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

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Abstract

Using Credit Default Swap spreads, we construct and validate a forward-looking, market-implied carbon risk (CR) factor and show that the impact of carbon regulations on firms' credit risk varies with the regulation's scope and stringency, and with the speed of mandated carbon reduction. We find that explicit carbon pricing sharpens lenders' evaluations, resulting in firms under such regimes incurring three times the additional credit protection costs. This impact escalates with the proportion of a firm's direct emissions subject to regulation – the policy's stringency – and varies by the sector in which the firm operates. With an increase in the CR factor, lenders foresee higher costs for short-term transitions.

Keywords: Carbon Risk, Climate Change, Climate Finance, Credit Risk, Transition Risk.

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

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1 Introduction

The transformation of the economy required to achieve net-zero targets will be profound and could generate sizable costs. Unquestionably, these costs could significantly impact firms' cash flows and valuations, undermining their ability to service and repay their debt, eventually leading to higher credit risks and probabilities of default (Kölbel et al., 2022; BIS, 2021; Carbone et al., 2021; DiVirgilio et al., 2022). There is already some evidence that climate regulation risk,[1] codified using firms' current carbon emissions data, influences credit risk (Ilhan et al., 2020; Duan et al., 2021; Zhang and Zhao, 2022). However, these studies do not clarify whether and how firms' emissions are actually regulated by carbon policies. Our findings suggest that the extent to which carbon regulations influence firms' credit risk is significantly determined by the policies' scope, stringency, and the pace at which they mandate carbon transformation. Together, these factors shape the actual impact and financial implications of carbon pricing policies, beyond mere emission levels or the emission intensity of firms. Understanding the drivers of carbon risk exposure is crucial because it directly influences how lenders assess and re-evaluate firms' creditworthiness. Firms perceived as more exposed to carbon risk see their valuations decrease, whereas those deemed less exposed may witness an increase in their valuations. Qualifying and quantifying the effect of these drivers form the core of our analysis in this paper.

While there has been increasing academic, industry, and regulatory attention to the risks associated with the low-carbon transition (e.g. Bolton et al., 2020; NZAM, 2022; NGFS, 2019), there is no comprehensive theoretical framework linking these risks to credit dynamics. Notwithstanding the complexity of precisely modeling specific risk drivers and transmission channels, markets are already recognizing that carbon policy, changing preferences, and ongoing technological change are reshaping economic growth patterns, potentially increasing default risks or reducing asset values for firms more exposed to transition risk.

Building on the understanding that firms may adapt to these changes at different times and at varied paces, we posit that lenders incorporate these differences into their valuation of firms. Capitalizing on this premise, we employ the daily spreads of Credit Default Swap (CDS) contracts to construct a *market-implied, high-frequency* and *forward-looking* carbon risk (CR) factor. The construction of this CR factor is our first main contribution. CDSs provide distinct benefits over traditional credit risk indicators, such as corporate bonds or ratings, due to their rapid responsiveness to macroeconomic, corporate, and, arguably, policy shifts (Jorion and Zhang, 2007, Acharya and Johnson, 2007, Berndt and Ostrovnaya, 2014, and Hana et al., 2017). Unlike equity and bond markets, the CDS market swiftly integrates changes in credit, market, and policy conditions (Blanco et al., 2005; Zhu, 2006). Additionally, the standardized trading terms of CDSs reduce distortions related to contractual variations (Blanco et al., 2005; Zhu, 2006; Norden and Weber, 2009) or liquidity issues (Longstaff et al., 2005; Ederington et al., 2015). Last, since there are CDS contracts with varying short-, medium- and long-term tenors, they allow us to incorporate lenders' collective forward-looking considerations.

[1]Climate change affects the economy through two main channels: Physical risks arise from damage to infrastructure, property, and business operations. Transition risk results from changes in climate policy regulations, technology, and consumer and market sentiment during the adjustment to a lower-carbon economy.

The CR 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.[2] When policy events (e.g. an announcement of tightening regulations) trigger a rise in carbon risk, lenders to more (less) exposed firms demand increased (decreased) protection, widening the CDS wedge – the distance between the price of default protection for polluting and clean companies. Conversely, if a loosening of regulation is expected, there is a narrowing of the wedge (or even a negative wedge). The CR factor thereby captures the perceived general carbon risk. 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 introduce a series of hypotheses aimed at identifying the drivers behind the impact of carbon price regulation, assessing their relevance and quantifying their influence. Specifically, using daily CDS data for more than 280 firms in Europe and North America for the period 2013 to 2019, we investigate how firms' CDS spread returns change in response to variations in the CR factor. We find that an increase in the market's perception of carbon risk leads to an increase in CDS spread returns. Considering a European 5-year CDS contract with a notional value of US\$100 million and a spread of 100 basis points (hence a yearly premium of US\$1 million), one standard deviation increase in carbon risk exposure results in lenders demanding US\$0.21 million more annual credit protection on this CDS contract.[3] The additional protection cost doubles under *extraordinary* credit conditions, namely when firms experience large shifts in their credit spreads. To investigate the impact of carbon risk under these extraordinary conditions, we employ quantile regressions. This method enables us to explore the full conditional distribution of the dependent variable, revealing variations in the response across different quantiles of the distribution. These findings are especially relevant for the regulatory framework of carbon risk. By quantifying the additional costs associated with carbon risk under various credit conditions, regulators can better assess the potential systemic risk posed to the financial system by the transition.

We find that increased perception of carbon risk exposure generally leads to higher default protection costs, yet the magnitude of this effect varies significantly by region. Specifically, the influence of carbon risk on CDS spread returns is more pronounced in Europe compared to North America – a disparity attributable to the distinct carbon pricing regulations in each area. Europe employs explicit carbon pricing mechanisms, such as the European Union Emission Trading System (EU ETS), whereas North America has largely utilized non-pricing emissions regulations (Aldy et al., 2022, Pryor et al., 2023). Nevertheless, a firm's carbon risk exposure is not solely determined by where it operates. Our findings show that the impact of carbon risk on CDS spread returns is also affected by the precise scope of the regulation. Firms subject to direct carbon pricing face an estimated additional annual cost

[2] Emission intensity is a commonly used measure – it allows for a more accurate comparison of emissions between different industries and firms. In Appendix F, we consider several alternative specifications for the construction of the CR factor, including absolute emissions. Importantly, the robustness of the proposed CR factor is maintained across these different factor construction approaches.

[3] Although arbitrarily chosen, these numbers represent a realistic setup for CDS contracts both in Europe and North America. For the sake of simplification, we will keep using this setup throughout the remainder of this paper.

of US$0.35 million for a one standard deviation increase in carbon risk – almost thrice the impact on firms outside direct carbon pricing frameworks (US$0.12 million). Since this holds across both Europe and North America, it underscores the influence of direct carbon pricing on perceived exposure to carbon risk. The lending market, with its inherently forward-looking approach, shows a keen sensitivity to these substantial regulatory differences, adapting its assessment of carbon risk based on the nature of firms' regulatory exposure.

Our analysis also reveals that the impact of carbon pricing on perceived carbon risk exposure is influenced by the share of a firm's direct emissions regulated by carbon pricing – the stringency of the carbon policy in question. Firms with a significant portion of their emissions covered by carbon pricing show a heightened responsiveness to changes in the CR factor. This is observable in both Europe and North America, with the effect being notably stronger in Europe. A 1% increase in the proportion of emissions under regulation translates to an estimated additional annual cost of US$0.24 million for every US$100 million of exposure in Europe, and US$0.11 million for every US$100 million of exposure in North America. These findings highlight the critical role of carbon policy stringency.

