.96	0.78	1035.52
$s^3_{i,t}$ (%)	-0.06	-1.04	0.00	0.20	3.74	-93.02	123.19	1.55	46.84
$s^5_{i,t}$ (%)	-0.05	-0.65	0.00	0.11	2.20	-85.00	103.68	1.75	81.66
$s^{10}_{i,t}$ (%)	-0.03	-0.44	0.00	0.13	1.62	-67.49	89.16	1.66	144.62
$s^{30}_{i,t}$ (%)	-0.02	-0.42	-0.01	0.19	2.15	-74.53	85.84	0.60	100.22
Independent variables									
$r_{i,t}$ (%)	0.01	-0.79	0.00	0.84	1.64	-44.33	28.98	-0.66	18.88
$\Delta\sigma_{i,t}$ (%)	-0.00	-0.03	-0.00	0.03	0.24	-19.80	15.28	-0.64	960.59
$\Delta\mathrm{MRI}^1_{i,t}$	-0.01	-0.20	0.00	0.15	1.14	-54.69	60.06	1.42	144.78
$\Delta\mathrm{MRI}^3_{i,t}$	-0.03	-0.41	-0.00	0.26	1.86	-113.32	128.25	2.36	404.38
$\Delta\mathrm{MRI}^5_{i,t}$	-0.04	-0.48	-0.01	0.25	2.29	-179.56	174.67	0.93	872.50
$\Delta\mathrm{MRI}^{10}_{i,t}$	-0.04	-0.50	-0.01	0.30	2.52	-226.28	213.96	-2.08	1385.98
$\Delta\mathrm{MRI}^{30}_{i,t}$	-0.04	-0.51	-0.02	0.38	2.96	-235.35	220.58	-1.27	809.32
$\Delta\mathrm{CR}^1_t$	-0.00	-0.27	0.00	0.25	1.06	-7.46	13.83	0.88	27.89
$\Delta\mathrm{CR}^3_t$	-0.01	-0.50	0.00	0.51	1.32	-9.95	7.58	0.15	10.27
$\Delta\mathrm{CR}^5_t$	-0.02	-0.52	0.00	0.49	1.61	-9.75	11.79	0.38	13.21
$\Delta\mathrm{CR}^{10}_t$	-0.01	-0.51	0.00	0.52	1.73	-24.38	10.66	-1.85	35.73
$\Delta\mathrm{CR}^{30}_t$	0.00	-0.53	0.00	0.54	2.02	-22.06	23.23	-0.55	31.02
North America									
Dependent variables									
$s^1_{i,t}$ (%)	-0.03	-0.14	0.00	0.10	7.08	-314.63	371.68	0.96	165.07
$s^3_{i,t}$ (%)	-0.03	-0.12	0.00	0.07	3.42	-151.15	149.83	0.40	140.39
$s^5_{i,t}$ (%)	-0.03	-0.12	0.00	0.05	2.40	-84.93	108.81	1.42	95.77
$s^{10}_{i,t}$ (%)	-0.02	-0.11	0.00	0.05	2.58	-164.77	167.00	1.25	252.18
$s^{30}_{i,t}$ (%)	-0.01	-0.13	0.00	0.06	3.16	-218.32	292.52	2.32	499.67
Independent variables									
$r_{i,t}$ (%)	0.03	-0.70	0.01	0.81	1.73	-42.79	43.14	-0.36	26.38
$\Delta\sigma_{i,t}$ (%)	0.00	-0.03	0.00	0.03	0.27	-25.81	24.89	-0.84	1082.45
$\Delta\mathrm{MRI}^1_{i,t}$	-0.01	-0.15	0.00	0.09	0.82	-34.63	38.21	1.45	110.59
$\Delta\mathrm{MRI}^3_{i,t}$	-0.02	-0.25	0.00	0.13	1.50	-88.44	90.83	-0.20	393.00
$\Delta\mathrm{MRI}^5_{i,t}$	-0.03	-0.36	0.00	0.16	2.10	-159.06	170.63	-0.17	947.99
$\Delta\mathrm{MRI}^{10}_{i,t}$	-0.03	-0.47	0.00	0.30	2.56	-178.57	189.77	-0.27	958.66
$\Delta\mathrm{MRI}^{30}_{i,t}$	-0.03	-0.51	-0.01	0.37	2.64	-174.64	197.60	-0.70	859.71
$\Delta\mathrm{CR}^1_t$	0.01	-0.21	0.00	0.24	0.70	-3.64	6.80	0.62	12.68
$\Delta\mathrm{CR}^3_t$	0.01	-0.35	0.00	0.37	1.18	-9.30	10.53	0.28	19.43
$\Delta\mathrm{CR}^5_t$	0.01	-0.49	0.00	0.49	1.58	-10.83	16.18	0.59	17.53
$\Delta\mathrm{CR}^{10}_t$	0.01	-0.73	0.00	0.77	2.31	-15.33	16.60	-0.03	12.41
$\Delta\mathrm{CR}^{30}_t$	0.01	-0.89	-0.01	0.81	3.21	-20.17	23.51	0.12	12.30

Table 1: This table presents descriptive statistics (mean, 1st quartile, median, 3rd quartile, standard deviation, minimum, maximum, skewness, kurtosis) for all independent and dependent variables (except term structure variables) in our sample.

(2019) finds that the impacts of the explanatory variables on CDS spread changes depend on the overall conditions of the credit market.

We adopt the QR framework for a panel setup with firm-specific fixed effects. Formally, let $y_{i,t}$ be the response of firm i at time t and $\boldsymbol{x}_{i,t}$ the m-dimensional covariate vector where $i = 1, \ldots, N$ and $t = 1, \ldots, T$. For a fixed quantile level $\tau \in (0, 1)$, the conditional quantile of $y_{i,t}$ given $\boldsymbol{x}_{i,t}$ is

$$Q_{y_{i,t}}(\tau|\boldsymbol{x}_{i,t}) = \alpha_{\tau,i} + \boldsymbol{x}'_{i,t}\boldsymbol{\beta}_\tau + \varepsilon_{i,t},$$

where $\alpha_{\tau,i}$ are the firm-specific fixed effects parameters and $\varepsilon_{i,t}$ is the error term. Note that this model cannot be straightforwardly estimated using the standard centering decomposition, as conditional quantiles are not linear operators. Consequently, numerous estimation techniques have been established over the past two decades (Koenker, 2004; Canay, 2011; Kato et al., 2012; Galvao and Wang, 2015; Galvao and Kato, 2016).[28] We follow Zhang et al. (2019) and implement a two-stage approach to estimate the parameter vector $\boldsymbol{\beta}_\tau$.[29] In a first stage, we run firm-specific quantile regressions to estimate the fixed effects $\alpha_{t,i}$

$$\left(\widetilde{\alpha}_{\tau,i}, \widetilde{\boldsymbol{\beta}}_{\tau,i}\right) = \underset{a \in \mathcal{A}_\tau, \mathbf{b} \in \Theta_\tau}{\operatorname{argmin}} \frac{1}{T} \sum_{t=1}^{T} \rho_\tau\left(y_{i,t} - a - \boldsymbol{x}'_{i,t}\mathbf{b}\right),$$

where $\mathcal{A}_\tau \in \mathbb{R}, \Theta_\tau \in \mathbb{R}^m$ and $\rho_\tau(u) = u\left(\tau - \mathbb{1}_{\{u<0\}}\right)$ denotes the quantile loss function. Provided T is sufficiently large, $\widetilde{\alpha}_{\tau,i}$ is $\sqrt{T}$-consistent estimate of $\alpha_{\tau,i}$ and so $y_{it} - \widetilde{\alpha}_{\tau,i}$ can be considered a proper approximation of $y_{it} - \alpha_{\tau,i}$. In a second stage, we then estimate

$$\widehat{\boldsymbol{\beta}}_\tau = \underset{\boldsymbol{b} \in \Theta_\tau}{\operatorname{argmin}} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \rho_\tau\left\{y_{i,t} - \boldsymbol{x}'_{i,t}\boldsymbol{b} - \widetilde{\alpha}_{\tau,i}\right\}.$$

The estimator at hand is easily implemented and, due to the dimensionality reduction, computationally inexpensive. However, to get reliable fixed effects estimates in the first stage, it is crucial to have sufficient data on the T dimension. Hence, most previous studies relying on lower frequency data, instead apply a pooling approach or consider a quantile-independent α_i.

To gauge the significance of the estimates, we rely on the asymptotic normality of $\boldsymbol{\beta}_\tau$. Specifically, inference within the panel QR framework is based on the asymptotic result

$$\sqrt{NT}\left(\widehat{\boldsymbol{\beta}}_\tau - \boldsymbol{\beta}_\tau\right) \xrightarrow{d} N\left(0, \Lambda_\tau^{-1} V_\tau \Lambda_\tau^{-1}\right),$$

where $\Lambda_\tau^{-1} V_\tau \Lambda_\tau^{-1}$ is the sandwich formula for the variance–covariance matrix. To estimate $\Lambda_\tau^{-1} V_\tau \Lambda_\tau^{-1}$ we follow Yoon and Galvao (2016) and estimate robust variants of Λ_τ and V_τ that account for heteroscedasticity and serial correlation.[30]

[28] A comprehensive overview of QR methods can be found in Koenker et al. (2017).

[29] Initially introduced to model different effects across subgroups, Zhang et al. (2019) propose a cluster-based fixed effects estimator for the group-specific slopes. Imposing the homogeneous slope assumption results in an estimator with quantile-specific fixed effects.

[30] An alternative approach for the estimation of standard errors in a panel QR setting is bootstrapping (see Hagemann, 2017). This is commonly used when the data sample is small, as convergence rates of the asymptotic estimates can be slow. This is not the case for the sample at hand.

4 Empirical results

4.1 The regional and sectoral impact of carbon risk

In this subsection, we examine the relationship between the carbon risk factor (proxy for the general perception of carbon risk exposure) and CDS spread returns. Following prior literature on CDS (Collin-Dufresne et al., 2001; Ericsson et al., 2009; Galil et al., 2014; Pereira et al., 2018) we include key known determinants of CDS spread returns in the baseline quantile regression, as follows:

$$Q_{s_{i,t}^m}\left(\tau|\boldsymbol{x}_{i,t}\right) = \alpha_{\tau,i} + \beta_{\tau,1} r_{i,t} + \beta_{\tau,2}\Delta\sigma_{i,t} + \beta_{\tau,3}\Delta\text{MRI}_{i,t} + \beta_{\tau,4}\Delta\text{CR}_t + \varepsilon_{i,t},$$

where, for the CDS issued by firm i, day t, we consider firm-specific factors (i.e. stock return $r_{i,t}$ and volatility $\Delta\sigma_{i,t}$), a common factor (i.e. the market condition $\Delta\text{MRI}_{i,t}$), and, finally, the market-implied proxy for carbon risk exposure ΔCR_t, which encapsulates an aggregate of all changes in carbon-related concerns.

The regression is run for every decile $\tau \in \{0.1, \ldots, 0.9\}$ to model the effect of each explanatory variable on the entire conditional distribution of CDS spread returns. In this way, we are able to model the relationship between CDS spread returns and the CR factor for firms that behave according to the median of the conditional distribution, as well as for firms that overperform and underperform relative to the median.[31] Note that (i) an increase in the CDS spread $\{\tau > 0.5\}$ reflects a deterioration in a firm's creditworthiness (credit deterioration), (ii) a decrease in the CDS spread $\{\tau < 0.5\}$ reflects an improvement in a firm's creditworthiness (credit improvement), and (iii) the mid decile $\{\tau = 0.5\}$ corresponds to the unchanged CDS spread case (invariable credit). In essence, the quantile regression allows us to distinctly examine the effect of each explanatory variable along the entire distribution of credit spread returns and, at the same time, to investigate the marginal impact of carbon risk above and beyond these explanatory variables.

Table 2 reports the estimated coefficients at different deciles for every tenor under investigation for Europe. First, across all maturities, we observe a positive relationship between CDS spread returns and the CR factor. That is, an increase in market's perception of carbon risk is associated with a rise in CDS spread returns. The coefficients are statistically significant at the 1% level and are also economically significant. For example, considering the 5Y tenor, a one standard deviation increase in the perceived carbon risk exposure (1.6112) is associated with a rise of 0.152 ($= 1.6112 \times 0.0942$) percentage points in the median CDS spread return. This increment accounts for a remarkable 6.9% of the standard deviation of CDS spread returns. To put this number into perspective, we look at the stock return, one of the key determinants of CDS spreads. A one standard deviation increase in the stock return (1.64%), merely decreases the median CDS spread return by 0.069 ($= 1.64 \times (-0.0422)$) percentage points, equivalent to 3.1% of the CDS spread return standard deviation.

[31] It is important to note that the notion of performance here refers to the credit dimension, and does not include unobserved firm-specific fundamental factors – these are incorporated in the fixed effects. Instead, it may be thought of as an idiosyncratic shock (e.g. good or bad news) causing a change in a firms' credit performance.

Second, starting from the median, we observe that the coefficients are increasingly larger toward the first and ninth deciles. Essentially, the more the state of the firms credit deteriorates or improves, the larger the effect of CR. Notably, the effect increases symmetrically (i.e. the coefficients are virtually the same moving from the median toward the extremes). While a decrease in the CR particularly helps firms experiencing a negative CDS spread shock, an increasing CR and with it more exposure to carbon risk leverages the already worsening effect if the firm is exposed to an extreme positive CDS spread shock. These results are consistent with Hypothesis 1a: there is a positive relationship between carbon risk and CDS spread returns. The relationship is exceptionally strong in the extremes of the conditional distribution of CDS spread returns.