The literature finds that the effect of carbon risk becomes more pronounced when considering exposures that are specific to certain industries (Bolton and Kacperczyk, 2021 and Ardia et al., 2022). Consequently, we explore whether the regulatory coverage of a specific sector's emissions amplifies the effect of carbon risk on CDS spread returns. Our findings suggest that lenders consider firms within the carbon-intensive sectors of Basic Materials, Utilities, and Energy as carrying increased risks. As carbon regulations become more stringent, it is plausible that these sectors will face rising operational costs, adversely affecting their financial stability and credit ratings. Indeed, our findings show that a one standard deviation rise in the CR factor equates to an additional estimated financial impact of US$0.23 million for European firms in Basic Materials, with this impact being more than two times higher for Utilities (US$0.52 million) and more than eight times greater for Energy (US$1.94 million). This underlines the escalating financial implications that tighter carbon regulations – aimed at achieving net-zero ambitions – would have for these sectors.

Finally, we find that carbon risk is influenced not only by the scope and stringency of regulations, but also by the expected speed of the transition towards a low-carbon economy. By analyzing the relationship between the term structures of CDS spreads and carbon risk, we show that an increase in carbon risk leads lenders to foresee higher costs for short-term transitions. This expectation is manifested through a more pronounced rise in CDS spreads for shorter tenors relative to longer ones, signaling a market anticipation of immediate financial implications stemming from increased carbon regulation. Such findings carry profound policy implications for central banks, particularly in relation to monetary strategies aimed at cushioning the potential negative impacts of a disorderly transition.[4] Our analysis suggests that re-pricing activities, spurred by the anticipated quickening pace of carbon reduction initiatives, are expected to occur predominantly in the near future.

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.

[4]This disorderly transition is characterized by abrupt repricing of risks, and the risk of assets becoming stranded.

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 and ultimately translate 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 and show that investors seek higher returns and require a higher premium for firms with greater emissions (Bolton and Kacperczyk, 2021; Cheema-Fox et al., 2020; Görgen et al., 2020; Hsu et al., 2023; Lioui, 2022), that the market requires adjustments in the capital structure of firms with emissions-intensive operations compared to their low-carbon counterparts (Nguyen and Phan, 2020; Kleimeier and Viehs, 2018), and that engagement efforts concentrate on large firms with high carbon emissions (Azar et al., 2021). In other words, firms with an emissions-intensive business model face higher carbon risks than their low-carbon peers. However, this approach does not reveal whether the emissions are subject to any carbon policies, nor does it indicate the policy's scope, ambition, or the actual impact of carbon regulations. It fails to measure the breadth of coverage (scope), proportion of emissions under regulation (stringency), or the targets and deadlines (speed) required by these policies. We extend this literature by documenting that the impact of carbon risk can vary significantly depending on the presence of carbon regulation – specifically direct carbon pricing – as well as the scope, stringency, and mandated transition speed of the carbon policy. By isolating these key regulatory factors – scope, stringency and speed – we enhance our ability to qualify and quantify the impact of carbon risk on credit risk.

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., 2024), 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 risk from a textual analysis of the 10-K financial form filings of US firms. Our paper extends the analysis by using firms' emissions to discipline the construction of a forward-looking and market-implied CR factor.

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 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 the effects differ significantly across different parts of the distribution (Pires et al., 2015; Koutmos, 2019). While these observations are important for risk management purposes, there has been limited research 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.

The remainder of this paper is organized as follows. Section 2 delves into the transition from carbon risk to credit risk, details the construction of the CR factor, and outlines the hypotheses for empirical testing. In Section 3, we describe the data and introduce the panel quantile regression framework. Section 4 presents the results and Section 5 concludes. In the appendix, we test the robustness of our findings by considering several alternative specifications for the construction of the CR factor. The appendix also includes a number of additional tables and figures, the results of an event study, and further evidence of the transmission of policy shifts through the CDS market.

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 scope and stringency of carbon regulations, and the speed of carbon emission reductions, which will necessarily restructure the economy. It is difficult to measure these transitions though; since the transition path cannot easily be observed, it must be inferred. However, it is far from clear which proxies are appropriate, especially for technologies and consumer preferences. To date, the finance literature has primarily focused on carbon emissions as the observable outcome of changes in the governmental policies and public regulations aimed at limiting these emissions (hereafter *carbon policies*). This literature has approached the pricing of *carbon risk* by focusing on how various financial assets reflect market concerns about these carbon policies. As of now, firms' exposure to carbon risk is most often codified using firms' *actual* emissions data.[5] However, this approach does not reveal whether the emissions are effectively subject to any carbon policies, nor does it indicate the scope of policy application or the ambition behind these policies. Essentially, it does not accurately measure the actual impact of carbon regulations or effectively capture the scope (breadth of coverage), stringency (proportion of emissions under regulation) and speed (targets and deadlines) of the carbon transformation required by these policies.

Carbon policies can generally be divided into two main types: pricing and non-pricing instruments (Pryor et al., 2023). The former assigns a direct monetary value to carbon emissions, thereby establishing an explicit carbon price, while the latter regulates carbon emissions without setting a direct monetary value. Although there may be costs associated with non-pricing policies, they are not explicit. Even in scenarios where an explicit carbon price exists, gauging the financial impact of carbon policies remains complex. The overall effect depends on a range of factors: the scope of application of the carbon policy across different sectors, the stringency of the policy, the pace implied, and the presence of measures that might mitigate

[5] Investigating carbon risk in the equity and debt markets, scholars have used levels and changes in carbon emissions (Bolton and Kacperczyk, 2021, Bolton and Kacperczyk, 2023, Atilgan et al., 2023, among others) and carbon intensities (Aswani et al., 2023, Atilgan et al., 2023, Ardia et al., 2022, among others).

the policy impact.[6] These factors collectively determine the real effect and financial consequences (cost) of carbon pricing policies. For example, firms may incur additional direct costs from emissions control and abatement initiatives, or through policy compliance and product modifications in response to changes in carbon policies 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. Carbon policies can also affect firms indirectly in various ways. For example, because carbon emissions are tied to fossil fuels, carbon abatement regulations often translate into higher energy costs for firms.[7] Furthermore, carbon costs can affect the entire supply chain. Suppliers, facing their own carbon regulation compliance costs, may pass these expenses on to their customers. This increase in energy prices or input costs leads to higher operating costs, which, in turn, result in lower cash flows. In other words, both pricing and non-pricing policies could significantly affect firms' cash flow, financial health and the value of their collateral. This may undermine their capacity to service and repay their debt, eventually leading to higher probabilities of default.[8] This results in repricing – with more exposed firms' valuations being bid down, and less exposed firms' valuations being bid up – in response to changing lender beliefs about firms' exposure to carbon risk. Crucially, firms may transition to a low-carbon business model at different times and different speeds, depending on the type, scope and stringency of the carbon regulations to which they are subjected. In other words, superficially similar firms can face vastly different levels of carbon risk depending on how and where they do business, and the actual effect of the carbon policies. This means that differential valuations (Meinerding et al., 2020) may depend on all of these factors, in addition to how much they emit. Furthermore, the way firms adapt, innovate and reorganize their operations in reaction to shifts in carbon regulations and market demands will further influence their unique exposure to carbon risk.

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 emission levels, changes in emissions, and emission intensity (Bolton and Kacperczyk, 2021; Azar et al., 2021; Görgen et al., 2020; Nguyen and Phan, 2020, Bolton and Kacperczyk, 2023, Aswani et al., 2023, Zhang, 2023), although academics and practitioners recognize the need to include firm-specific information on expected future emissions as well. Recent work attempts to address this by adding information about firms' abatement commitments and strategies (Carbone et al.,

[6]These measures often reduce the scope and speed of the carbon policy, either by limiting the amount of emissions subject to the policy or by decreasing the carbon cost for businesses that meet specific criteria (Pryor et al., 2023).

[7]The European Central Bank recently acknowledged the potential risks that the transition to a low-carbon economy could have on the economy, particularly due to an increase in the contribution of energy to overall inflation (Schnabel, 2022).

[8]In Appendix A, we illustrate the differential impact of carbon-related costs on the valuation of diverse firms through the application of the Merton, 1974 model of credit risk. This model provides an insightful foundation for understanding how costs related to carbon regulations influence the credit spread. It also enables us to establish a theoretically grounded connection between a firm's exposure to carbon risk and the corresponding credit spread.