	1	2	3	4	5	6	7	8	9
					1Y				
StockReturn	-281.31^{***}	-247.59^{***}	-178.22^{***}	-112.11^{***}	-60.86^{***}	-99.17^{***}	-175.62^{***}	-267.20^{***}	-312.87^{***}
	(13.99)	(8.22)	(6.25)	(4.28)	(2.78)	(3.68)	(5.78)	(10.81)	(19.48)
ΔVolatility	-427.47^{***}	-369.58^{***}	-230.60^{***}	-76.49^{***}	26.65^{**}	275.75^{***}	555.11^{***}	828.02^{***}	980.86^{***}
	(46.03)	(34.73)	(35.25)	(18.13)	(9.88)	(20.90)	(25.40)	(23.04)	(34.26)
ΔMRI	1372.18^{***}	1404.51^{***}	1362.87^{***}	1287.57^{***}	1239.30^{***}	1256.63^{***}	1348.04^{***}	1462.28^{***}	1550.98^{***}
	(37.32)	(30.38)	(34.78)	(36.30)	(34.67)	(33.54)	(42.29)	(48.26)	(69.59)
ΔCR	472.70^{***}	347.21^{***}	244.04^{***}	174.88^{***}	122.72^{***}	150.17^{***}	231.54^{***}	347.49^{***}	498.42^{***}
	(27.98)	(15.72)	(14.18)	(11.78)	(9.86)	(11.55)	(15.28)	(22.61)	(31.53)
					3Y				
StockReturn	-218.05^{***}	-204.43^{***}	-164.17^{***}	-109.89^{***}	-64.93^{***}	-95.65^{***}	-163.75^{***}	-217.69^{***}	-273.69^{***}
	(7.79)	(5.80)	(4.95)	(3.70)	(2.67)	(3.25)	(4.65)	(7.73)	(12.82)
ΔVolatility	-391.99^{***}	-291.47^{***}	-185.26^{***}	-83.30^{***}	26.23^{*}	238.16^{***}	465.15^{***}	639.01^{***}	857.06
	(52.48)	(48.54)	(23.11)	(18.64)	(11.73)	(18.92)	(20.50)	(15.22)	(7.76)
ΔMRI	558.77^{***}	608.43^{***}	606.76^{***}	586.68^{***}	571.57^{***}	580.52^{***}	612.67^{***}	648.76^{***}	679.99^{***}
	(15.30)	(12.89)	(13.59)	(13.48)	(12.22)	(14.24)	(14.11)	(20.86)	(27.32)
ΔCR	283.18^{***}	228.69^{***}	182.44^{***}	132.27^{***}	92.18^{***}	114.66^{***}	168.78^{***}	221.26^{***}	272.84^{***}
	(9.60)	(7.35)	(7.34)	(6.53)	(5.42)	(5.74)	(6.99)	(9.12)	(14.95)
					5Y				
StockReturn	-143.14^{***}	-124.36^{***}	-98.92^{***}	-66.91^{***}	-42.19^{***}	-56.64^{***}	-94.32^{***}	-132.90^{***}	-174.75^{***}
	(4.55)	(3.60)	(2.94)	(2.29)	(1.72)	(1.94)	(2.82)	(4.68)	(9.14)
ΔVolatility	-279.71^{***}	-202.00^{***}	-137.36^{***}	-58.96^{***}	14.33^{*}	136.81^{***}	279.67^{***}	430.51^{***}	564.96
	(11.10)	(25.64)	(19.57)	(12.68)	(6.72)	(10.69)	(11.84)	(8.31)	(4.72)
ΔMRI	303.66^{***}	332.01^{***}	336.54^{***}	334.85^{***}	332.87^{***}	330.28^{***}	346.04^{***}	365.62^{***}	374.22^{***}
	(5.54)	(7.67)	(8.07)	(7.75)	(7.04)	(7.83)	(9.58)	(9.69)	(16.61)
ΔCR	192.34^{***}	168.24^{***}	140.16^{***}	113.92^{***}	94.25^{***}	99.57^{***}	127.03^{***}	152.62^{***}	180.98^{***}
	(6.47)	(4.87)	(4.54)	(4.65)	(4.28)	(4.31)	(4.74)	(5.29)	(8.29)
					10Y				
StockReturn	-110.20^{***}	-88.55^{***}	-70.03^{***}	-50.39^{***}	-33.36^{***}	-42.92^{***}	-67.90^{***}	-94.80^{***}	-131.77^{***}
	(3.06)	(2.38)	(1.95)	(1.65)	(1.25)	(1.41)	(1.82)	(2.94)	(5.87)
ΔVolatility	-214.75^{***}	-162.14^{***}	-111.86^{***}	-52.23^{***}	5.32	87.17^{***}	193.04^{***}	293.51^{***}	401.34
	(10.84)	(8.68)	(13.26)	(9.71)	(3.78)	(7.71)	(5.31)	(4.25)	(6.32)
ΔMRI	219.39^{***}	236.69^{***}	240.25^{***}	236.04^{***}	234.50^{***}	234.73^{***}	243.35^{***}	253.46^{***}	260.76^{***}
	(4.76)	(5.02)	(4.38)	(4.91)	(4.97)	(4.91)	(5.04)	(4.94)	(9.79)
ΔCR	116.78^{***}	95.30^{***}	80.82^{***}	66.27^{***}	54.92^{***}	58.93^{***}	72.89^{***}	90.44^{***}	112.52^{***}
	(3.23)	(3.43)	(3.02)	(2.58)	(2.56)	(2.68)	(2.64)	(3.37)	(5.84)
					30Y				
StockReturn	-102.92^{***}	-83.70^{***}	-67.15^{***}	-48.99^{***}	-36.33^{***}	-44.11^{***}	-66.63^{***}	-92.10^{***}	-126.36^{***}
	(2.58)	(2.26)	(1.86)	(1.53)	(1.32)	(1.39)	(1.95)	(3.31)	(6.64)
ΔVolatility	-220.25^{***}	-158.34^{***}	-102.71^{***}	-48.46^{***}	5.92	88.53^{***}	189.72^{***}	277.96^{***}	395.18
	(6.04)	(12.13)	(13.24)	(10.89)	(4.19)	(6.79)	(9.12)	(7.27)	(6.66)
ΔMRI	254.53^{***}	248.01^{***}	242.34^{***}	240.95^{***}	240.51^{***}	241.22^{***}	248.85^{***}	263.19^{***}	285.87^{***}
	(5.13)	(4.95)	(4.86)	(4.77)	(5.59)	(5.47)	(6.14)	(6.77)	(9.99)
ΔCR	70.96^{***}	63.55^{***}	54.31^{***}	44.89^{***}	36.51^{***}	39.05^{***}	47.27^{***}	59.98^{***}	79.86^{***}
	(2.61)	(2.22)	(1.83)	(1.60)	(1.69)	(1.63)	(1.96)	(2.28)	(4.22)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Table 2: This table reports the coefficient estimates of the base panel quantile regression model for 1-year (top), 3-year (upper center), 5-year (center), 10-year (lower center) and 30-year (bottom) CDS spread returns. The sample includes data of 137 European firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

We next examine Hypothesis 1b, which posits that the effect of carbon risk on CDS spread returns is stronger in Europe than in North America. We re-estimate our baseline QR separately for each North American tenor. Consistent with the prediction of Hypothesis 1b, Table 3 shows a substantially weaker relationship between CDS spread returns and the CR factor for the North American sample. For example, considering the 3Y tenor, the coefficient estimate of CR for the median CDS spread return (0.0003) is nearly 300 times smaller than its European counterpart (0.0922). Not only are estimates considerably smaller, but they are also only occasionally statistically significant. While the heterogeneity in the magnitudes of the CR effect persists, the symmetry in the effect of CR breaks off in the North American sample. In fact, the 10Y tenor apart, the effect on the ninth decile is at least twice as high as the effect on the first decile, suggesting that in North America, credit risk exposure is particularly relevant when firms' credit spreads deteriorate.

	1	2	3	4	5	6	7	8	9
					1Y				
StockReturn	-31.94^{***}	-17.78^{***}	-4.75^{***}	-0.65^{***}	-0.16^{***}	-1.12^{***}	-7.88^{***}	-28.76^{***}	-58.73^{***}
	(4.25)	(1.43)	(0.46)	(0.07)	(0.02)	(0.10)	(0.74)	(2.84)	(6.76)
ΔVolatility	-139.05^{***}	-60.98^{***}	-8.90^{***}	-0.13	0.15	5.88^{***}	45.23^{***}	162.38^{***}	393.44^{***}
	(20.75)	(6.38)	(1.68)	(0.26)	(0.10)	(0.63)	(3.96)	(14.79)	(23.74)
ΔMRI	147.45^{***}	88.33^{***}	29.52^{***}	7.34^{***}	2.29^{***}	11.26^{***}	49.92^{***}	165.57^{***}	431.97^{***}
	(23.75)	(9.30)	(3.75)	(0.88)	(0.30)	(1.18)	(6.03)	(19.30)	(50.85)
ΔCR	-1.76	1.50^{**}	1.00^{***}	0.21^{***}	0.06^{***}	0.48^{***}	3.63^{***}	15.84^{***}	49.28^{***}
	(1.17)	(0.57)	(0.17)	(0.04)	(0.02)	(0.07)	(0.46)	(1.87)	(6.69)
					3Y				
StockReturn	-48.53^{***}	-25.76^{***}	-14.46^{***}	-8.22^{***}	-3.50^{***}	-8.63^{***}	-16.40^{***}	-30.52^{***}	-58.80^{***}
	(3.41)	(1.50)	(0.83)	(0.54)	(0.22)	(0.49)	(1.00)	(2.33)	(6.17)
ΔVolatility	-194.68^{***}	-79.67^{***}	-27.60^{***}	-5.58^{***}	0.65	31.52^{***}	77.91^{***}	169.53^{***}	366.50^{***}
	(18.62)	(5.88)	(4.07)	(1.10)	(0.71)	(2.82)	(4.97)	(10.32)	(18.30)
ΔMRI	97.06^{***}	70.35^{***}	41.86^{***}	27.24^{***}	13.44^{***}	28.71^{***}	50.78^{***}	94.52^{***}	186.17^{***}
	(7.83)	(4.97)	(3.81)	(2.66)	(1.18)	(2.52)	(4.20)	(7.59)	(15.39)
ΔCR	3.97^{***}	2.30^{***}	1.48^{***}	0.83^{***}	0.32^{***}	0.65^{***}	1.46^{***}	3.59^{***}	10.01^{***}
	(0.66)	(0.38)	(0.24)	(0.14)	(0.07)	(0.14)	(0.25)	(0.53)	(1.72)
					5Y				
StockReturn	-45.91^{***}	-23.04^{***}	-12.94^{***}	-8.68^{***}	-4.45^{***}	-8.42^{***}	-14.57^{***}	-25.85^{***}	-49.55^{***}
	(2.70)	(1.36)	(0.70)	(0.47)	(0.24)	(0.43)	(0.84)	(1.92)	(4.42)
ΔVolatility	-175.67^{***}	-67.39^{***}	-23.18^{***}	-5.19^{***}	0.55	31.39^{***}	71.73^{***}	149.92^{***}	319.64^{***}
	(12.62)	(6.44)	(3.25)	(1.50)	(0.55)	(2.05)	(4.17)	(8.19)	(12.17)
ΔMRI	53.46^{***}	40.40^{***}	25.13^{***}	18.58^{***}	10.06^{***}	18.26^{***}	31.50^{***}	59.79^{***}	112.81^{***}
	(4.00)	(3.45)	(2.25)	(1.55)	(0.80)	(1.35)	(2.15)	(4.72)	(9.64)
ΔCR	-0.19	0.54^{**}	0.23^{*}	$0.12^{\cdot}$	0.04	0.39^{***}	1.11^{***}	2.78^{***}	7.70^{***}
	(0.42)	(0.20)	(0.10)	(0.07)	(0.04)	(0.07)	(0.12)	(0.31)	(0.95)
					10Y				
StockReturn	-39.83^{***}	-19.99^{***}	-11.16^{***}	-6.90^{***}	-3.49^{***}	-6.29^{***}	-10.86^{***}	-19.49^{***}	-40.61^{***}
	(1.60)	(0.96)	(0.51)	(0.31)	(0.18)	(0.28)	(0.56)	(1.59)	(3.47)
ΔVolatility	-144.49^{***}	-59.47^{***}	-20.50^{***}	-3.86^{***}	1.44^{***}	23.62^{***}	54.58^{***}	114.41^{***}	256.02^{***}
	(6.09)	(5.63)	(2.49)	(0.73)	(0.31)	(1.52)	(2.68)	(6.75)	(8.82)
ΔMRI	36.28^{***}	24.94^{***}	15.54^{***}	10.96^{***}	6.56^{***}	10.80^{***}	17.23^{***}	31.42^{***}	56.29^{***}
	(2.71)	(1.68)	(0.90)	(0.71)	(0.39)	(0.63)	(0.96)	(2.91)	(5.21)
ΔCR	3.57^{***}	1.77^{***}	1.02^{***}	0.47^{***}	0.18^{***}	0.39^{***}	0.73^{***}	1.58^{***}	3.81^{***}
	(0.32)	(0.17)	(0.10)	(0.06)	(0.04)	(0.05)	(0.09)	(0.21)	(0.47)
					30Y				
StockReturn	-46.48^{***}	-25.17^{***}	-15.00^{***}	-9.41^{***}	-5.23^{***}	-8.05^{***}	-13.80^{***}	-23.92^{***}	-47.26^{***}
	(1.84)	(0.93)	(0.58)	(0.38)	(0.22)	(0.34)	(0.65)	(1.49)	(3.48)
ΔVolatility	-156.57^{***}	-72.74^{***}	-28.47^{***}	-8.52^{***}	2.64^{***}	28.93^{***}	64.86^{***}	127.40^{***}	267.00^{***}
	(8.94)	(6.13)	(3.63)	(1.72)	(0.74)	(1.94)	(2.65)	(4.43)	(5.87)
ΔMRI	38.51^{***}	26.58^{***}	17.44^{***}	12.30^{***}	8.47^{***}	11.49^{***}	17.31^{***}	28.99^{***}	51.91^{***}
	(2.27)	(1.29)	(0.90)	(0.67)	(0.45)	(0.60)	(0.98)	(1.94)	(3.87)
ΔCR	1.30^{***}	0.36^{*}	0.14	0.00	0.02	0.22^{***}	0.61^{***}	1.32^{***}	2.78^{***}
	(0.32)	(0.15)	(0.10)	(0.06)	(0.04)	(0.06)	(0.10)	(0.20)	(0.48)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Table 3: This table reports the coefficient estimates of the base panel quantile regression model for 1-year (top), 3-year (upper center), 5-year (center), 10-year (lower center) and 30-year (bottom) CDS spread returns. The sample comprises of data for 281 North American firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

While there is some evidence that even in North America the *average* firm is exposed to carbon risk, certain (generally carbon-intensive) sectors of the economy may have a disproportionately high exposure. A growing body of empirical literature identifies activities directly related to the production of energy and emissions-intensive goods, especially steel and cement (Dietz et al., 2020), as the most exposed categories.

To empirically validate these findings and develop a more nuanced picture of differential sectoral exposure, we re-estimate our baseline QR, regrouping the firms by using Refinitiv's 9-sector classification (TRBC 2020).[32] We include sector dummies and interaction terms with our CR in the baseline regression:

$$Q_{s^m_{i,t}}(\tau|\boldsymbol{x}_{i,t}) = \alpha_{\tau,i} + \beta_{\tau,1} r_{i,t} + \beta_{\tau,2}\Delta\sigma_{i,t} + \beta_{\tau,3}\Delta\mathrm{MRI}^m_{i,t} + \beta_{\tau,4}\Delta\mathrm{CR}^m_t + \sum_{j=5}^{12}\beta_{\tau,j}\mathrm{Sector}_i + \sum_{k=13}^{20}\beta_{\tau,k}\mathrm{Sector}_i\Delta\mathrm{CR}^m_t + \varepsilon_{i,t},$$

where Sector_i indicates firm i's Thomson Reuters Business Classification (TRBC) classification.

Table 4 reports the coefficient estimates of the interaction terms for the 5-year sector model of the European and North American samples, respectively.[33] Note that the estimate of $\mathrm{BM} \times \Delta\mathrm{CR}$ serves as a reference coefficient. All remaining interaction term estimates should be considered in reference to this coefficient. For example, the unscaled coefficient for the CCGS (consumer cyclicals) interaction term in Europe is $0.1164 - 0.0374 = 0.079$. Consistent with the argument that there is a strong relationship between total emissions and sectoral carbon risk exposure, Table 4 shows that the coefficients on the interaction term between the sector and $\Delta\mathrm{CR}_t$ is positive and highly significant for Basic Materials (BM), Energy and Utilities. These sectors exhibit the largest effect sizes within their respective regions. For the remaining sectors, the coefficient estimates are significantly smaller and – in the North American sample – can even be negative or insignificant. These findings support the observations in recent literature: carbon risk impacts firms' valuation differently, and it is concentrated in specific sectors. Therefore, a growing difference in carbon risk exposure could translate into higher credit risk for firms in carbon-intensive sectors like construction materials (Basic Materials), fossil fuels (Energy) and Utilities. Conversely, businesses in sectors like industrial and commercial services (Industrials), technology equipment (Technology) and Healthcare are seen as capable of providing the innovation and technologies necessary to facilitate a low-carbon transformation. As such, they are less affected by a growing difference in carbon risk exposure.

4.2 Attention to climate change

Next, we empirically examine Hypothesis 2, which postulates that the perceived exposure to carbon risk surges when attention to climate change is high. For Europe, we adopt the

[32] A detailed description of the sector classification of The Refinitiv Business Classification (TRBC) is available here.

[33] The estimation results for the remaining maturities do not differ qualitatively, as reported in Table 9 and 10, respectively, in Appendix C.

	1	2	3	4	5	6	7	8	9
Europe									
BM × ΔCR	263.50***	203.99***	162.23***	136.76***	116.39***	119.03***	150.63***	187.96***	248.33***
	(13.72)	(10.65)	(13.55)	(12.42)	(11.27)	(11.68)	(13.54)	(13.97)	(15.01)
CCGS × ΔCR	−125.98***	−55.06**	−41.43*	−39.23*	−37.43*	−29.45*	−32.98$^{\cdot}$	−51.53**	−97.90***
	(18.72)	(16.90)	(17.07)	(16.05)	(15.01)	(14.74)	(17.02)	(19.89)	(28.60)
Energy × ΔCR	321.07***	379.94***	415.77***	397.75***	405.50***	392.74***	394.60***	414.31***	415.58***
	(25.86)	(23.60)	(31.29)	(31.56)	(38.08)	(37.93)	(39.29)	(38.01)	(32.73)
Healthcare × ΔCR	−53.32	−43.05$^{\cdot}$	−69.39**	−86.88***	−86.04***	−79.89***	−81.81***	−61.35*	−62.44***
	(41.05)	(22.48)	(24.47)	(18.19)	(15.38)	(16.04)	(21.78)	(24.31)	(18.92)
Industrials × ΔCR	−153.48***	−116.20***	−87.11***	−85.56***	−81.18***	−78.38***	−90.75***	−113.46***	−144.85***
	(19.78)	(15.40)	(17.18)	(14.97)	(13.28)	(14.12)	(16.05)	(19.20)	(23.84)
NCGS × ΔCR	−87.68***	−64.77***	−50.52**	−59.43***	−53.54***	−50.87***	−50.57**	−47.28*	−57.45*
	(19.14)	(17.18)	(17.41)	(14.99)	(14.37)	(14.46)	(16.52)	(19.93)	(22.66)
Real Estate × ΔCR	−50.35	−75.95**	−62.13**	−66.15**	−61.22**	−64.54***	−84.64***	−85.31**	−103.82***
	(68.53)	(26.43)	(20.46)	(24.56)	(21.65)	(18.87)	(24.24)	(30.76)	(18.01)
Technology × ΔCR	−118.80***	−75.02***	−38.00*	−31.99$^{\cdot}$	−32.23*	−30.24*	−45.00**	−71.86**	−128.72***
	(27.11)	(18.16)	(17.45)	(16.61)	(15.27)	(14.95)	(17.23)	(22.34)	(32.38)
Utilities × ΔCR	64.30**	106.26***	131.57***	124.31***	118.32***	115.90***	114.41***	94.43**	37.97
	(24.46)	(29.54)	(23.74)	(24.08)	(23.72)	(22.30)	(21.90)	(29.32)	(44.24)
North America									
BM × ΔCR	13.42***	7.32***	2.69***	0.90**	0.52**	1.76***	5.11***	15.82***	47.59***
	(2.21)	(2.10)	(0.66)	(0.33)	(0.19)	(0.35)	(0.87)	(2.56)	(8.73)
CCGS × ΔCR	−26.88***	−10.85***	−4.26***	−1.74***	−0.85**	−1.57***	−4.04***	−9.87***	−29.22**
	(4.79)	(2.94)	(0.88)	(0.47)	(0.27)	(0.47)	(1.03)	(2.91)	(10.44)
Energy × ΔCR	35.99**	10.74***	2.59**	1.32**	0.67*	0.69	1.79	7.54	29.05*
	(12.03)	(2.82)	(0.93)	(0.51)	(0.31)	(0.54)	(1.40)	(5.32)	(12.95)
Healthcare × ΔCR	−31.78***	−12.05***	−4.29***	−1.60***	−0.90**	−2.28***	−5.13***	−12.93***	−35.26***
	(6.18)	(2.40)	(1.00)	(0.44)	(0.29)	(0.49)	(1.00)	(2.79)	(8.86)
Industrials × ΔCR	−5.89$^{\cdot}$	−5.05*	−1.87*	−0.48	−0.46$^{\cdot}$	−1.53***	−3.96***	−10.08***	−24.46*
	(3.37)	(2.43)	(0.78)	(0.41)	(0.23)	(0.41)	(0.94)	(2.74)	(9.91)
NCGS × ΔCR	−20.58***	−9.70***	−3.82***	−1.30**	−0.69**	−2.17***	−4.96***	−12.66***	−38.72***
	(3.42)	(2.49)	(0.84)	(0.41)	(0.24)	(0.42)	(0.98)	(2.84)	(9.60)
Real Estate × ΔCR	−8.94	−5.93*	−2.14**	−0.59	−0.38$^{\cdot}$	−1.66***	−4.68***	−12.97***	−31.79**
	(7.69)	(2.90)	(0.82)	(0.40)	(0.22)	(0.40)	(0.97)	(3.32)	(10.46)
Technology × ΔCR	−13.10***	−8.87***	−3.52***	−1.17***	−0.61**	−1.66***	−4.59***	−11.95***	−36.58***
	(2.76)	(2.31)	(0.73)	(0.35)	(0.21)	(0.37)	(0.91)	(2.72)	(8.83)
Utilities × ΔCR	−5.58*	−3.77$^{\cdot}$	−1.54*	−0.35	−0.27	−1.15**	−3.68***	−11.38***	−32.46***
	(2.76)	(2.21)	(0.72)	(0.36)	(0.21)	(0.38)	(0.92)	(2.62)	(9.00)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Table 4: This table reports the coefficient estimates of the interaction terms of the sector panel quantile regression model for 5-year CDS spread returns in Europe (top) and North America (bottom). The sample comprises of data from 137 European firms resp. 281 North American firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

Transition Risk Concern (TRC) index of Bua et al. (2022) as our aggregate attention measure. The TRC scans Reuters News to detect items with a European regional focus that relate to the introduction of new regulations to curb emissions. For North America we use the Media Climate Change Concerns (MCCC) index of Ardia et al. (2022). For each day, the MCCC index generates an aggregate score based on the number of articles related to climate change in major US newspapers and their tone. Because the aggregate MCCC index includes news relating to physical climate risk, we use a variant that only incorporates topics belonging to the superordinate themes "Financial and Regulation", "Agreement and Summit" and "Public Impact".[34] The adjusted MCCC index thereby provides daily information on the coverage and sentiment of North American carbon-related news and excludes any physical climate component.

Following Huynh and Xia (2021), we define a high-attention day for Europe (North America) as any day with a value greater than the median of the TRC (MCCC) index series. Accordingly, we construct the dummy variable HCNA_t (High Climate News Attention) which takes the value 1 if the TRC (MCCC) is above its median at day t, indicating high attention to cli-

[34]See Table 4 (p. 30) in Ardia et al. (2020) for details.

mate change for that day in Europe (North America), and 0 otherwise. We interact HCNA_t with our CR factor and re-examine the baseline QR by including both the interaction term $\text{HCNA}_t \times \Delta\text{CR}_t$ and HCNA_t:

$$Q_{s_{i,t}^m}(\tau|\boldsymbol{x}_{i,t}) = \alpha_{\tau,i} + \beta_{\tau,1} r_{i,t} + \beta_{\tau,2}\Delta\sigma_{i,t} + \beta_{\tau,3}\Delta\text{MRI}_{i,t} + \beta_{\tau,4}\Delta\text{CR}_t + \beta_{\tau,5}\text{HCNA}_t + \beta_{\tau,6}\text{HCNA}_t \times \Delta\text{CR}_t + \varepsilon_{i,t},$$

	1	2	3	4	5	6	7	8	9
					1Y				
ΔCR	-62.21^{***}	-5.44^{***}	-0.21^{**}	0.00	0.00	$0.01^{\cdot}$	0.60^{***}	8.74^{***}	72.37^{***}
	(7.96)	(0.89)	(0.07)	(0.00)	(0.00)	(0.00)	(0.15)	(1.77)	(12.82)
ΔCR × HCNA	98.79^{***}	11.63^{***}	1.09^{***}	0.00^{**}	0.00	0.02^{**}	1.02^{***}	10.23^{***}	56.43^{***}
	(10.49)	(1.54)	(0.14)	(0.00)	(0.00)	(0.01)	(0.21)	(1.90)	(14.26)
					3Y				
ΔCR	26.65^{***}	5.01^{***}	1.50^{***}	0.47^{***}	0.13^{**}	0.36^{***}	0.54^{**}	1.69^{**}	11.63^{***}
	(2.82)	(0.71)	(0.21)	(0.10)	(0.04)	(0.09)	(0.18)	(0.62)	(3.18)
ΔCR × HCNA	-16.72^{***}	-0.71	-0.12	0.01	0.02	0.16	1.61^{***}	6.84^{***}	33.13^{***}
	(3.69)	(0.91)	(0.27)	(0.12)	(0.06)	(0.13)	(0.36)	(1.11)	(6.66)
					5Y				
ΔCR	-1.22	-0.23	-0.02	0.00	0.02	0.06	0.17^{*}	$0.47^{\cdot}$	3.68^{*}
	(1.46)	(0.44)	(0.10)	(0.04)	(0.02)	(0.04)	(0.07)	(0.27)	(1.43)
ΔCR × HCNA	5.12^{**}	1.98^{***}	0.41^{*}	0.17^{*}	0.08	0.42^{***}	1.67^{***}	7.30^{***}	32.04^{***}
	(1.89)	(0.57)	(0.16)	(0.08)	(0.05)	(0.10)	(0.23)	(1.02)	(4.90)
					10Y				
ΔCR	8.69^{***}	2.63^{***}	1.01^{***}	0.35^{***}	0.11^{***}	0.20^{***}	0.23^{**}	$0.55^{\cdot}$	-0.00
	(1.05)	(0.28)	(0.10)	(0.05)	(0.03)	(0.05)	(0.09)	(0.30)	(1.20)
ΔCR × HCNA	-4.08^{***}	$-0.66^{\cdot}$	-0.19	-0.03	$0.09^{\cdot}$	0.31^{***}	1.13^{***}	4.67^{***}	23.48^{***}
	(1.23)	(0.37)	(0.15)	(0.08)	(0.05)	(0.08)	(0.16)	(0.57)	(3.30)
					30Y				
ΔCR	7.29^{***}	1.66^{***}	0.58^{***}	0.16^{*}	0.06	0.18^{**}	0.19^{*}	$0.44^{\cdot}$	0.26
	(0.99)	(0.25)	(0.13)	(0.07)	(0.04)	(0.06)	(0.09)	(0.25)	(0.71)
ΔCR × HCNA	-7.53^{***}	-0.72^{*}	-0.16	0.00	0.09	0.22^{**}	0.95^{***}	3.34^{***}	16.76^{***}
	(1.30)	(0.36)	(0.17)	(0.10)	(0.07)	(0.08)	(0.15)	(0.46)	(1.86)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Table 5: This table reports the coefficient estimates of ΔCR and $\Delta\text{CR} \times \text{HCNA}$ of the climate attention panel quantile regression model for 1-year (top), 3-year (upper center), 5-year (center), 10-year (lower center) and 30-year (bottom) CDS spread returns. The sample comprises of data for 281 North American firms from 2013/01/01 to 2018/06/29 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

We first discuss the estimation results for North America, as shown in Table 5. Consistent with the prediction in Hypothesis 2, Table 5 shows that the coefficient on the interaction term between HCNA and CR is positive and significant especially for the shortest maturity of 1Y, indicating a strengthening effect of carbon risk when attention to climate change is high. This observation is largely persistent across all deciles and the effects are more pronounced at the extremes of the conditional distribution. Although tenors longer than 3Y seem to be less affected by heightened attention to climate change – possibly confirming the general short-lived impact of news – the amplifying effect of climate change attention does not completely vanish. In fact, it endures and gains relevance especially during periods of credit deterioration (see top deciles 5Y, 10Y, and 30Y).