2021; Bolton and Kacperczyk, 2022; ECB and ESRB, 2022).[9] Yet, headline pledges are often ambiguous and emission reduction commitments are limited, raising credibility issues and demanding a more appropriate way to assess firms' efforts to align with the net-zero trajectory. Additionally, and perhaps more importantly, evaluating market perceptions of firms' carbon risk exposures requires insight into how carbon policies impact firms' carbon emission profiles (BIS, 2021 and ECB and ESRB, 2022, Carradori et al., 2023).

Our approach to measuring carbon risk therefore relies on analyzing credit spreads, which indicate how the market perceives the actual impact of carbon policies on firms' emission profiles. Changes in these credit spreads encapsulate the collective assessment of lenders regarding the financial and credit impact of these policies. To capture this variation, we utilize the information contained in the spreads of the CDS contracts. CDS contracts have four crucial advantages: CDS have a higher degree of informational efficiency, with a number of studies showing that the CDS market responds more rapidly to macroeconomic and corporate events compared to equity and bond markets (Jorion and Zhang, 2007, Acharya and Johnson, 2007, Berndt and Ostrovnaya, 2014, and Hana et al., 2017). Furthermore, CDS spreads respond quickly to changes in credit and market (and arguably policy) conditions (Blanco et al., 2005; Zhu, 2006). This swiftness in incorporating new information highlights the CDS market's ability to translate changes in (perceived) carbon risk exposure into changes in credit spreads. This responsiveness to new developments is further demonstrated in Appendix B, where we compare the integration of new information related to unexpected policy changes by both the CDS and equity markets for the same entities. Also, CDSs are typically traded on standardized terms, eliminating distortions due to differences in contractual arrangements or liquidity concerns (Longstaff et al., 2005). Finally, CDS contracts have varying tenors up to 30 years, allowing 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.[10] Investigating carbon risk in the US corporate bond market, Xia and Zulaica (2022) document that the carbon risk differs across maturities, giving rise to a hump-shaped term structure of carbon premia. Given these reasons, CDS spreads provide a unique window for viewing the effect of carbon risk through the lens of lenders' perceptions of carbon risk. The fundamental insight is illustrated in Figure 1, where we plot the evolution of the CDS spreads for two pairs of companies (starting with a similar credit rating on 02 November 2015) before and after the 2015 Conference Of the Parties (COP21), which culminated in the landmark Paris Agreement.[11] Similar reactions to policy changes are explored in Meinerding

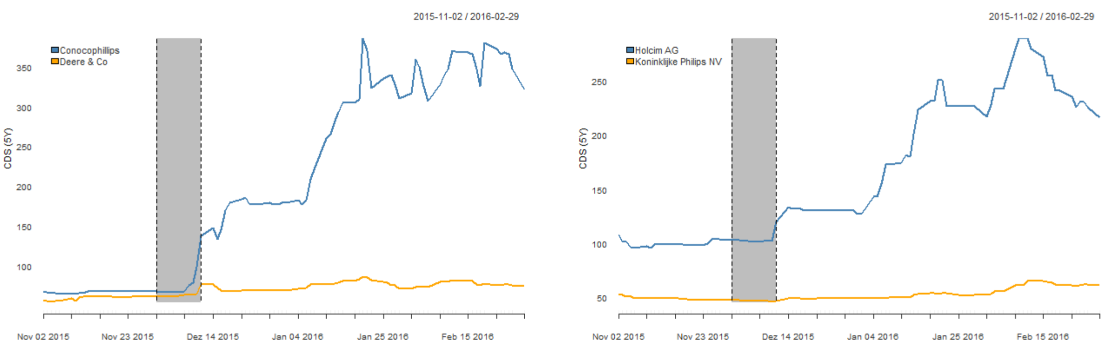
[9] We refer to Campiglio et al. (2022) for a review of the emerging literature that uses forward-looking methodologies to estimate the effect of transition risks on asset prices.

[10] The analysis presented in the main text focuses on CDS contracts with tenors up to 10 years. Findings related to contracts with a 30-year tenor are detailed in the Appendix G.

[11] In this figure, we provide data on two exemplary high-emitting/polluting firms (ConocoPhillips and Holcim AG) and two exemplary low-emitting/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.

et al., 2020. A formal analysis is presented later.

Figure 1 illustrates that the distance in CDS spreads is approximately constant until the occurrence of a policy-relevant event – the Paris Agreement – at which point the spreads diverge. We interpret this 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.[12] 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 carbon regulation-related aspects that can impact firms' credit risk profiles.[13] Effectively, we compute a market-implied and forward-looking CR factor, offering a tool to evaluate the cumulative effect of public carbon pricing regulations together with firms' voluntary actions aligned with their net-zero ambitions.



(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).

2.2 Construction of the carbon risk factor

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. In most studies, firms' exposure to carbon risk is codified using their emission data,[14] on the premise that high-emitting firms may incur greater costs from carbon policy changes – through emissions abatement

[12] Figure 14 in Appendix D illustrates comparable trends among companies within the same sectors – Energy and Basic Materials – highlighting that markets acknowledge firms may adapt to carbon policies at varying times and speeds. This underscores the importance of the insights gleaned from CDS data.

[13] 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 CDS market concentrates on the credit risk component.

[14] 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.

and the adoption of new technologies – and product changes in response to shifting 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 emission intensities, 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., 2023; Nguyen and Phan, 2020; Bolton and Kacperczyk, 2023; Aswani et al., 2023).

As with this literature, we construct firms' carbon profiles using yearly emissions intensities (Scope 1 & 2 emissions normalized by revenue) from LSEG Data & Analytics (formerly known as Refinitiv) as our primary dataset.[15] Estimates are used in cases where no actual emissions were reported. These data have been shown to be sufficiently consistent across different data providers (Busch et al., 2018).[16] The emissions of firms in our sample account for a significant fraction – approximately 30% – of the total emissions in the universe of companies represented in the LSEG Data & Analytics database.

The construction of our CR factor is informed by existing literature, which suggests that businesses with higher emissions are potentially more exposed to carbon risk than those with lower emissions. This increased exposure arises from factors such as the potentially higher direct costs of compliance with emission control and abatement policies (depending on the scope and stringency of those policies), and adjustments in production processes in anticipation of potential new carbon regulations, or as part of a voluntary initiative to achieve net-zero targets. Ideally, the CR factor should track shifts in firms' carbon risk exposure, mirroring the evolution in lenders' perceptions and expectations regarding this risk. To that end, we follow the standard approach used in empirical asset pricing for factor construction (Fama and French, 1992). Specifically, we sort the universe of firms according to each one's emission intensity profile, and then subdivide them into quintiles. In this and subsequent sections, we focus on our baseline factor construction and results. We also conduct an extensive set of robustness tests on the formulation of the CR factor by experimenting with absolute emissions, and then including bivariate sorts that account for firm characteristics such as size, book-to-market ratio, and leverage (Bolton and Kacperczyk, 2023, Pastor et al., 2021, Bauer et al., 2023, and Zhang, 2023). Baseline findings are robust to these alternative CR factor constructions and are discussed in Appendix F.

We group the firms into portfolios to mimic the underlying risk factor in returns related to carbon.[17] 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 repeat this procedure for every day t.[18]

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

[16] We chose firms' emissions 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).