Table 6 reports the estimation results for Europe. The findings here are less clear-cut. While attention seems to have some effect on 3Y and 10Y tenors, we draw attention to a more relevant and remarkable result. Contradicting Hypothesis 2, but consistent with the findings that the effect of carbon risk on CDS spread returns for the 1Y tenor is substantially large, news about adjustments in European carbon regulations are irrelevant. When market-wide concern about climate change risk is elevated, lenders appear to only be more sensitive to carbon risk for longer tenors.

	1	2	3	4	5	6	7	8	9
					1Y				
ΔCR	551.67^{***}	392.13^{***}	274.80^{***}	178.65^{***}	124.82^{***}	164.28^{***}	248.73^{***}	361.48^{***}	472.87^{***}
	(27.52)	(26.52)	(20.56)	(16.13)	(13.50)	(15.25)	(19.88)	(29.01)	(49.68)
ΔCR $\times$ HCNA	$-76.13^{\cdot}$	-30.65	$-39.48^{\cdot}$	-19.57	-11.91	-20.45	1.46	76.74^{***}	189.62^{***}
	(40.07)	(28.23)	(21.90)	(17.17)	(12.83)	(13.65)	(15.44)	(15.21)	(22.56)
					3Y				
ΔCR	344.32^{***}	236.58^{***}	182.21^{***}	122.14^{***}	87.18^{***}	108.04^{***}	173.25^{***}	233.74^{***}	297.92^{***}
	(10.42)	(9.24)	(8.80)	(7.50)	(6.29)	(6.25)	(7.42)	(11.04)	(21.64)
ΔCR $\times$ HCNA	-41.83^{**}	17.34	12.06	21.00^{*}	14.42^{*}	29.48^{***}	31.38^{***}	57.78^{***}	90.46^{***}
	(13.94)	(10.67)	(9.78)	(8.52)	(7.16)	(7.52)	(7.99)	(8.70)	(15.34)
					5Y				
ΔCR	210.45^{***}	174.22^{***}	140.25^{***}	107.75^{***}	86.13^{***}	88.75^{***}	116.09^{***}	144.75^{***}	172.42^{***}
	(8.31)	(6.18)	(5.00)	(5.26)	(4.93)	(4.65)	(5.24)	(6.86)	(11.12)
ΔCR $\times$ HCNA	-33.45^{***}	-18.34^{**}	-9.72^{*}	-1.41	7.68	17.37^{**}	21.06^{***}	28.79^{***}	41.74^{***}
	(7.21)	(5.58)	(4.87)	(5.43)	(5.67)	(5.81)	(6.35)	(7.60)	(11.64)
					10Y				
ΔCR	100.48^{***}	68.77^{***}	54.67^{***}	44.37^{***}	35.38^{***}	42.11^{***}	56.40^{***}	74.41^{***}	93.40^{***}
	(4.22)	(2.63)	(3.08)	(2.25)	(2.27)	(2.49)	(2.90)	(3.04)	(5.55)
ΔCR $\times$ HCNA	23.68^{***}	26.11^{***}	21.26^{***}	13.90^{***}	10.25^{**}	10.12^{***}	15.00^{***}	21.25^{***}	26.79^{***}
	(4.59)	(3.88)	(3.74)	(3.27)	(3.37)	(2.98)	(3.36)	(3.74)	(5.88)
					30Y				
ΔCR	90.60^{***}	75.02^{***}	63.68^{***}	48.09^{***}	42.21^{***}	45.84^{***}	55.08^{***}	64.18^{***}	73.74^{***}
	(4.43)	(3.54)	(2.57)	(2.29)	(2.44)	(2.52)	(2.80)	(2.80)	(6.69)
ΔCR $\times$ HCNA	-32.23^{***}	-26.95^{***}	-21.58^{***}	-12.45^{***}	-13.99^{***}	-14.57^{***}	-13.89^{***}	-2.10	17.28^{***}
	(5.07)	(3.88)	(2.87)	(2.66)	(2.59)	(2.60)	(2.50)	(2.43)	(4.35)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Table 6: This table reports the coefficient estimates of ΔCR and ΔCR $\times$ HCNA of the climate attention panel quantile regression model for 1-year (top), 3-year (upper center), 5-year (center), 10-year (lower center) and 30-year (bottom) CDS spread returns. The sample comprises of data from 137 European firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

4.3 Term structure

The previous sections provide evidence of CR being a relevant determinant of CDS spread returns across different tenors, geographies and sectors. We now examine lenders' different expectations about how fast the transition to a low-carbon economy needs to occur. A revision of the expected pace of transition could affect companies differently, depending on their location and the nature of their business. To empirically test Hypothesis 3, we examine how a change in the expected temporal materialization of carbon risk affects the term structure of a firm's credit risk. We do this by extracting information about carbon risk over a specific time horizon using the slope of the CR factor, namely the difference between CR over different time horizons. Then, we build up a model similar to the base model from Section 4.1, replacing the relevant variables with the appropriate slope measures $\Delta\text{CDSSlope}_{i,t}^{mn}$ and $\Delta\text{CRSlope}_{t}^{mn}$. Regarding the relevant slopes, we select the 5Y-1Y slope and 30Y-5Y slope. This collection allows us to examine two limiting cases: the short- and long-term effects of carbon risk on the CDS spread curve. We thus estimate the model with the inclusion of the term structure control variables:

$$Q_{\Delta\text{CDSSlope}_{i,t}^{mn}}(\tau|\boldsymbol{x}_{i,t}) = \alpha_{\tau,i} + \beta_{\tau,1}\Delta\sigma_{i,t} + \beta_{\tau,2}\Delta\text{MRISlope}_{i,t}^{mn} + \beta_{\tau,3}\Delta\text{IR}_t + \beta_{\tau,4}\Delta\text{IR}_t^2 \\ + \beta_{\tau,5}\Delta\text{Term}_t + +\beta_{\tau,6}\Delta\text{CRSlope}_t^{mn} + \varepsilon_{i,t}.$$

Table 7 reports the estimation results for the 5Y-1Y CR slope as well as 30Y-5Y CR slope for Europe and North America.[35] Before proceeding with the discussion of the results, we recall

[35]The results with the estimates for all control variables can be found in Table 11 in Appendix C.

that a positively sloped term structure indicates higher costs of default protection for the longer tenors. Following this logic, a positive CRSlope_t^{mn} reveals the incremental (positive) exposure to transition risk for the longer term vis-a-vis the shorter term.

	1	2	3	4	5	6	7	8	9
Europe									
5Y-1Y									
ΔCRSlope	35.36***	21.52***	11.30***	5.83***	4.00***	4.42***	7.87***	17.91***	29.85***
	(1.68)	(1.37)	(0.86)	(0.39)	(0.26)	(0.29)	(0.61)	(1.46)	(2.88)
30Y-5Y									
ΔCRSlope	4.26***	2.30***	1.58***	1.21***	1.02***	1.07***	1.45***	2.35***	5.11***
	(0.45)	(0.24)	(0.14)	(0.11)	(0.12)	(0.14)	(0.21)	(0.33)	(0.87)
North America									
5Y-1Y									
ΔCRSlope	0.59*	0.17	0.09·	0.01	0.01	0.08***	0.00	0.38**	0.77*
	(0.24)	(0.11)	(0.05)	(0.03)	(0.01)	(0.02)	(0.05)	(0.12)	(0.38)
30Y-5Y									
ΔCRSlope	1.99***	0.69***	0.16***	0.03·	0.00	0.00	0.22***	0.95***	2.22***
	(0.25)	(0.12)	(0.05)	(0.01)	(0.00)	(0.00)	(0.04)	(0.11)	(0.43)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Table 7: This table reports the coefficient estimates of ΔCRSlope of the term structure panel quantile regression model for 5Y-1Y and 30Y-5Y CDS spread slope changes in Europe (top) and North America (bottom). The sample comprises of data for 137 European firms resp. 281 North American firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

The results in Table 7 show that an increase in the CR slope – a shift in the relative cost-impact of carbon regulation toward future cash flows – steepens the CDS curve. This relationship is especially strong (i) in the extremes of the movements of the credit risk term structure, and (ii) for the shorter 5Y-1Y slope versus the 30Y-5Y slope. These results confirm Hypothesis 3 for Europe. A rapid acceleration of the transformation is likely to have significant and relatively larger financial impacts in the near future and, consequently, a faster decline in credit quality in the nearer vs longer term. The case of North America is less clear-cut: coefficients are mostly insignificant and the effects on the 5Y-1Y and the 30Y-5Y slopes are virtually indistinguishable.

5 Conclusions

The decarbonization prescribed by net-zero carbon emissions policies will require a massive economic transformation. Unquestionably, these changes can generate sizable costs with consequential impacts on business valuations, especially for firms that are unprepared for the transition. Understanding the impact of these transformational changes requires the measurement of carbon risk exposure in a way that also appropriately reflects firms' future carbon profiles. To date, this has proven to be a formidable challenge. Theoretical arguments indicate, however, that firms' relative differential exposure to carbon risk might be detected in their credit spreads. We therefore utilize the information contained in CDS spreads to construct the CR factor — a market-implied proxy for carbon risk exposure. Our paper proposes a method for constructing a forward-looking proxy for carbon risk exposure and studies how it affects firms' creditworthiness.

We then study how carbon risk affects firms' creditworthiness, and find a positive relationship between lenders' perceived exposure to carbon risk and firms' cost of default protection. The

relevance of the observed relationship is significantly stronger in Europe – notably pro-carbon regulation – than in North America.
In addition, using QRs, we show that the magnitude of the exposure to carbon risk differs considerably along the entire distribution of CDS spread returns. The marginal impact of carbon risk is exceptionally pronounced when firms experience extraordinary credit movements (i.e. when a firm's credit improvement or deterioration is especially strong). This speaks directly to the relevance of this work for the risk management practices of institutional investors and regulators.
Exposure to carbon risk also varies substantially across industries. While we observe a high sensitivity to carbon risk in the CDS spreads of the classical carbon-intensive sectors (e.g. Energy, Basic Materials, Utilities), the market seems to regard other sectors (Industrials, Technology, Healthcare) as capable of making the necessary adjustments to facilitate a low-carbon transformation. These sectors therefore benefit from a surge in carbon risk.
Further analysis suggests that the effect of carbon risk on CDS spread returns is stronger during times of heightened attention to climate change news. When market-wide concern about climate change risk is elevated, lenders demand more credit protection for those borrowers perceived to be more exposed to carbon risk.
Finally we examine whether lenders' expectations about the necessary pace of the transition affect the CDS spread curve. We find that there is a positive relationship between the term structure of carbon risk and the CDS spread slopes in Europe, effectively demonstrating that carbon risk is particularly salient for shorter time horizons, and confirming that lenders expect adjustments in European carbon regulations to cause relatively larger costs in the near future.

Overall, our results add to the growing evidence on the effect of carbon risk on CDS spreads, and provide some quantitative assessment of its economic impact. Our findings also have important policy implications. They suggest that an improvement in the quality and comparability of current carbon emissions disclosures and emissions reduction strategies would facilitate better assessment of firm-level carbon and credit risk. As such, our findings are relevant for the regulatory framework. In particular, they highlight the relevance of a periodic and transparent disclosure practice in the market to better reflect firm-level carbon and transition risk.

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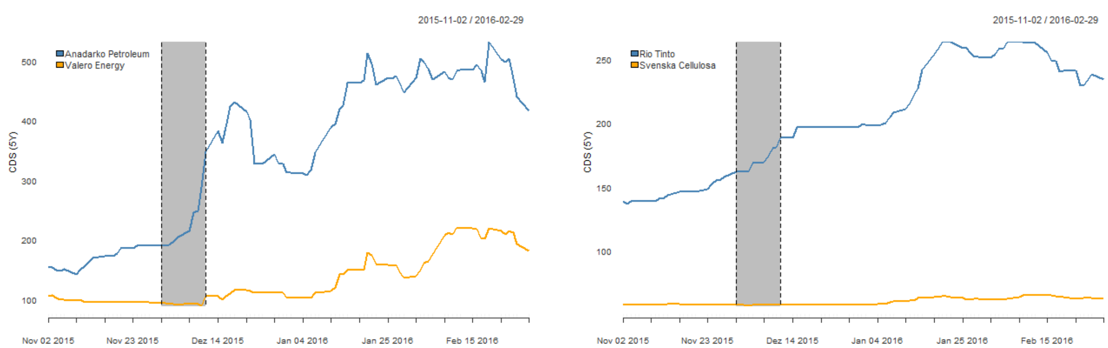
A Lenders' perception of differential exposure to carbon risk: sectoral examples

Similar to Figure 1 this section provides two additional examples of firm pairs who operate in the same industry, but are still differently exposed to carbon risk. In particular, Figure 4 depicts the evolution of the CDS spreads of two pairs of companies operating in the same industry (with the same credit rating) in North America (left panel) and Europe (right panel) before and after COP21. The selected firms in North America (Anadarko Petroleum and Valero Energy) operate in the Energy sector, whereas the selected firms in Europe (Rio Tinto and Svenska Cellulosa) operate in the Basic Materials sector.

Anadarko Petroleum (acquired by Occidental Petroleum in 2019) was a US-based energy corporate engaged in hydrocarbon exploration, and was ranked 47th among the World's Top 100 Polluters (CDP, 2017). On the other hand, Valero Energy – an international, US-based manufacturer and marketer of transportation fuels – is among the corporates with the lowest emission intensity in their industry – albeit a carbon-intensive industry.

Rio Tinto is a multinational, UK-based corporation mainly engaged in mining and production of metals. It was ranked 24th among the World's Top 100 Polluters (CDP, 2017). Svenska Cellulosa – a Swedish forestry company producing wood-based products and biofuel – is Europe's largest private forest owner. With its large-scale provision of lease of land for wind farm operators it is considered an environmental forerunner within the Basic Materials sector.



(a) North America (b) Europe

Figure 4: Evolution of the 5Y-CDS spreads of Anadarko Petroleum (blue) and Valero Energy (orange) on the left diagram, and Rio Tinto (blue) and Svenska Cellulosa (orange) on the right diagram. The time period spans from 02 November 2015 to 29 February 2016. The gray-shaded area indicates the time period of COP21 (30th Nov 2015 – 12th Dec 2015).

B Constituents of clean & polluting class

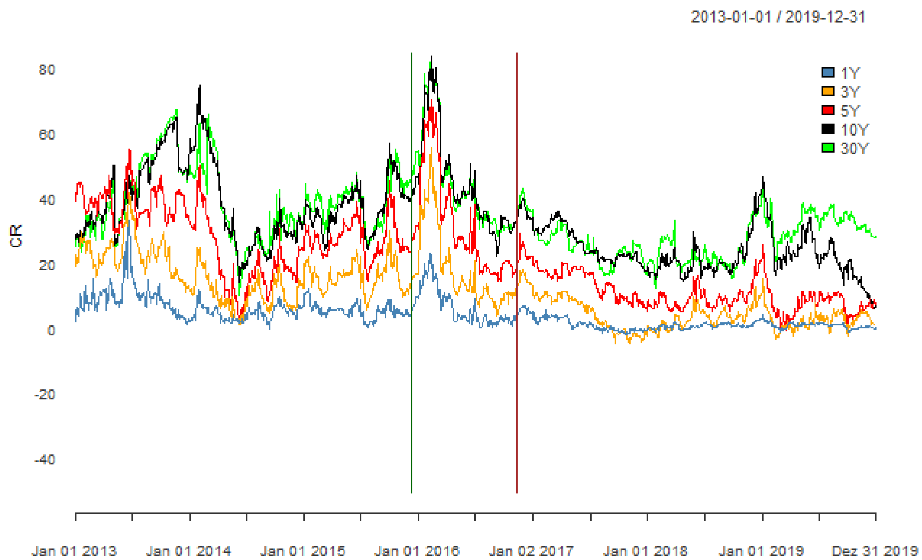
Table 8 displays all firms that were constituents of the clean and polluting class, respectively, at some point during our sample period of 2013 to 2019. Firms in bold are those that represent the median firm (based on the 5Y CDS spread) at least once within their respective group. In total, 34 (35) firms entered the clean (polluting) class in Europe, whereas 82 (73) firms entered the clean (polluting) class in North America. In Europe, the majority of clean firms are in the Industrials sector with a share of approximately 35% of the sample, while the majority of polluting firms come from the Basic Materials and Utilities sectors, respectively, with a share of 40% each. In North America, the majority of clean firms are in the Consumer Cyclicals (CCGS) sector with a share of approximately 38% of the sample, while the majority of polluting firms come from the Utilities sector with a share of approximately 29%.

Europe	
Pollutive	Clean
Accor SA, **Anglo American PLC**, ArcelorMittal SA, Carnival PLC, **Deutsche Lufthansa AG**, **E.ON SE**, **EDP Energias de Portugal SA**, **Edison SpA**, **Electricite de France SA**, **Endesa SA**, **Enel SpA**, Engie SA, **Eni SpA**, **Fortum Oyj**, Gazprom PAO, **HeidelbergCement AG**, **Holcim AG**, **Iberdrola SA**, Koninklijke DSM NV, L'Air Liquide Societe Anonyme pour l'Etude et l'Exploitation des Procedes George, **Lafarge SA**, **Lanxess AG**, Linde AG, National Grid PLC, **Naturgy Energy Group SA**, **RWE AG**, **Repsol SA**, **Rio Tinto PLC**, **SSE PLC**, **Solvay SA**, Svenska Cellulosa SCA AB, **Tate & Lyle PLC**, **UPM-Kymmene Oyj**, **Veolia Environnement SA**, thyssenkrupp AG	**Adecco Group AG**, **Airbus SE**, **Alstom SA**, **Atlas Copco AB**, **Bayerische Motoren Werke AG**, Compass Group PLC, Daily Mail and General Trust PLC, **Experian Finance PLC**, ITV PLC, **Imperial Brands PLC**, **Kering SA**, Koninklijke KPN NV, **Koninklijke Philips NV**, LVMH Moet Hennessy Louis Vuitton SE, Nokia Oyj, **Pearson PLC**, **PostNL NV**, **Publicis Groupe SA**, **SES SA**, **Scania AB**, **Schneider Electric SE**, Siemens AG, **Sodexo SA**, **Svenska Cellulosa SCA AB**, **Swisscom AG**, Telecom Italia SpA, **Telefonaktiebolaget LM Ericsson**, **Television Francaise 1 SA**, **Telia Company AB**, **Thales SA**, **Vivendi SE**, **Volvo AB**, Wendel SE, **Wolters Kluwer NV**
North America	
Pollutive	Clean
AES Corp, **Air Products and Chemicals Inc**, Alliant Energy Corp, **Ameren Corp**, American Airlines Group Inc, American Electric Power Company Inc, **Anadarko Petroleum Corp**, Avis Budget Group Inc, **Avnet Inc**, **Barrick Gold Corp**, **CMS Energy Corp**, Canadian National Railway Co, **Canadian Natural Resources Ltd**, **Carnival Corp**, CenterPoint Energy Inc, **Chevron Corp**, **Conocophillips**, **DTE Energy Co**, Delta Air Lines Inc, **Devon Energy Corp**, Dominion Energy Inc, Domtar Corp, **Dow Chemical Co**, E I Du Pont De Nemours and Co, **Eastman Chemical Co**, **Encana Corp**, **Entergy Corp**, **Exelon Corp**, Exxon Mobil Corp, **FirstEnergy Corp**, **Glatfelter Corp**, Hess Corp, **Husky Energy Inc**, **International Paper Co**, JetBlue Airways Corp, **Kinder Morgan Energy Partners LP**, Legacy Vulcan Corp, Linde Inc, Marathon Oil Corp, **Marriott International Inc**, **Martin Marietta Materials Inc**, Murphy Oil Corp, NRG Energy Inc, **Newmont Corporation**, **Nextera Energy Inc**, **Noble Energy Inc**, Norbord Inc, **Nucor Corp**, ONEOK Inc, **Occidental Petroleum Corp**, Olin Corp, PPL Corp, **Pepco Holdings LLC**, **Pioneer Natural Resources Co**, **RPM International Inc**, **Republic Services Inc**, Royal Caribbean Cruises Ltd, **Sempra Energy**, Southern California Edison Co, **Southern Co**, **Southwest Airlines Co**, **Suncor Energy Inc**, TECO Energy Inc, TransAlta Corp, **Transcanada Pipelines Ltd**, USG Corp, Union Pacific Corp, United States Steel Corp, **Waste Management Inc**, **Westrock MWV LLC**, **Williams Companies Inc**, **Xcel Energy Inc**, Yellow Corp	**Advanced Micro Devices Inc**, **Agilent Technologies Inc**, Allergan Inc, **Altria Group Inc**, **Amerisourcebergen Corp**, Amgen Inc, Anthem Inc, **Applied Materials Inc**, **Arrow Electronics Inc**, Avon Products Inc, Bath & Body Works Inc, Beazer Homes USA Inc, Belo Corp, **Best Buy Co Inc**, Biomet Inc, Boeing Co, Bombardier Inc, **Boston Scientific Corp**, Bristol-Myers Squibb Co, Brunswick Corp, Bunge Ltd, **CA Inc**, Cablevision Systems Corp, **Cardinal Health Inc**, Cincinnati Bell Inc, Cisco Systems Inc, **Comcast Corp**, Costco Wholesale Corp, **D R Horton Inc**, **DST Systems Inc**, Danaher Corp, **Deere & Co**, **Deluxe Corp**, Dillard's Inc, **EMC Corp**, Estee Lauder Companies Inc, First Data Corp, **HP Inc**, **Hasbro Inc**, Health Net Inc, **Humana Inc**, **International Business Machines Corp**, International Game Technology, **Interpublic Group of Companies Inc**, **Intuit Inc**, Johnson & Johnson, KB Home, Kate Spade & Co, **L3harris Technologies Inc**, Lennar Corp, Lockheed Martin Corp, **MDC Holdings Inc**, **Masco Corp**, Mattel Inc, **Mckesson Corp**, Meritage Homes Corp, Microsoft Corp, **Motorola Solutions Inc**, **New York Times Co**, Nike Inc, Nordstrom Inc, Northrop Grumman Corp, Omnicom Group Inc, Oracle Corp, **Prologis Inc**, **Pultegroup Inc**, RR Donnelley & Sons Co, Raytheon Co, **Rogers Communications Inc**, Sandisk LLC, Sysco Corp, Tenet Healthcare Corp, **Thomson Reuters Corp**, **Time Warner Cable Inc**, **Time Warner Inc**, **Toll Brothers Inc**, United States Cellular Corp, UnitedHealth Group Inc, **VF Corp**, **Viacom Inc**, **ViacomCBS Inc**, Western Union Co

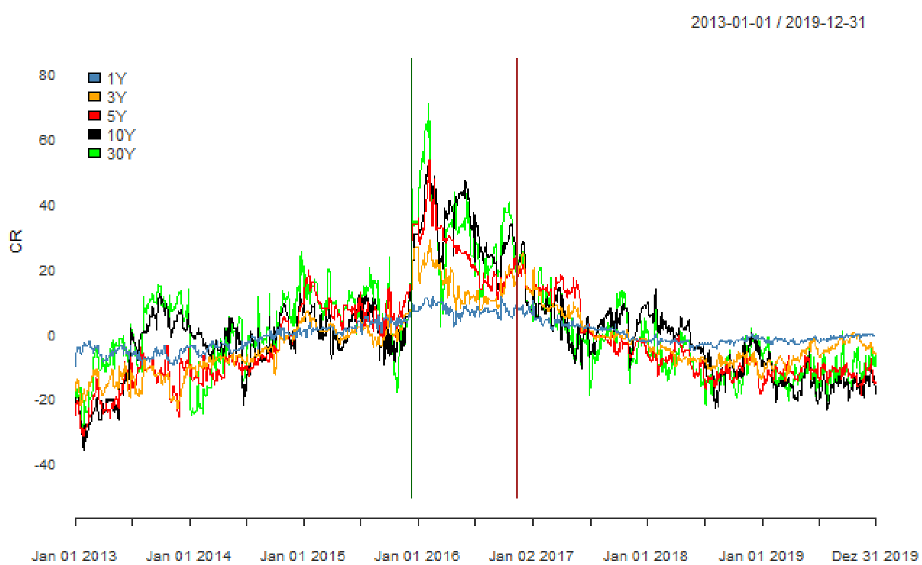
Table 8: This table displays all firms that were constituents of the green resp. brown class at some point time (2013-2019) in Europe (top) and North America (bottom). Firms in bold are firms that represent the median firm (based on the 5Y CDS spread) at least once within their respective group.

C Additional figures and tables

This section provides supplementary material in the form of additional figures and tables. Figure 5 depicts the evolution of the CR for all tenors (1Y, 3Y, 5Y, 10Y, 30Y) in Europe (top) and North America (bottom). Table 9 and Table 10 report the coefficient estimates of the interaction terms of the sector model from Section 4.1 for the 1Y and 30Y tenors, respectively. Table 11 reports all coefficient estimates of the term structure model from Section 4.3.



(a) Europe



(b) North America

Figure 5: Evolution of the CR over time for maturities 1Y (blue), 3Y (orange), 5Y (red), 10Y (black) and 30Y (green) for Europe (top) and North America (bottom). The vertical solid lines refer to the Paris Agreement (dark green) and Trump election (brown), respectively.

	1	2	3	4	5	6	7	8	9
					Europe				
BM × ΔCR	528.94^{***}	365.15^{***}	247.62^{***}	202.90^{***}	136.77^{***}	154.93^{***}	223.53^{***}	318.46^{***}	497.52^{***}
	(58.07)	(38.42)	(27.76)	(27.87)	(23.21)	(27.36)	(35.05)	(63.14)	(125.63)
CCGS × ΔCR	$-226.41^{\cdot}$	-132.15^{*}	-77.46	-98.75^{*}	$-62.09^{\cdot}$	-62.78	-70.05	-70.88	-123.99
	(126.98)	(67.13)	(51.01)	(42.99)	(35.87)	(40.69)	(58.81)	(86.63)	(181.31)
Energy × ΔCR	987.47^{***}	839.52^{***}	776.47^{***}	580.93^{***}	547.64^{***}	574.49^{***}	635.36^{***}	783.19^{***}	921.54^{***}
	(102.03)	(70.01)	(76.20)	(94.23)	(84.83)	(102.29)	(75.73)	(72.59)	(266.73)
Healthcare × ΔCR	-124.66^{*}	$-129.14^{\cdot}$	-171.39^{***}	-170.87^{***}	-123.05^{***}	-133.32^{***}	-172.64^{***}	-121.70	24.43
	(61.56)	(78.13)	(51.56)	(35.88)	(27.71)	(33.61)	(52.29)	(142.29)	(173.92)
Industrials × ΔCR	-230.98^{**}	-174.43^{***}	-131.81^{**}	-132.90^{***}	-77.00^{**}	-80.60^{*}	$-83.40^{\cdot}$	-84.90	-107.92
	(74.00)	(52.96)	(40.69)	(32.48)	(28.88)	(33.93)	(48.78)	(84.66)	(170.87)
NCGS × ΔCR	40.99	34.11	14.18	-45.25	-26.75	-16.26	33.34	121.34	157.84
	(131.01)	(62.57)	(48.17)	(38.74)	(33.49)	(37.22)	(48.38)	(90.58)	(148.50)
Real Estate × ΔCR	274.95^{*}	106.30	24.01	11.33	14.28	34.77	64.96	185.23	303.74
	(117.50)	(145.35)	(102.34)	(94.71)	(95.55)	(114.95)	(100.22)	(149.55)	(253.25)
Technology × ΔCR	-217.61^{**}	-81.18	-35.36	-47.05	-34.54	-24.82	-33.97	-92.62	-218.47
	(73.67)	(65.20)	(58.67)	(47.73)	(38.10)	(43.31)	(54.66)	(93.63)	(159.85)
Utilities × ΔCR	495.94^{***}	374.85^{***}	353.01^{***}	240.77^{***}	231.30^{***}	248.95^{***}	322.94^{***}	428.22^{***}	460.96^{*}
	(64.91)	(77.71)	(73.71)	(68.29)	(54.18)	(59.44)	(73.80)	(112.78)	(208.96)
					North America				
BM × ΔCR	$93.36^{\cdot}$	16.84^{***}	4.33^{*}	$0.44^{\cdot}$	$0.18^{\cdot}$	1.31^{**}	11.77^{***}	50.45^{***}	214.81^{***}
	(48.17)	(4.94)	(1.68)	(0.24)	(0.11)	(0.49)	(2.46)	(11.83)	(55.23)
CCGS × ΔCR	-228.28^{***}	-40.73^{***}	-7.58^{***}	-0.46	-0.14	$-1.08^{\cdot}$	-9.21^{**}	-31.90^{*}	$-112.57^{\cdot}$
	(52.62)	(6.77)	(2.17)	(0.32)	(0.15)	(0.60)	(2.95)	(13.40)	(65.41)
Energy × ΔCR	16.25	14.95	5.16^{*}	0.27	-0.02	0.05	0.52	3.07	-23.24
	(51.98)	(9.10)	(2.46)	(0.32)	(0.13)	(0.58)	(3.28)	(14.09)	(64.49)
Healthcare × ΔCR	-241.07^{***}	-26.50^{***}	-4.50^{*}	-0.43	-0.15	$-1.12^{\cdot}$	-10.39^{***}	-30.12^{*}	-90.44
	(54.87)	(5.99)	(1.93)	(0.35)	(0.18)	(0.59)	(2.87)	(13.44)	(71.06)
Industrials × ΔCR	$-92.66^{\cdot}$	-12.98^{*}	-2.32	-0.21	-0.11	-0.80	-6.68^{*}	-25.10^{*}	$-112.59^{\cdot}$
	(48.92)	(5.59)	(1.83)	(0.26)	(0.11)	(0.51)	(2.65)	(12.58)	(62.86)
NCGS × ΔCR	-97.79^{*}	-15.13^{**}	-2.41	-0.27	-0.13	-0.80	-6.35^{*}	-29.13^{*}	$-118.63^{\cdot}$
	(48.91)	(5.47)	(1.83)	(0.27)	(0.12)	(0.53)	(2.85)	(12.81)	(65.40)
Real Estate × ΔCR	-82.23	-17.05^{**}	$-3.03^{\cdot}$	-0.16	-0.11	$-0.94^{\cdot}$	-9.22^{**}	-35.20^{**}	-128.60^{*}
	(50.12)	(5.46)	(1.84)	(0.27)	(0.12)	(0.52)	(2.86)	(13.44)	(58.36)
Technology × ΔCR	-112.40^{*}	-20.14^{***}	-4.29^{*}	-0.33	-0.13	-0.75	-8.21^{***}	-32.55^{**}	-149.53^{*}
	(48.46)	(5.25)	(1.75)	(0.25)	(0.11)	(0.50)	(2.48)	(11.93)	(59.78)
Utilities × ΔCR	-44.78	-1.85	-0.24	0.02	-0.07	-0.56	-5.46^{*}	-24.95^{*}	$-105.61^{\cdot}$
	(48.38)	(5.28)	(1.75)	(0.25)	(0.11)	(0.50)	(2.54)	(11.93)	(55.02)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Table 9: This table reports the coefficient estimates of the interaction terms of the sector panel quantile regression model for 1-year CDS spread returns in Europe (top) and North America (bottom). The sample comprises of data from 137 European firms resp. 281 North American firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