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

[18] Table 3 in Appendix E contains a comprehensive list of all firms entering the "clean" and "polluting"

We then obtain the median cost of default protection for clean and polluting firms by calculating the median m-year CDS spread level for each tenor $m \in \{1, 3, 5, 10\}$ 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. The difference, or wedge, between these two spreads 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, the CR factor 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 firm.[19] When policy events (e.g. expectation of a tighter future regulatory framework) trigger a rise in carbon risk, 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.[20] These changes in perceived exposure to carbon risk are accurately represented by the behavior of the CR factor.[21]

To illustrate the relevance of the CR factor, we first examine its behavior in response to events that affect firms' exposure to carbon risk. Figure 2 displays the evolution of the CR factor over time, for tenors of 1, 5 and 10 years for the universe of CDSs of firms listed in Europe (top panel) and North America (bottom panel), respectively.[22] These graphs also highlight two events, identified in Meinerding et al. (2020), that oppositely affected market perceptions of carbon risk: the signing of the Paris Agreement and the election of Donald Trump in the US; these events are represented in Figure 2 with vertical dark green and brown lines, respectively. We validate the informational content of our proposed CR factor using a model-free, event-study approach. Borrowing from the work of Meinerding et al., 2020, we analyze how the CR factor reacts to a series of additional climate-policy-relevant events. We utilize news data in conjunction with the CR factor to identify possible dates associated with important climate policy events. The subsequent analysis reveals that the identified dates indeed match real-world climate policy events and shows that the CR factor is highly sensitive to these occurrences. As such, the changes in the CR factor validate our proposed

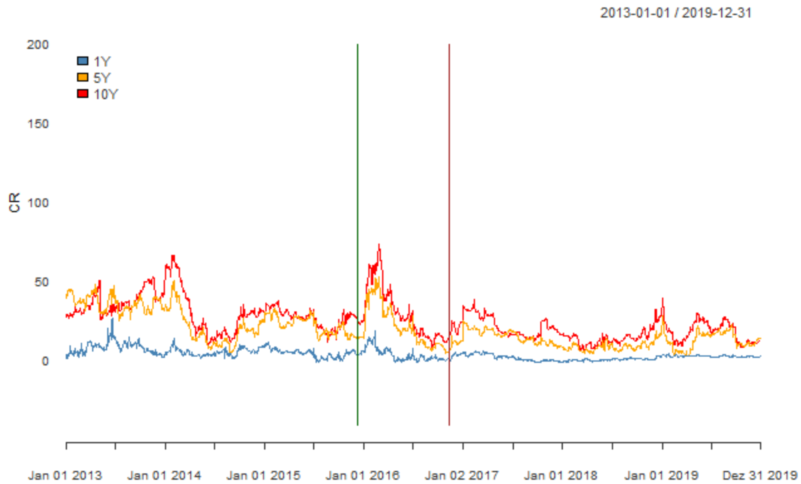
class (including median firms), respectively, during our sample period.

[19] 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.

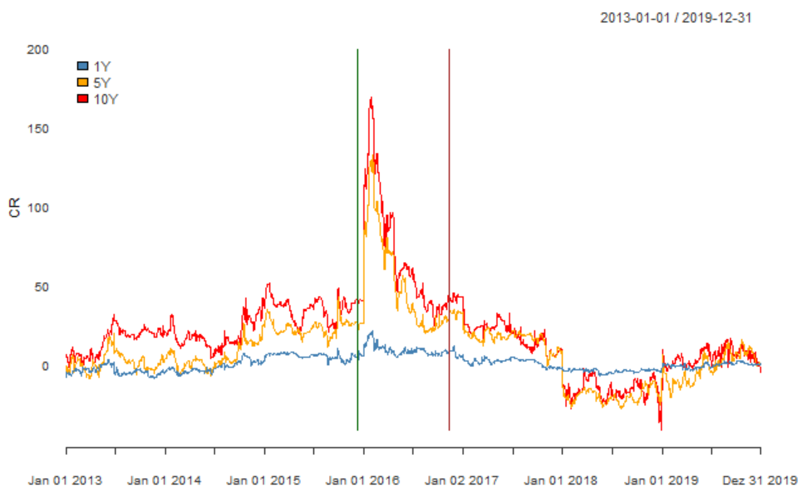
[20] This might occur where the expected profits of actively compliant firms are hampered by a policy reversal. The increased costs associated with the previously tighter regulation are perceived as unnecessary expenditure.

[21] The value of the CR factor appears similar to the measure proposed in van Binsbergen and Brøgger (2022), but is perhaps easier to derive in practice since it does not require the introduction of a new financial instrument, namely firm-level emission futures contracts.

[22] All available tenors, including 3Y and 30Y, are reported in Appendix G and illustrated in Figure 15.



(a) Europe



(b) North America

Figure 2: Evolution of the CR factor over time for maturities 1Y (blue), 5Y (orange) and 10Y (red) for Europe (top) and North America (bottom). The vertical solid lines indicate the timing of the Paris Agreement (dark green) and Trump election (brown), respectively.

metric as an effective tool for tracking market responses to shifts in climate policy. A detailed description of the event-study analysis is provided in Appendix C.

Examining the figure, we observe that the CR factor displays two significant traits. First, we observe that the CR factor squarely reflects changes in lenders' demand for default protection in response to significant policy-relevant events. For instance, COP21 advocated for more ambitious emission reduction policies and plans, which positively influenced carbon risk, indicating a heightened awareness and concern about this risk. It is reasonable to argue that policies following this event can increase the expected costs for firms that are less prepared to transition to a low-carbon economy, and benefit firms that are more adequately prepared.[23]

[23] Similar reactions have been documented in the equity and bond markets (Meinerding et al., 2020), Bolton and Kacperczyk, 2021, Ardia et al., 2020, Engle et al., 2020).

The CR factor response is significantly more marked in North America, where explicit carbon pricing mechanisms are less common, meaning the outcome of COP21 will have potentially heavier financial implications. Conversely, the election of Donald Trump, known for his skepticism towards climate change, likely led to a distinctly negative CR factor reaction, indicating a decreased perception of carbon risk due to expected policy relaxations. In this case, however, the impact of this election was geographically confined to the North American CR factor, mainly reflecting the limited influence of US climate policy on European firms. Second, it is notable that all CR factor time series in Europe remain consistently non-negative, likely influenced by the more prominent implementation of carbon pricing regulations in the region: lenders demand more (less) protection for European firms that are perceived to be more (less) exposed to carbon risk in Europe. This contrasts with the CR factor time series in North America, where the 5-year and 10-year tenors exhibit periods of prolonged positivity before experiencing a reversal in the sign after 2018. Collectively, these findings underscore the CR factor's ability to reflect the continual evolution in aggregate lenders' perceptions of carbon risk. This includes the ambiguity in North America surrounding short-term carbon policies (1-year) – indicated by fluctuations in the 1-year tenor between positive and negative values – and the absence of uniform, nationwide carbon pricing strategies – indicated by shifts in policy direction (5-year and 10-year). Thus, the CR factor allows us to understand lenders' demand for *more* or *less* protection according to their perception of a firm's ability to absorb the costs associated with changes in carbon regulations. This leads to continuous adjustments in the CDS spread wedge. Essentially, this is what makes the CR factor an observable, forward-looking and market-implied proxy for carbon risk exposure.

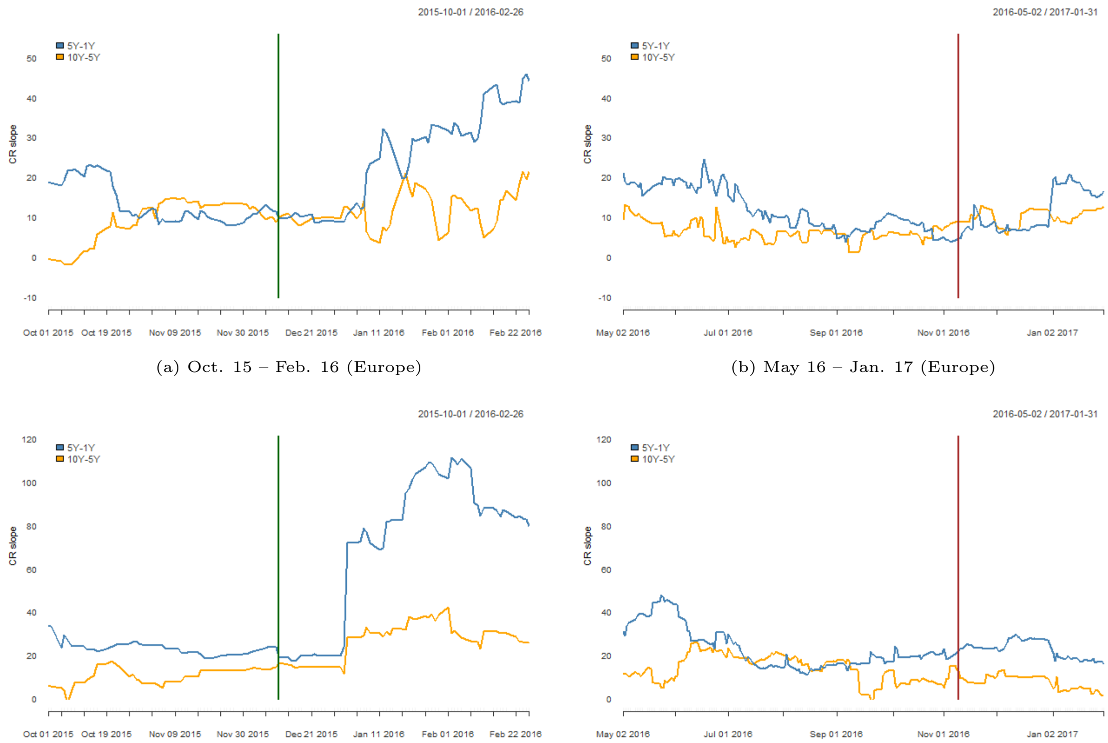
Furthermore, we can extract valuable information about carbon risk over a specific time horizon by considering the difference between a long- and a short-tenor CR factor. This difference constitutes the slope of the CR factor (CR slope),[24] constructed as

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

where the relationship between tenors is $m > n$. Conceptually, starting from a carbon risk exposure over the next n years, CRSlope_t^{mn} describes how the exposure to carbon risk is perceived over the remaining m-n years. CRSlope_t^{mn} can take positive and negative values, depending on how the market's perception of carbon risk evolves. Essentially, the slope of the CR factor represents the relationship between carbon risk (anticipated costs induced by policy) and various time horizons. 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, resulting in larger (smaller) policy-induced costs.

This is depicted in Figure 3. Pre-COP21, the CRSlope_t^{mn} for 5Y-1Y and 10Y-5Y in both Europe and North America are very close to each other, indicating expectations of similar carbon risk in the near term and the longer term. However, in the immediate aftermath of COP21, the distance between these slopes widens, with lenders anticipating significantly higher policy-implied costs in the near term, especially in North America. As the Trump election approached, the distance between the 5Y-1Y and 10Y-5Y slopes decreased. This convergence suggests that, just prior to the Trump election, lenders' expectations for significant

[24]Later in the analysis, we examine the effect of said information about carbon risk on the entire CDS spread curve.



(a) Oct. 15 – Feb. 16 (Europe)

(b) May 16 – Jan. 17 (Europe)

(c) Oct. 15 – Feb. 16 (NA)

(d) May 16 – Jan. 17 (NA)

Figure 3: Evolution of the CR slope over different time periods for 5Y-1Y (blue) and 10Y-5Y (orange) for Europe (top three) and North America (bottom three). The vertical solid lines indicate the timing of the Paris Agreement (dark green) and Trump election (brown), respectively.

differences in policy-implied costs across varying time frames began to diminish, indicating a re-calibration of risk perceptions towards a more uniform outlook.

2.3 Hypothesis development

In the previous section, we argued that CR factor represents lenders' perceptions of carbon risk exposure, such that a higher CR factor corresponds to a higher perceived market-wide carbon risk. We also argued that a firm with higher actual exposure to carbon risk may experience a decline in its valuation, a higher probability of default, and, therefore, a higher CDS spread. We thus propose the first hypothesis:

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

Recent studies suggest that carbon risk differs across regions due to their varying degrees of ambition in environmental regulations and diverse restrictions on carbon emissions (Huij et al., 2021; Bolton and Kacperczyk, 2023).[25] Europe is widely recognized as a global leader in deploying explicit carbon pricing policies through mechanisms like the European Union Emissions Trading System (EU ETS), while North America, especially the US, has mainly

[25] There are currently 68 carbon pricing instruments in operation (36 carbon taxes and 32 emissions trading systems), spanning a broad range of carbon tax rates and carbon caps (World Bank Group, 2024).

focused on non-pricing emissions regulations (Aldy et al., 2022 and Pryor et al., 2023). Consequently, carbon pricing visibility is notably higher in Europe than in North America. This should lead to increased CDS spreads for firms operating predominantly in Europe, and the difference should underscore the higher salience of carbon risks within the European regulatory framework. We undertake tests to explore these variations further, aiming to quantify and understand the regional regulatory disparities in carbon risk exposure.

Hypothesis 2. *The influence of carbon risk on CDS spread returns is significantly stronger in regions that have explicit carbon pricing mechanisms, such as Europe, in contrast with regions like North America, where explicit carbon pricing has not been widely adopted.*

A firm's exposure to carbon pricing is not solely determined by the presence or absence of the policy in the country where it predominantly operates. The breadth of coverage of the regulation – the scope – is also a crucial factor. When companies are subject to explicit carbon pricing, they incur specific costs for their emissions, leading to more immediate and predictable adjustments in their operational tactics and financial strategies. There is mounting evidence that explicit carbon pricing mechanisms have environmental and economic impacts on companies directly subjected to them (Martin et al., 2014 and Colmer et al., 2024). But while the presence or absence of an explicit carbon pricing regime can indicate a firm's potential carbon-related financial liabilities, its impact will depend on the specific scope of the carbon policy. Lenders, as keen risk assessors, are likely to take this into account when evaluating a company's creditworthiness, directly influencing the CDS spreads. Given this backdrop, our third hypothesis emerges:

Hypothesis 3. *The impact of carbon risk on CDS spread returns is not uniformly determined by the presence of carbon pricing within a region, but is significantly influenced by the specific scope of the regulation.*

While the presence of carbon pricing regulations matters, their influence on firms extends beyond the scope of the regulation. A second critical aspect is the stringency of the carbon policy, highlighting that the effect on firms depends not only on being subject to regulation but also on the proportion of their emissions that fall under the regulatory framework. For instance, two similar firms under explicit carbon pricing regulations could face varying financial consequences based on the extent of their emissions coverage. If one firm has 50% of its direct emissions regulated, while another has just 30%, the financial repercussions for the firms could be markedly distinct. From a lender's perspective, the proportion of a firm's regulated emissions can serve as a barometer for potential financial liabilities and, consequently, for the firm's credit risk. Thus, the stringency of the carbon regulation should be considered in addition to merely being subject to carbon regulation. This leads to our fourth hypothesis:

Hypothesis 4. *The impact of carbon risk on CDS spread returns depends on the stringency of the carbon regulation.*

The exposure to carbon risk is not uniformly distributed across all sectors of the economy, as highlighted by Dietz et al., 2020. While every firm, on average, might grapple with the implications of carbon risk, the intensity of this exposure is more pronounced in certain sectors – especially those that are inherently carbon-intensive. Their carbon intensity not only puts them at the forefront of regulatory scrutiny, but also amplifies the financial risks they face from carbon pricing. As carbon regulations tighten, these sectors could see escalating operational costs, which in turn can impact their financial stability and creditworthiness. Lenders are likely to perceive heightened risks associated with firms operating in these sectors, leading them to seek additional credit protection, manifesting as increased CDS spreads. This is expressed in our fifth hypothesis:

Hypothesis 5. *The emissions intensity of a sector intensifies or mitigates the impact of carbon risk on CDS spread returns.*

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 tenors would be higher (steeper sloped) than in the spread of the CDS with longer tenors. We therefore propose the following testable hypothesis:

Hypothesis 6. *The influence of carbon risk on the term structure of CDS spreads is more pronounced in the short-term*

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 obtained price quotes of 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 and 10 years for publicly listed European[26] 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).[27] We exclude all firms that defaulted during the sample period or that exhibit illiquid CDSs, but in general retain firms with large CDS

[26] 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.