	1	2	3	4	5	6	7	8	9
					Europe				
BM × ΔCR	105.77***	87.55***	77.04***	63.19***	54.49***	57.28***	68.12***	87.47***	113.73***
	(6.33)	(7.45)	(5.76)	(4.70)	(4.40)	(5.26)	(5.16)	(7.21)	(11.83)
CCGS × ΔCR	−60.03***	−41.68***	−31.91***	−26.97***	−25.69***	−27.20***	−31.07***	−37.76***	−57.50**
	(7.78)	(10.15)	(6.99)	(6.39)	(5.95)	(6.44)	(6.49)	(8.83)	(18.57)
Energy × ΔCR	196.98***	188.38***	169.60***	155.85***	152.47***	151.46***	163.80***	190.18***	228.31***
	(17.81)	(18.29)	(15.33)	(25.77)	(22.67)	(22.92)	(16.61)	(16.95)	(42.20)
Healthcare × ΔCR	−8.84	−14.55	−24.71*	−27.75**	−30.48***	−29.87***	−28.54**	−22.32*	−12.13
	(22.79)	(14.23)	(10.57)	(10.55)	(6.80)	(7.68)	(8.72)	(10.96)	(14.73)
Industrials × ΔCR	−63.66***	−56.91***	−49.14***	−42.98***	−39.77***	−40.38***	−45.95***	−55.95***	−73.37***
	(7.08)	(8.99)	(6.98)	(5.62)	(5.11)	(5.97)	(5.77)	(8.57)	(13.04)
NCGS × ΔCR	−48.34***	−38.09***	−36.99***	−32.90***	−30.47***	−31.55***	−35.56***	−42.85***	−42.31**
	(8.99)	(8.00)	(6.80)	(5.71)	(5.26)	(5.91)	(6.16)	(8.79)	(14.60)
Real Estate × ΔCR	−19.41*	−22.81	−33.82**	−32.28**	−28.30***	−29.29***	−33.75**	−36.30**	−32.94**
	(9.03)	(14.74)	(10.61)	(10.24)	(6.27)	(6.77)	(11.00)	(13.30)	(12.47)
Technology × ΔCR	−61.04***	−43.41***	−36.75***	−27.33***	−26.33***	−29.75***	−34.46***	−46.62***	−63.98**
	(9.65)	(9.45)	(7.91)	(6.65)	(6.26)	(7.21)	(7.19)	(11.20)	(19.44)
Utilities × ΔCR	12.71	30.01*	30.24**	27.88**	30.17**	30.57**	32.06**	24.22	8.53
	(10.39)	(12.34)	(10.99)	(10.44)	(9.98)	(10.47)	(11.71)	(15.79)	(21.73)
					North America				
BM × ΔCR	2.86*	2.38*	0.73·	0.21	0.30	0.82**	1.98***	5.48***	14.19***
	(1.25)	(0.99)	(0.44)	(0.27)	(0.19)	(0.25)	(0.47)	(1.26)	(3.40)
CCGS × ΔCR	−0.21	−2.45·	−0.61	−0.45	−0.46*	−0.51	−0.96	−3.61*	−11.02**
	(1.86)	(1.35)	(0.59)	(0.34)	(0.24)	(0.33)	(0.60)	(1.55)	(3.78)
Energy × ΔCR	15.82***	4.43**	2.44***	0.84*	0.12	0.10	0.60	3.55	12.81*
	(2.20)	(1.45)	(0.68)	(0.40)	(0.26)	(0.35)	(0.66)	(2.23)	(6.13)
Healthcare × ΔCR	−5.04*	−3.55*	−1.22*	−0.61·	−0.51*	−0.90**	−1.74**	−4.03*	−13.03**
	(1.99)	(1.48)	(0.55)	(0.31)	(0.24)	(0.32)	(0.61)	(1.65)	(4.90)
Industrials × ΔCR	2.46	−0.94	−0.13	−0.07	−0.21	−0.67*	−0.97·	−2.99*	−4.69
	(1.90)	(1.13)	(0.52)	(0.32)	(0.22)	(0.29)	(0.54)	(1.39)	(4.07)
NCGS × ΔCR	−4.46*	−2.09·	−0.94	−0.36	−0.35	−0.85**	−1.74**	−5.43***	−14.01***
	(1.87)	(1.16)	(0.58)	(0.33)	(0.23)	(0.30)	(0.55)	(1.44)	(3.64)
Real Estate × ΔCR	1.24	−1.89·	−0.74	−0.18	−0.23	−0.68*	−1.56**	−4.60**	−10.50**
	(1.58)	(1.11)	(0.49)	(0.32)	(0.23)	(0.31)	(0.57)	(1.46)	(3.65)
Technology × ΔCR	−6.41***	−3.96***	−1.39**	−0.50	−0.52*	−0.96***	−2.16***	−5.59***	−14.30***
	(1.56)	(1.10)	(0.49)	(0.31)	(0.21)	(0.28)	(0.52)	(1.37)	(3.55)
Utilities × ΔCR	6.09***	0.35	−0.04	−0.15	−0.20	−0.59*	−1.35*	−2.26	−2.57
	(1.81)	(1.07)	(0.52)	(0.30)	(0.21)	(0.28)	(0.53)	(1.50)	(4.03)

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; ·$p < 0.1$

Table 10: This table reports the coefficient estimates of the interaction terms of the sector panel quantile regression model for 30-year CDS spread returns in Europe (top) and North America (bottom). The sample comprises of data from 137 European firms resp. 281 North American firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

	1	2	3	4	5	6	7	8	9
Europe									
5Y-1Y									
ΔVolatility	-98.60^{***}	-34.55^{***}	-11.94^{**}	-3.38^{*}	0.43	11.59^{***}	33.79^{***}	98.54^{***}	207.75^{***}
	(8.04)	(6.51)	(3.99)	(1.37)	(0.66)	(1.19)	(0.84)	(4.63)	(4.08)
ΔMRISlope	163.65^{***}	126.91^{***}	79.79^{***}	40.70^{***}	26.20^{***}	29.12^{***}	52.76^{***}	106.36^{***}	175.60^{***}
	(7.42)	(5.53)	(5.67)	(3.08)	(1.75)	(1.90)	(3.60)	(5.61)	(9.87)
ΔIR	-1885.03^{***}	-1216.58^{***}	-656.26^{***}	-38223^{***}	-29095^{***}	-30667^{***}	-483.27^{***}	-1140.05^{***}	-2123.89^{***}
	(199.01)	(100.20)	(48.93)	(21.71)	(15.05)	(16.88)	(35.45)	(114.02)	(240.88)
ΔIR^2	-33991.38^{***}	-1366666^{***}	-360647^{***}	579.54^{***}	132007^{***}	158396^{***}	6202.08^{***}	33173.70^{***}	93446.34^{***}
	(3309.47)	(1061.94)	(441.45)	(123.56)	(91.62)	(109.25)	(595.51)	(2442.52)	(6389.28)
ΔTerm	694.93^{***}	534.21^{***}	265.72^{***}	158.11^{***}	107.96^{***}	84.60^{***}	12.82	-264.65^{***}	-911.83^{***}
	(203.82)	(95.49)	(44.57)	(19.13)	(13.49)	(14.64)	(26.14)	(57.53)	(133.06)
ΔCRSlope	35.36^{***}	21.52^{***}	11.30^{***}	5.83^{***}	4.00^{***}	4.42^{***}	7.87^{***}	17.91^{***}	29.85^{***}
	(1.68)	(1.37)	(0.86)	(0.39)	(0.26)	(0.29)	(0.61)	(1.46)	(2.88)
30Y-5Y									
ΔVolatility	-49.71^{***}	-26.86^{***}	-16.48^{***}	-8.77^{***}	-3.11^{**}	0.18	5.64^{***}	13.80^{***}	35.29^{***}
	(6.15)	(2.69)	(1.79)	(1.15)	(0.95)	(1.26)	(1.41)	(1.71)	(2.48)
ΔMRISlope	63.45^{***}	28.80^{***}	18.79^{***}	14.59^{***}	13.19^{***}	14.36^{***}	17.27^{***}	26.42^{***}	61.34^{***}
	(2.67)	(1.39)	(0.93)	(0.77)	(0.79)	(0.77)	(1.05)	(1.53)	(5.12)
ΔIR	503.78^{***}	459.91^{***}	368.14^{***}	334.34^{***}	274.11^{***}	316.29^{***}	351.37^{***}	368.44^{***}	384.35^{**}
	(94.24)	(39.36)	(24.52)	(19.89)	(18.03)	(18.56)	(21.37)	(35.71)	(117.56)
ΔIR^2	-13476.76^{***}	-5965.58^{***}	-328710^{***}	-159379^{***}	-36501^{***}	550.89^{***}	1570.59^{***}	4017.69^{***}	14666.93^{***}
	(1172.96)	(428.95)	(263.29)	(143.92)	(92.55)	(92.16)	(161.05)	(328.21)	(2161.82)
ΔTerm	-929.52^{***}	-569.48^{***}	-406.05^{***}	-34787^{***}	-27544^{***}	-30135^{***}	-319.81^{***}	-300.17^{***}	-331.85^{**}
	(95.20)	(40.64)	(26.92)	(21.25)	(19.64)	(20.65)	(22.03)	(36.42)	(116.80)
ΔCRSlope	4.26^{***}	2.30^{***}	1.58^{***}	1.21^{***}	1.02^{***}	1.07^{***}	1.45^{***}	2.35^{***}	5.11^{***}
	(0.45)	(0.24)	(0.14)	(0.11)	(0.12)	(0.14)	(0.21)	(0.33)	(0.87)
North America									
5Y-1Y									
ΔVolatility	-61.58^{***}	-13.85^{***}	-3.80^{***}	-0.43	0.42^{*}	5.88^{***}	18.89^{***}	60.14^{***}	178.41^{***}
	(7.10)	(1.94)	(0.68)	(0.32)	(0.17)	(0.65)	(1.18)	(13.42)	(14.88)
ΔMRISlope	23.00^{***}	12.85^{***}	5.82^{***}	2.71^{***}	1.33^{***}	2.79^{***}	6.47^{***}	18.26^{***}	48.83^{***}
	(1.16)	(0.82)	(0.35)	(0.19)	(0.12)	(0.18)	(0.37)	(1.40)	(6.53)
ΔIR	-1537.42^{***}	-562.87^{***}	-251.68^{***}	-12513^{***}	-52.42^{***}	-13346^{***}	-294.28^{***}	-861.79^{***}	-2571.31^{***}
	(75.52)	(21.79)	(10.59)	(6.79)	(3.95)	(6.71)	(12.62)	(58.56)	(222.16)
ΔIR^2	-18173.98^{***}	-3804.54^{***}	-635.25^{***}	$50.95^{\cdot}$	285.25^{***}	701.45^{***}	1530.59^{***}	8688.51^{***}	46660.43^{***}
	(1284.55)	(228.95)	(52.47)	(27.24)	(20.36)	(33.54)	(84.16)	(759.19)	(4491.22)
ΔTerm	591.11^{***}	274.20^{***}	147.90^{***}	76.13^{***}	28.08^{***}	64.23^{***}	146.00^{***}	310.57^{***}	636.12^{***}
	(39.68)	(18.11)	(9.77)	(5.86)	(3.09)	(5.15)	(8.58)	(23.27)	(64.44)
ΔCRSlope	0.59^{*}	0.17	$0.09^{\cdot}$	0.01	0.01	0.08^{***}	0.00	0.38^{**}	0.77^{*}
	(0.24)	(0.11)	(0.05)	(0.03)	(0.01)	(0.02)	(0.05)	(0.12)	(0.38)
30Y-5Y									
ΔVolatility	-56.56^{***}	-25.08^{***}	-9.01^{***}	-1.18^{*}	0.00	0.00	13.20^{***}	39.30^{***}	103.35^{***}
	(4.96)	(2.33)	(1.48)	(0.52)	(0.00)	(0.00)	(1.27)	(2.54)	(11.48)
ΔMRISlope	14.31^{***}	6.52^{***}	2.41^{***}	0.54^{***}	0.00	0.00	1.31^{***}	4.05^{***}	10.98^{***}
	(0.87)	(0.34)	(0.17)	(0.07)	(0.00)	(0.00)	(0.15)	(0.34)	(1.16)
ΔIR	-345.28^{***}	-70.01^{*}	-7.21	3.16	-0.00	0.00	-8.04	-152.23^{***}	-575.73^{***}
	(88.69)	(29.52)	(11.42)	(4.04)	(0.00)	(0.00)	(6.54)	(23.50)	(110.81)
ΔIR^2	-9269.27^{***}	-2541.36^{***}	-109895^{***}	-26810^{***}	-0.00	0.00	680.56^{***}	2500.78^{***}	12820.23^{***}
	(696.54)	(234.91)	(92.63)	(34.56)	(0.00)	(0.00)	(86.32)	(293.18)	(2003.66)
ΔTerm	243.00^{**}	66.56^{*}	$19.96^{\cdot}$	2.23	0.00	0.00	9.29	93.58^{***}	332.01^{***}
	(90.46)	(28.88)	(10.93)	(3.65)	(0.00)	(0.00)	(5.71)	(19.20)	(79.69)
ΔCRSlope	1.99^{***}	0.69^{***}	0.16^{***}	$0.03^{\cdot}$	0.00	0.00	0.22^{***}	0.95^{***}	2.22^{***}
	(0.25)	(0.12)	(0.05)	(0.01)	(0.00)	(0.00)	(0.04)	(0.11)	(0.43)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Table 11: This table reports the coefficient estimates of the term structure panel quantile regression model for 5Y-1Y and 30Y-5Y CDS spread slope changes in Europe (top) and North America (bottom). The sample comprises of data from 137 European firms resp. 281 North American firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