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

spreads.[28] To account for possible distorting effects from the COVID-19 pandemic, we exclude the year 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 202,860 and 264,617 CDS spreads-day observations for an unbalanced panel covering 119 European firms and 164 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:

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

where $\mathrm{CDS}_{i,t}^m$ 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 $m \neq n$

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

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

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

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).[29]

[28] Illiquid CDSs are those contracts where no spread movement is recorded for a minimum of 25 consecutive trading days. Some studies also exclude firms with CDS spreads exceeding specific thresholds (Zhang et al., 2009; Kölbel et al., 2022; Barth et al., 2022). The quantile regression modeling approach (described later) allows us to dispense with this exclusionary criterion by eliminating exclusively illiquid CDSs.

[29] 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.

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 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 incorporate information that reflects the current state of the credit market, specifically focusing on a market condition variable known as the Median Rated Index (MRI). The MRI is a vital indicator that captures the perceived general economic climate, serving as a barometer for market-wide conditions. Defined as the median CDS spread of all firms in the S&P rating supercategories "AAA/AA", "A", "BBB" and "BB+ or lower," the MRI provides insights into the broader financial environment. The general assumption underlying the use of the MRI is that improvements in these market-wide conditions are indicative of a decreased probability of default among firms, leading automatically to lower credit spreads. We follow Galil et al. (2014) and measure the current business climate using the change in the MRI $\Delta\text{MRI}^m_{i,t}$. Previous research, such as that documented by Galil et al., 2014, has established a positive relationship between the MRI and CDS spreads, further underscoring its significance in reflecting the overall economic sentiment.

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.[30] The extreme CDS spread statistics presented in Table 1 align with findings in existing literature, highlighting the unconventional characteristics of CDS data (Pires et al., 2015).[31] These descriptive statistics reveal that CDS returns are fraught with outliers and extremely heavy-tailed distributions, challenging standard assumptions typically employed in standard statistical methods. To effectively address these challenges, we introduce Quantile Regression in the subsequent section as a suitable analytical approach.

3.4 Panel quantile regression

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). A standard linear conditional mean regression framework can obscure the full distributional relationship, where the impact of variables may vary by sign and magnitudes across the distribution. For this reason, we use a quantile regression (QR) approach. QR allows for a more comprehensive analysis by examining the entire conditional distribution of CDS spread returns. It enables the exploration of carbon risk's link to CDS spread returns across both normal and extraordinary circumstances, such as notable shifts in credit spreads. Within the QR framework, these scenarios are represented by the extreme deciles of the CDS distribution. Introduced by Koenker and Bassett (1978), QR extends the classical conditional mean model to a series of models for different conditional quantile functions, allowing for a nuanced examination of variable effects across the distribution. This is crucial in credit risk analysis, where understanding the tails of the distribution is vital. QR's ability to capture the marginal impact of carbon risk across the distribution presents a more thorough view of its influences on credit spread returns under both standard and exceptional circumstances.

Additionally, QR can mitigate some of the typical empirical problems frequently encountered in the CDS literature (e.g. the presence of outliers, non-normality) which also apply to our data as illustrated in Table 1. While these empirical characteristics challenge the validity of Ordinary Least Squared (OLS) estimates and their standard errors, QR is robust to these data characteristics and thus a better 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

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

[31] 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	-1.19	0.00	0.46	6.95	-514.39	514.31	0.69	671.21
$s^3_{i,t}$ (%)	-0.06	-1.18	0.00	0.38	3.81	-93.02	123.19	1.73	45.08
$s^5_{i,t}$ (%)	-0.05	-0.72	0.00	0.17	2.26	-85.00	103.68	1.96	80.24
$s^{10}_{i,t}$ (%)	-0.03	-0.49	0.00	0.18	1.67	-67.49	89.16	1.87	143.34
$s^{30}_{i,t}$ (%)	-0.02	-0.45	-0.01	0.22	2.18	-74.53	85.84	0.75	98.16
Independent variables									
$r_{i,t}$ (%)	0.01	-0.78	0.00	0.83	1.64	-44.33	28.98	-0.65	18.61
$\Delta\sigma_{i,t}$ (%)	0.00	-0.03	0.00	0.03	0.24	-19.80	15.28	-1.93	943.63
$\Delta\text{MRI}^1_{i,t}$	-0.01	-0.20	0.00	0.14	1.15	-54.28	50.78	2.11	156.62
$\Delta\text{MRI}^3_{i,t}$	-0.03	-0.48	0.00	0.27	1.92	-112.16	119.99	1.78	340.47
$\Delta\text{MRI}^5_{i,t}$	-0.04	-0.49	-0.01	0.26	2.33	-171.28	164.54	0.81	721.00
$\Delta\text{MRI}^{10}_{i,t}$	-0.04	-0.50	-0.01	0.36	2.58	-222.69	210.01	-2.09	1221.55
$\Delta\text{MRI}^{30}_{i,t}$	-0.04	-0.54	-0.02	0.41	3.07	-230.02	215.69	-1.69	683.98
ΔCR^1_t	0.00	-0.28	0.00	0.26	1.02	-11.34	10.28	-0.37	27.89
ΔCR^3_t	-0.01	-0.50	0.00	0.50	1.31	-10.03	8.70	0.17	11.29
ΔCR^5_t	-0.01	-0.50	0.00	0.48	1.52	-9.38	12.81	0.98	16.99
ΔCR^{10}_t	-0.01	-0.50	0.01	0.50	1.77	-24.38	16.86	-1.10	36.88
ΔCR^{30}_t	0.00	-0.52	0.01	0.54	2.09	-22.06	16.89	-0.86	26.12
North America									
Dependent variables									
$s^1_{i,t}$ (%)	-0.05	-0.66	0.00	0.24	7.00	-272.69	310.39	0.88	73.23
$s^3_{i,t}$ (%)	-0.05	-0.62	0.00	0.17	3.06	-84.50	113.88	1.26	42.57
$s^5_{i,t}$ (%)	-0.04	-0.52	0.00	0.13	2.30	-84.93	106.74	1.58	56.44
$s^{10}_{i,t}$ (%)	-0.03	-0.41	0.00	0.14	2.15	-84.67	95.49	0.74	96.40
$s^{30}_{i,t}$ (%)	-0.02	-0.38	-0.01	0.17	2.40	-87.95	110.88	0.41	135.47
Independent variables									
$r_{i,t}$ (%)	0.03	-0.73	0.01	0.85	1.81	-42.79	42.06	-0.31	24.14
$\Delta\sigma_{i,t}$ (%)	0.00	-0.03	0.00	0.03	0.29	-25.81	18.21	-3.97	874.90
$\Delta\text{MRI}^1_{i,t}$	-0.01	-0.17	0.00	0.10	0.97	-28.92	41.83	0.86	95.10
$\Delta\text{MRI}^3_{i,t}$	-0.03	-0.30	0.00	0.18	1.68	-96.49	112.05	0.89	456.40
$\Delta\text{MRI}^5_{i,t}$	-0.04	-0.47	-0.01	0.22	2.30	-161.90	188.12	0.16	1174.07
$\Delta\text{MRI}^{10}_{i,t}$	-0.04	-0.55	-0.01	0.37	2.84	-197.51	214.31	0.004	1057.63
$\Delta\text{MRI}^{30}_{i,t}$	-0.04	-0.65	-0.01	0.46	3.10	-196.34	231.70	-0.83	846.14
ΔCR^1_t	0.01	-0.25	0.00	0.26	0.81	-5.38	6.18	0.31	13.45
ΔCR^3_t	0.00	-0.48	0.00	0.42	1.41	-11.08	16.73	0.77	25.99
ΔCR^5_t	0.00	-0.62	0.00	0.50	2.46	-22.32	54.54	6.50	158.07
ΔCR^{10}_t	0.00	-0.90	0.01	0.76	3.48	-21.68	71.42	6.17	130.86
ΔCR^{30}_t	0.00	-1.04	-0.01	0.96	3.92	-31.10	51.19	1.53	37.48

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.

spreads vary according to whether firms have conditionally high or low credit risk. Koutmos (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

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

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).[32] We follow Zhang et al. (2019) and implement a two-stage approach to estimate the parameter vector $\boldsymbol{\beta}_\tau$.[33] 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.[34]

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

[33] 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.

[34] 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 general and regional impact of carbon risk

In this subsection, we examine the relationship between the CR 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:

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

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 $\Delta\mathrm{MRI}_{i,t}$) and, finally, the market-implied factor for carbon risk exposure $\Delta\mathrm{CR}_t$.

The regression is run for every decile $\tau \in \{0.1, \dots, 0.9\}$ 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 or underperform relative to the median.[35] 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 (invariant 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, investigate the marginal impact of carbon risk above and beyond these explanatory variables.

Figure 4 reports the estimated coefficients at the first, fifth, and ninth deciles for three key tenors in Europe.[36] For completeness, Figure 4 also includes coefficient estimates from a fixed-effect (FE) model estimated using ordinary least squares (OLS).[37] First, focusing on the QR results across all maturities, we observe a positive relationship between CDS spread returns and the CR factor. That is, an increase in the 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 and $\tau = 0.5$, a one standard deviation increase in the perceived carbon risk exposure (1.52) is associated with a rise of 0.08 ($= 1.52 \times 0.05097$) percentage points in the median CDS spread

[35]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, the performance shock may be thought of as an idiosyncratic shock (e.g. good or bad news) causing a change in a firm's credit performance.

[36]The coefficients for each decile across all tenors under study can be found in the Appendix G.

[37]OLS estimates give an average effect of the explanatory variables on CDS spread returns across the entire sample, offering a baseline comparison. This is useful for understanding the overall relationship between variables under standard conditions.

return.[38] To contextualize this impact, assuming a 5-year CDS contract with a notional value of US$100 million and a spread of 100 basis points (hence a yearly premium of US$1 million), a one standard deviation rise in the CR factor equates to an additional estimated annual cost of US$0.21 million in protection expenses.

Second, starting from the median value $\tau = 0.5$, we observe that the coefficients are larger toward the ninth and first deciles. Essentially, the more the firm's credit improves or deteriorates, the larger the effect of the CR factor. Notably, the effect increases symmetrically – the coefficients are virtually the same for a given distance from the median, whether left or right. Essentially, an increase (decrease) in the CR factor, indicating greater (lesser) exposure to carbon risk, amplifies the existing deterioration (enhancement) in creditworthiness for firms experiencing a significant positive (negative) CDS spread shock. In fact, at the extremes, a one standard deviation rise in the CR factor corresponds to an estimated saving of US$0.40 million (first decile), or an extra cost of US$0.55 million (ninth decile), for every US$100 million exposure. These results are consistent with Hypothesis 1: there is a positive relationship between carbon risk and CDS spread returns. The relationship significantly intensifies for firms undergoing exceptionally large positive or negative shocks in the credit market.

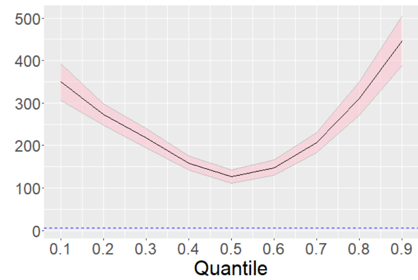
Next we examine Hypothesis 2, which posits that the effect of carbon risk is stronger in Europe than in North America. We re-estimate our baseline QR separately for each North American tenor. Consistent with the prediction of Hypothesis 2, Figure 5 shows a weaker relationship between CDS spread returns and the CR factor for the North American sample. For instance, considering the 5Y tenor, the coefficient estimate of the CR factor for the median CDS spread return is approximately 20 times smaller than its European counterpart. Interestingly, the symmetrical intensification of the effect persists as we move towards the extremes of the distribution.

To better understand the difference in the results between Europe and North America, it is crucial to examine the carbon pricing regulations prevalent in each region (Pryor et al., 2023). Europe has been at the forefront of implementing explicit carbon pricing mechanisms, most notably through the EU ETS. This system mandates companies to pay for emission permits, effectively introducing a direct cost for emitting carbon dioxide and other greenhouse gases. Since these costs can directly impact companies' operational expenses and profitability, such explicit carbon pricing may have a more salient and pronounced effect on firms' financials. These financial implications are likely to be reflected in their CDS spread returns. On the other hand, North America has predominantly relied on non-pricing emissions regulations (Aldy et al., 2022). In fact, neither the US nor Canada have very much explicit carbon pricing at national or subnational levels. The US and Canada are more likely to opt for policies that have the effect of reducing emissions, but without directly targeting carbon. At the US federal level, these include tax credits for renewable energy, electric vehicle tax credits, vehicle fuel economy standards, other efficiency standards, and the renewable fuel standard (Aldy et al., 2022). While these non-pricing regulations can still impose costs on

[38]In comparison to the CR factor, a one standard deviation increase in the MRI (2.33), which is the most significant driver of CDS spread returns, increases the median CDS spread return by 0.9 ($= 2.33 \times 0.38815$) percentage points. MRI and carbon risk contribute, respectively, 17% and 2% to the standard deviation of the CDS spread return.

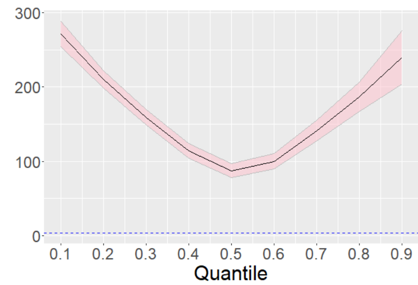
1Y	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$	OLS
StockReturn	-41424^{***}	-81.90^{***}	-43619^{***}	-478^{***}
	(14.24)	(3.36)	(23.71)	(0.29)
ΔVolatility	-58153^{***}	35.82^{*}	1106.00^{***}	4.67^{***}
	(32.27)	(13.98)	(37.66)	(0.94)
ΔMRI	1608.99^{***}	1433.21^{***}	1831.08^{***}	17.86^{***}
	(34.20)	(36.27)	(92.70)	(1.54)
ΔCR	349.28^{***}	126.31^{***}	445.79^{***}	4.84^{***}
	(22.10)	(7.97)	(29.92)	(0.43)

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



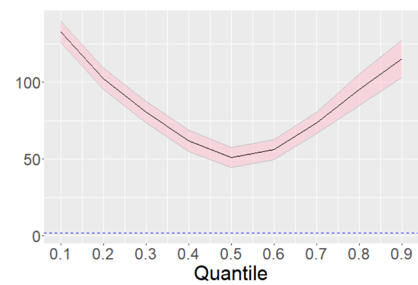
3Y	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$	OLS
StockReturn	-30504^{***}	-8206^{***}	-36210^{***}	-375^{***}
	(8.06)	(3.23)	(15.23)	(0.20)
ΔVolatility	-50054^{***}	33.27^{*}	948.30	3.90^{***}
	(59.56)	(14.55)	(30.33)	(0.56)
ΔMRI	638.54^{***}	645.99^{***}	748.49^{***}	6.54^{***}
	(17.32)	(15.23)	(40.51)	(0.58)
ΔCR	271.37^{***}	87.44^{***}	239.89^{***}	3.05^{***}
	(8.67)	(4.67)	(18.22)	(0.21)

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



5Y	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$	OLS
StockReturn	-19854^{***}	-5232^{***}	-23151^{***}	-260^{***}
	(4.95)	(2.00)	(9.14)	(0.14)
ΔVolatility	-33562^{***}	$16.11^{\cdot}$	650.17	3.04^{***}
	(20.04)	(8.43)	(11.76)	(0.45)
ΔMRI	379.33^{***}	388.15^{***}	447.97^{***}	3.32^{***}
	(9.78)	(8.96)	(15.03)	(0.29)
ΔCR	132.63^{***}	50.97^{***}	115.18^{***}	1.62^{***}
	(3.61)	(3.32)	(6.19)	(0.11)