D Robustness checks

In this section, we perform a number of robustness checks to confirm our baseline findings. We carry on the robustness checks for the remaining models too (i.e. sectoral, attention and term structure model) and find no significant differences. Results for these models are available upon request. First, we examine whether the varying degree of liquidity of CDS contracts poses an issue for our analysis. Second, we consider alternative specifications for the construction of our CR factor.

D.1 Liquidity of CDS spreads

In the baseline analysis, we exclude from our sample a CDS contract when "no spread movement for 245 days" is detected. We acknowledge this restriction is rather lax. Yet, it ensures a sufficient number of contracts in our sample – 137 European firms and 281 North American firms. We then examine the effect of a significantly more stringent condition: "no spread movement for 25 days".[36] After applying this more stringent condition, the number of firms in our sample decreases to 166 in North America and 120 in Europe, respectively. We then construct our CF factor and run the baseline regression. Table 12 shows that the results for both Europe and North America remain unchanged with respect to the baseline findings reported in Section 4.1.

[36] An augmentation of our model with an appropriate liquidity measure is not possible due to the lack of available data.

	1	2	3	4	5	6	7	8	9
					Europe				
					1Y				
ΔCR	510.07***	360.83***	269.14***	203.81***	158.42***	178.86***	253.62***	371.89***	583.46***
	(15.75)	(14.18)	(13.15)	(11.18)	(10.83)	(11.99)	(16.17)	(22.44)	(38.45)
					3Y				
ΔCR	230.20***	193.71***	164.30***	129.86***	110.80***	125.50***	169.24***	220.72***	275.02***
	(6.03)	(6.68)	(6.72)	(6.39)	(6.15)	(6.02)	(7.22)	(9.45)	(14.28)
					5Y				
ΔCR	148.86***	137.82***	111.89***	89.78***	74.64***	82.98***	108.83***	134.58***	174.86***
	(6.84)	(5.03)	(4.37)	(4.37)	(4.04)	(3.97)	(4.29)	(5.25)	(7.41)
					10Y				
ΔCR	96.60***	76.15***	62.18***	50.24***	41.64***	45.53***	56.39***	71.10***	90.02***
	(3.07)	(2.72)	(2.47)	(2.28)	(2.27)	(2.16)	(2.26)	(2.89)	(3.22)
					30Y				
ΔCR	58.97***	50.17***	40.31***	31.41***	26.51***	28.48***	34.68***	44.12***	56.23***
	(3.00)	(2.29)	(1.89)	(1.81)	(1.79)	(1.94)	(2.14)	(2.88)	(4.20)
					North America				
					1Y				
ΔCR	26.71**	20.31***	18.14***	9.87***	3.00***	9.23***	26.46***	62.59***	134.40***
	(8.23)	(3.92)	(2.39)	(1.40)	(0.61)	(1.15)	(2.88)	(6.50)	(16.11)
					3Y				
ΔCR	27.11***	12.13***	7.42***	3.17***	1.60***	2.80***	8.90***	18.84***	38.12***
	(3.22)	(2.30)	(1.94)	(0.70)	(0.36)	(0.68)	(1.81)	(3.10)	(5.89)
					5Y				
ΔCR	14.44***	9.49***	6.93***	3.96***	1.42***	2.47***	5.39***	11.24***	21.91***
	(1.63)	(1.28)	(1.01)	(0.63)	(0.39)	(0.48)	(0.85)	(1.77)	(2.32)
					10Y				
ΔCR	8.67***	5.84***	4.32***	2.87***	1.40***	2.20***	3.71***	5.93***	11.13***
	(0.84)	(0.75)	(0.41)	(0.33)	(0.21)	(0.23)	(0.40)	(0.66)	(0.92)
					30Y				
ΔCR	8.91***	4.58***	3.29***	2.13***	1.14***	1.86***	3.35***	5.42***	7.69***
	(1.32)	(0.59)	(0.43)	(0.30)	(0.19)	(0.22)	(0.40)	(0.73)	(1.49)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Table 12: This table reports the ΔCR coefficient estimates of the base panel quantile regression model for CDS spread returns of all tenors in both regions. The sample now includes data for 166 and 120 North American and European firms, respectively, from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

D.2 Alternative specifications for factor construction

The baseline CR factor is constructed by a univariate sorting of firms with respect to their emission profiles. That is, our CDS universe is sorted by emission intensity from low to high. The use of firms' emission intensity allows for a straightforward interpretation of the CR factor. Such a construction, however, might have shortcomings. Alternative emission classifications may be more suitable (absolute emissions vs emission intensity). Also, univariate sorting might have its own limitations. Double sorting helps control for the possibility that other firm-specific characteristics (size, leverage, etc.) may consistently coincide with the firm's emission profile. To demonstrate that the identification of carbon risk exposure via firms' emission profiles is not misspecified, we examine alternative specifications for the construction of the CR factor and rerun our base model.

D.2.1 Absolute emissions

While the classification of firms' emission profiles via their emission intensities allows for a straightforward comparison between firms' carbon footprints, there is some evidence that the absolute level of emissions is of the upmost importance. For example, for stock returns, Bolton and Kacperczyk (2021) explain that a companies' total level of carbon emissions is what matters most. For this study, however, we show that our main results do not depend on firms' emission classification. Table 13 shows that new coefficient estimates (using absolute emissions to construct the CR factor) remain broadly in line with baseline results (using emissions intensity to construct our CR factor). Our main results suggest that the amplifying effect of carbon risk on credit risk is present in Europe, but virtually absent in North America, regardless of whether the CR factor is based on absolute emissions or emissions intensity.

	1	2	3	4	5	6	7	8	9
					Europe				
					1Y				
ΔCR	462.09***	349.06***	238.21***	163.59***	122.68***	161.98***	248.93***	376.70***	521.56***
	(22.87)	(16.30)	(12.93)	(9.89)	(8.73)	(10.70)	(14.88)	(24.00)	(37.17)
					3Y				
ΔCR	339.82***	288.41***	232.13***	174.15***	137.76***	156.03***	209.04***	270.16***	319.65***
	(12.10)	(8.71)	(7.29)	(6.95)	(6.45)	(6.96)	(7.99)	(10.36)	(17.33)
					5Y				
ΔCR	224.84***	193.53***	158.53***	127.77***	103.60***	110.54***	142.22***	179.05***	215.70***
	(5.89)	(5.83)	(5.35)	(4.97)	(4.84)	(4.59)	(5.15)	(6.57)	(9.22)
					10Y				
ΔCR	104.56***	85.20***	71.64***	57.69***	47.01***	51.12***	64.06***	81.32***	108.40***
	(3.25)	(2.91)	(2.95)	(2.29)	(2.23)	(2.34)	(2.64)	(3.04)	(3.51)
					30Y				
ΔCR	52.56***	49.02***	43.00***	35.33***	28.05***	28.53***	33.37***	41.78***	43.52***
	(2.62)	(2.19)	(2.01)	(1.64)	(1.66)	(1.71)	(1.80)	(2.54)	(5.20)
					North America				
					1Y				
ΔCR	−19.88***	−8.75***	−2.19***	−0.34***	−0.09***	−0.83***	−5.42***	−23.03***	−71.85***
	(2.09)	(0.94)	(0.28)	(0.05)	(0.02)	(0.10)	(0.60)	(2.42)	(7.71)
					3Y				
ΔCR	−2.08***	−0.93**	−0.64**	−0.27*	−0.06	−0.38**	−1.05***	−2.90***	−10.85***
	(0.55)	(0.29)	(0.20)	(0.12)	(0.07)	(0.13)	(0.24)	(0.50)	(1.53)
					5Y				
ΔCR	−3.10***	−1.23***	−0.64***	−0.24***	−0.08*	−0.15**	−0.33**	−0.75*	−2.77***
	(0.40)	(0.18)	(0.10)	(0.06)	(0.04)	(0.06)	(0.12)	(0.29)	(0.72)
					10Y				
ΔCR	−4.21***	−1.98***	−1.14***	−0.68***	−0.27***	−0.47***	−0.84***	−1.56***	−4.44***
	(0.26)	(0.13)	(0.08)	(0.05)	(0.03)	(0.04)	(0.08)	(0.18)	(0.56)
					30Y				
ΔCR	−0.84***	−0.61***	−0.51***	−0.39***	−0.31***	−0.42***	−0.68***	−1.16***	−2.70***
	(0.21)	(0.13)	(0.08)	(0.05)	(0.04)	(0.06)	(0.11)	(0.20)	(0.48)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Table 13: This table reports the coefficient estimates of ΔCR (sorted on absolute emissions) of the base panel quantile regression model for CDS spread returns of all tenors in both regions. The sample includes data for 137 European firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

D.2.2 Lagged emission intensities

Noting that emissions data are generally reported with a one-year lag, we re-construct our CR factor using one-year lagged emission intensities and show that estimates are robust to the choice of the lag structure. By construction, the performance of the newly constructed CR factor is identical to the performance of an insurance strategy where default protection is bought for a polluting firm and sold for a clean firm given the information available at time t. Table 14 shows that the coefficient estimates remain almost unchanged when comparing one-year lag to the no-lag baseline results.

	1	2	3	4	5	6	7	8	9
Europe									
1Y									
ΔCR	368.96***	305.21***	210.91***	146.75***	101.10***	131.97***	217.33***	349.25***	504.30***
	(23.52)	(15.86)	(12.91)	(10.03)	(7.74)	(9.80)	(15.38)	(23.05)	(41.82)
3Y									
ΔCR	285.72***	241.95***	197.23***	137.86***	92.48***	110.01***	155.28***	207.11***	243.92***
	(11.82)	(9.24)	(7.63)	(6.01)	(4.94)	(5.60)	(7.64)	(10.84)	(16.42)
5Y									
ΔCR	172.51***	150.96***	119.90***	92.64***	70.16***	80.34***	106.99***	139.90***	176.27***
	(7.40)	(5.40)	(4.55)	(4.44)	(4.28)	(4.18)	(4.55)	(5.61)	(9.21)
10Y									
ΔCR	88.38***	73.63***	60.69***	47.69***	36.61***	41.25***	52.77***	68.56***	91.77***
	(3.00)	(2.97)	(2.70)	(2.19)	(1.85)	(2.04)	(2.54)	(3.42)	(5.48)
30Y									
ΔCR	60.98***	51.77***	45.34***	36.38***	30.42***	32.97***	39.17***	45.10***	51.74***
	(2.94)	(2.40)	(2.29)	(1.78)	(1.64)	(1.90)	(2.18)	(3.26)	(6.23)
North America									
1Y									
ΔCR	−2.35*	0.69	0.75***	0.15***	0.04**	0.31***	2.38***	11.44***	38.99***
	(1.08)	(0.56)	(0.15)	(0.04)	(0.02)	(0.06)	(0.39)	(1.62)	(5.85)
3Y									
ΔCR	4.57***	2.74***	1.59***	0.91***	0.31***	0.52***	1.44***	3.95***	12.04***
	(0.75)	(0.30)	(0.18)	(0.12)	(0.06)	(0.12)	(0.29)	(0.65)	(1.87)
5Y									
ΔCR	0.49	0.66***	0.52***	0.23**	0.01	0.23**	1.03***	2.95***	9.71***
	(0.40)	(0.16)	(0.11)	(0.08)	(0.03)	(0.09)	(0.19)	(0.47)	(1.35)
10Y									
ΔCR	4.44***	1.78***	0.96***	0.45***	0.15***	0.24***	0.40***	0.86***	1.64**
	(0.48)	(0.18)	(0.10)	(0.06)	(0.04)	(0.06)	(0.10)	(0.21)	(0.55)
30Y									
ΔCR	2.14***	0.54***	0.18·	−0.01	−0.04	−0.04	−0.10	−0.00	0.33
	(0.35)	(0.14)	(0.09)	(0.06)	(0.04)	(0.05)	(0.09)	(0.17)	(0.51)

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; ·$p < 0.1$

Table 14: This table reports the coefficient estimates of ΔCR (sorted on lagged emission intensities) of the base panel quantile regression model for CDS spread returns of all tenors in both regions. The sample includes data for 137 European firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

D.2.3 Possible confounding variables

We begin by noting the strong relationship documented in the literature between firms' emissions and some key firm characteristics. High absolute emissions are related to (log)size, high book-to-market ratios, and highly leveraged firms. Conversely, emission intensities are weakly negatively related to size (Bolton and Kacperczyk, 2021; Huij et al., 2021). Thus, sorting firms solely on emissions intensity may result in an inappropriate categorization of small firms as polluting firms and big firms as clean firms. Double sorting helps control for this potential bias and inaccurate representation of firms' emission profiles, ultimately reducing the risk of over- or underestimating exposure to carbon risk.

We therefore construct alternative, conditionally double-sorted versions of the CR factor. For every day t, we first sort the CDS sample into two quantiles $\mathcal{X}_t^m$ and $\mathcal{Y}_t^m$ of the (one-year lagged) candidate variable (size, book-to-market ratio, leverage, etc.). Then, we sort firms within each group into five quantiles of one-year lagged emission intensities. Firms below the first quintile are the clean subgroup ($\mathcal{XC}_t^m$ or $\mathcal{YC}_t^m$), whereas firms above the fifth quintile are the polluting subgroup ($\mathcal{XP}_t^m$ or $\mathcal{YP}_t^m$). Then, we compute the median CDS spread in each subgroup resulting in four different medians (XP_t^m, XC_t^m, YP_t^m, YC_t^m) in total. Finally, we compute the conditional, double-sort CR as follows:

$$\mathrm{CR}_t^m = \frac{1}{2}\left(\mathrm{XP}_t^m + \mathrm{YP}_t^m\right) - \frac{1}{2}\left(\mathrm{XC}_t^m + \mathrm{YC}_t^m\right), \tag{3}$$

and replace the original CR with the new CR in the base model from Section 4.1 to check the robustness of our baseline CR.

D.2.3.1 Size

First, we consider firms' market capitalization – the size variable. We sort the CDS sample into two quantiles of market capitalization (lagged by one year) to distinguish between small (S) and big firms (B). Sorting on emission intensities afterwards, and computing the median CDS spread, leaves us with four groups: small and polluting SP_t^m, small and clean SC_t^m, big and polluting BP_t^m, and big and clean BC_t^m. We can then straightforwardly obtain the size-adjusted CR by using Equation (3) and replace X with small (S) and Y with big (B):

$$\mathrm{CR}_t^m = \frac{1}{2}\left(\mathrm{SP}_t^m + \mathrm{BP}_t^m\right) - \frac{1}{2}\left(\mathrm{SC}_t^m + \mathrm{BC}_t^m\right),$$

Table 15 reports the new coefficient estimates and shows that using the size-adjusted CR leaves results virtually unchanged with respect to the baseline.

	1	2	3	4	5	6	7	8	9
					Europe				
					1Y				
ΔCR	528.60^{***}	430.50^{***}	321.71^{***}	259.19^{***}	207.47^{***}	254.19^{***}	345.97^{***}	489.90^{***}	693.25^{***}
	(25.40)	(17.98)	(18.40)	(15.07)	(15.26)	(16.14)	(20.12)	(27.57)	(47.67)
					3Y				
ΔCR	295.24^{***}	280.36^{***}	250.29^{***}	201.32^{***}	159.19^{***}	185.81^{***}	242.81^{***}	301.14^{***}	354.31^{***}
	(9.73)	(10.13)	(9.02)	(8.74)	(9.13)	(8.57)	(10.07)	(13.00)	(19.44)
					5Y				
ΔCR	162.33^{***}	162.72^{***}	145.93^{***}	124.96^{***}	111.58^{***}	127.79^{***}	163.15^{***}	195.92^{***}	227.36^{***}
	(7.23)	(7.40)	(6.06)	(5.37)	(5.67)	(5.56)	(5.45)	(7.07)	(9.83)
					10Y				
ΔCR	81.72^{***}	78.38^{***}	76.48^{***}	65.83^{***}	56.72^{***}	65.53^{***}	83.01^{***}	102.28^{***}	134.31^{***}
	(3.51)	(4.30)	(3.56)	(3.10)	(3.04)	(3.00)	(3.22)	(4.06)	(5.43)
					30Y				
ΔCR	62.81^{***}	57.61^{***}	55.41^{***}	49.52^{***}	44.64^{***}	49.73^{***}	60.52^{***}	76.13^{***}	99.96^{***}
	(2.70)	(2.53)	(2.79)	(2.48)	(2.40)	(2.39)	(2.86)	(3.70)	(4.83)
					North America				
					1Y				
ΔCR	-5.88^{***}	-0.11	$0.27^{\cdot}$	0.09^{*}	0.02	0.03	0.27	1.08	2.04
	(1.32)	(0.48)	(0.14)	(0.04)	(0.02)	(0.05)	(0.22)	(1.03)	(2.60)
					3Y				
ΔCR	-7.38^{***}	-2.52^{***}	-0.96^{**}	-0.26^{**}	-0.13^{**}	-1.18^{***}	-2.04^{***}	-3.88^{***}	-9.80^{***}
	(1.14)	(0.51)	(0.30)	(0.08)	(0.05)	(0.17)	(0.28)	(0.59)	(1.41)
					5Y				
ΔCR	-9.19^{***}	-3.91^{***}	-2.46^{***}	-1.56^{***}	-0.81^{***}	-1.32^{***}	-1.79^{***}	-2.57^{***}	-4.80^{***}
	(0.97)	(0.43)	(0.24)	(0.14)	(0.08)	(0.14)	(0.23)	(0.41)	(0.80)
					10Y				
ΔCR	-4.27^{***}	-1.95^{***}	-1.09^{***}	-0.67^{***}	-0.31^{***}	-0.58^{***}	-0.97^{***}	-1.72^{***}	-3.95^{***}
	(0.40)	(0.19)	(0.10)	(0.07)	(0.04)	(0.06)	(0.09)	(0.20)	(0.44)
					30Y				
ΔCR	1.58^{***}	0.35^{*}	0.06	-0.02	$-0.07^{\cdot}$	-0.35^{***}	-0.63^{***}	-1.26^{***}	-2.43^{***}
	(0.29)	(0.15)	(0.09)	(0.06)	(0.04)	(0.05)	(0.09)	(0.18)	(0.39)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Table 15: This table reports the coefficient estimates of ΔCR (double-sorted on size) of the base panel quantile regression model for CDS spread returns of all tenors in both regions. The sample includes data for 134 (276) European (North American) firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

D.2.3.2 Book-to-market ratio

Second, we consider the book-to-market ratio (B/M), defined as the book value of equity divided by the market value of equity (market cap). Pastor et al. (2021) documented that polluting firms tend to be disproportionately more represented by value firms, whereas clean firms tend to be disproportionately more represented by growth firms. Similar to size, we use the median B/M (lagged by one year) to divide firms between value (H) and growth (L) firms – where now X=H and Y=L in Equation (3). Table 16 shows again that, using the B/M-adjusted CR, the baseline findings remain valid.

	1	2	3	4	5	6	7	8	9
					Europe				
					1Y				
ΔCR	369.88***	280.11***	218.97***	172.09***	131.28***	158.64***	245.88***	377.94***	565.10***
	(20.82)	(17.19)	(14.18)	(11.43)	(10.37)	(11.43)	(15.60)	(23.06)	(46.31)
					3Y				
ΔCR	272.95***	234.97***	188.86***	139.09***	93.75***	114.95***	165.16***	206.45***	254.22***
	(12.83)	(8.41)	(8.34)	(6.75)	(5.49)	(6.06)	(8.21)	(10.61)	(12.77)
					5Y				
ΔCR	162.40***	130.91***	107.89***	83.51***	62.48***	70.44***	102.26***	137.10***	173.71***
	(4.60)	(4.25)	(3.98)	(3.54)	(3.08)	(3.25)	(4.11)	(5.94)	(10.11)
					10Y				
ΔCR	116.89***	92.30***	74.19***	58.33***	46.64***	52.62***	70.34***	87.55***	125.58***
	(3.72)	(2.78)	(2.50)	(2.48)	(2.05)	(2.03)	(2.59)	(3.06)	(3.61)
					30Y				
ΔCR	90.61***	70.85***	59.64***	48.83***	42.45***	47.93***	59.24***	72.35***	105.55***
	(3.57)	(2.60)	(2.45)	(2.31)	(1.88)	(2.07)	(2.64)	(3.22)	(4.26)
					North America				
					1Y				
ΔCR	−13.08***	−4.17***	−0.31$^{\cdot}$	0.02	0.02	0.10$^{\cdot}$	0.46	0.79	−0.21
	(2.04)	(0.89)	(0.18)	(0.04)	(0.02)	(0.06)	(0.29)	(0.96)	(1.58)
					3Y				
ΔCR	−7.91***	−3.04***	−1.35***	−0.57***	−0.25***	−1.48***	−2.84***	−4.89***	−11.51***
	(1.22)	(0.62)	(0.31)	(0.14)	(0.07)	(0.20)	(0.36)	(0.76)	(2.31)
					5Y				
ΔCR	−2.37***	−1.13***	−0.76***	−0.47***	−0.22***	−0.49***	−0.69***	−0.93***	−2.09**
	(0.49)	(0.22)	(0.13)	(0.08)	(0.05)	(0.08)	(0.14)	(0.24)	(0.70)
					10Y				
ΔCR	1.72***	0.31*	0.11	0.01	−0.05	−0.16**	−0.25**	−0.55***	−2.02***
	(0.31)	(0.15)	(0.09)	(0.05)	(0.03)	(0.05)	(0.09)	(0.15)	(0.42)
					30Y				
ΔCR	0.98*	−0.36$^{\cdot}$	−0.11	−0.13	−0.16**	−0.55***	−0.79***	−1.24***	−1.70**
	(0.41)	(0.19)	(0.13)	(0.09)	(0.06)	(0.09)	(0.14)	(0.24)	(0.55)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Table 16: This table reports the coefficient estimates of ΔCR (double-sorted on book-to-market ratio) of the base panel quantile regression model for CDS spread returns of all tenors in both regions. The sample includes data for 134 (276) European (North American) firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

D.2.3.3 Leverage

Third, we consider the leverage ratio, defined as the book value of debt divided by the book value of assets, for the first sorting. Polluting firms tend to have disproportionately more tangible assets compared to clean firms (Iovino et al., 2021), hence we control for the possibility that higher leverage ratios entirely capture the exposure to carbon risk. We use the median leverage ratio (lagged by one year) to distinguish between firms with high (HL) and low (LL) leverage ratios; where now X=HL and Y=LL in Equation (3). Table 17 displays the results of the base model using the leverage-adjusted CR for Europe and North America, respectively. Again, using the leverage-adjusted CR leaves results virtually unchanged with respect to the baseline.

	1	2	3	4	5	6	7	8	9
Europe									
1Y									
ΔCR	649.63^{***}	483.81^{***}	328.43^{***}	222.79^{***}	162.19^{***}	203.31^{***}	298.94^{***}	459.84^{***}	677.61^{***}
	(26.17)	(22.85)	(17.90)	(14.32)	(12.96)	(14.17)	(19.50)	(27.28)	(33.88)
3Y									
ΔCR	317.12^{***}	283.38^{***}	247.58^{***}	199.84^{***}	158.24^{***}	183.13^{***}	240.93^{***}	302.28^{***}	354.94^{***}
	(12.12)	(8.61)	(9.06)	(8.28)	(7.73)	(7.94)	(9.54)	(11.78)	(21.32)
5Y									
ΔCR	181.15^{***}	160.50^{***}	132.16^{***}	107.91^{***}	91.67^{***}	98.75^{***}	124.60^{***}	155.24^{***}	188.77^{***}
	(5.97)	(5.92)	(5.26)	(5.21)	(4.99)	(5.21)	(5.28)	(7.08)	(9.58)
10Y									
ΔCR	90.74^{***}	76.21^{***}	66.39^{***}	56.11^{***}	47.28^{***}	53.22^{***}	67.93^{***}	86.08^{***}	108.92^{***}
	(2.26)	(3.41)	(2.96)	(2.85)	(2.67)	(2.81)	(2.93)	(3.70)	(5.40)
30Y									
ΔCR	66.58^{***}	59.44^{***}	51.15^{***}	42.38^{***}	38.40^{***}	42.42^{***}	52.10^{***}	66.27^{***}	83.85^{***}
	(1.94)	(2.37)	(2.16)	(2.13)	(2.19)	(2.36)	(2.57)	(2.89)	(3.87)
North America									
1Y									
ΔCR	-3.25^{**}	0.73	0.56^{**}	0.11^{*}	0.03	$0.11^{\cdot}$	0.70^{*}	3.50^{**}	$5.96^{\cdot}$
	(1.22)	(0.59)	(0.17)	(0.05)	(0.02)	(0.06)	(0.30)	(1.19)	(3.23)
3Y									
ΔCR	-6.82^{***}	-2.79^{***}	-1.35^{***}	-0.34^{***}	-0.13^{*}	-0.42^{***}	-1.18^{***}	-2.68^{***}	-6.32^{***}
	(0.94)	(0.46)	(0.26)	(0.09)	(0.05)	(0.12)	(0.28)	(0.64)	(1.37)
5Y									
ΔCR	-11.17^{***}	-5.02^{***}	-3.06^{***}	-2.10^{***}	-1.17^{***}	-2.02^{***}	-3.28^{***}	-5.01^{***}	-9.05^{***}
	(0.90)	(0.40)	(0.24)	(0.16)	(0.10)	(0.15)	(0.28)	(0.54)	(1.34)
10Y									
ΔCR	-3.10^{***}	-1.58^{***}	-0.95^{***}	-0.59^{***}	-0.34^{***}	-0.66^{***}	-1.09^{***}	-1.72^{***}	-3.67^{***}
	(0.41)	(0.18)	(0.12)	(0.06)	(0.04)	(0.06)	(0.10)	(0.20)	(0.64)
30Y									
ΔCR	-0.63	-1.09^{***}	-0.91^{***}	-0.80^{***}	-0.59^{***}	-1.17^{***}	-2.08^{***}	-3.83^{***}	-8.97^{***}
	(0.44)	(0.22)	(0.14)	(0.10)	(0.07)	(0.09)	(0.15)	(0.29)	(0.82)

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Table 17: This table reports the coefficient estimates of ΔCR (double-sorted on leverage ratio) of the base panel quantile regression model for CDS spread returns of all tenors in both regions. The sample includes data for 134 (276) European (North American) firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.