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



10Y	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$	OLS
StockReturn	-13514^{***}	-3863^{***}	-15959^{***}	-183^{***}
	(3.35)	(1.44)	(6.46)	(0.11)
ΔVolatility	-23411^{***}	$7.00^{\cdot}$	436.88	1.74^{***}
	(13.59)	(4.00)	(7.88)	(0.33)
ΔMRI	264.37^{***}	270.45^{***}	304.63^{***}	2.02^{***}
	(5.32)	(5.76)	(7.65)	(0.19)
ΔCR	80.74^{***}	34.46^{***}	76.91^{***}	1.09^{***}
	(2.18)	(1.82)	(4.72)	(0.08)

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

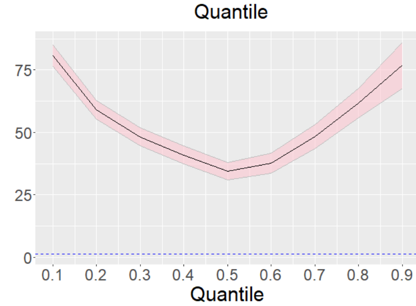
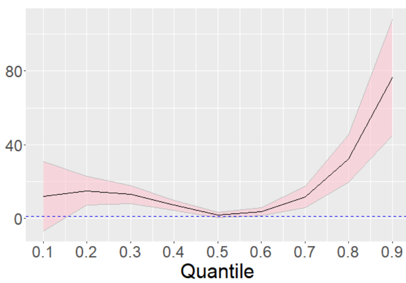


Figure 4: **Left panels**: Coefficient estimates of the base panel QR model as well as the mean (OLS) regression model for 1-year (top), 3-year (upper center), 5-year (lower center), and 10-year (bottom) CDS spread returns. The sample comprises data for 119 European firms from 2013/01/01 to 2019/12/31 in daily frequency. Estimates and standard errors (in brackets) are reported for the 1st, 5th, and 9th decile, and the mean. All estimates are scaled by factor 1000. **Right panels**: Graphic visualization of the ΔCR QR estimates for all nine deciles. The pink-shaded area indicates the 95% confidence interval. The blue dashed line represents the respective value of the OLS estimate.

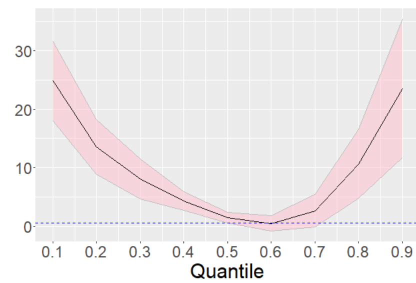
1Y	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$	OLS
StockReturn	-25776^{***}	-1897^{***}	-27410^{***}	-402^{***}
	(12.91)	(1.15)	(17.54)	(0.26)
ΔVolatility	-60347^{***}	6.69	961.42	3.85^{***}
	(35.80)	(4.39)	(100.12)	(0.85)
ΔMRI	768.00^{***}	136.48^{***}	1040.43^{***}	13.20^{***}
	(42.05)	(11.85)	(74.67)	(0.84)
ΔCR	11.97	1.79^{**}	76.53^{***}	1.08^{**}
	(9.70)	(0.68)	(16.13)	(0.39)

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



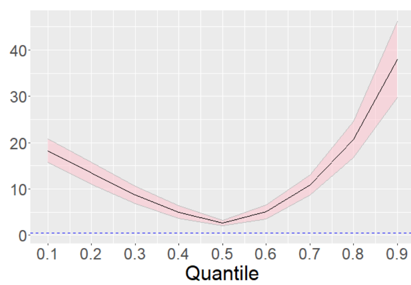
3Y	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$	OLS
StockReturn	-22851^{***}	-4072^{***}	-22444^{***}	-297^{***}
	(7.07)	(1.63)	(10.94)	(0.18)
ΔVolatility	-37854^{***}	6.65	742.54	2.15^{***}
	(27.89)	(4.68)	(27.34)	(0.39)
ΔMRI	286.68^{***}	176.04^{***}	417.01^{***}	4.14^{***}
	(10.64)	(7.47)	(15.79)	(0.27)
ΔCR	24.83^{***}	1.44^{**}	23.55^{***}	0.51^{***}
	(3.45)	(0.48)	(6.05)	(0.10)

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



5Y	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$	OLS
StockReturn	-18654^{***}	-3926^{***}	-18294^{***}	-258^{***}
	(4.94)	(1.60)	(6.66)	(0.16)
ΔVolatility	-32667^{***}	13.24^{*}	630.46	2.19^{***}
	(14.61)	(5.70)	(8.88)	(0.38)
ΔMRI	205.82^{***}	156.34^{***}	283.21^{***}	2.45^{***}
	(7.27)	(5.72)	(8.86)	(0.20)
ΔCR	18.27^{***}	2.64^{***}	37.96^{***}	0.43^{***}
	(1.28)	(0.31)	(4.20)	(0.04)

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



10Y	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$	OLS
StockReturn	-13733^{***}	-2589^{***}	-13823^{***}	-188^{***}
	(3.33)	(1.14)	(5.83)	(0.12)
ΔVolatility	-23267^{***}	9.83^{*}	469.83	1.71^{***}
	(12.97)	(4.05)	(10.83)	(0.31)
ΔMRI	128.02^{***}	72.55^{***}	168.73^{***}	1.43^{***}
	(4.28)	(3.89)	(7.43)	(0.11)
ΔCR	10.61^{***}	0.61^{***}	8.41^{***}	0.18^{***}
	(0.86)	(0.12)	(1.90)	(0.03)

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

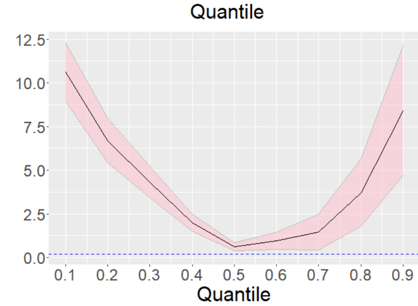
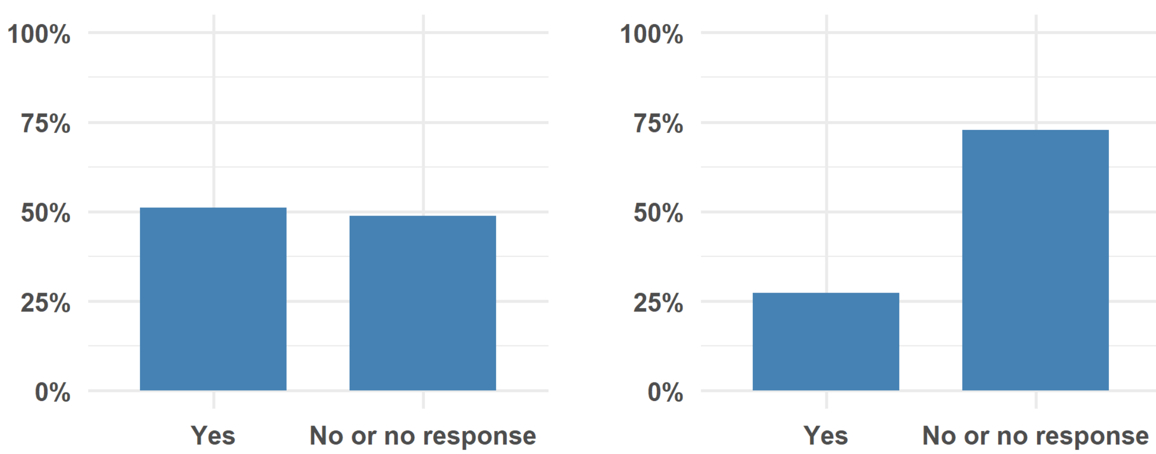


Figure 5: **Left panels**: Coefficient estimates of the base panel QR model as well as the mean (OLS) regression model for 1-year (top), 3-year (upper center), 5-year (lower center), and 10-year (bottom) CDS spread returns. The sample comprises data for 164 North American firms from 2013/01/01 to 2019/12/31 in daily frequency. Estimates and standard errors (in brackets) are reported for the 1st, 5th, and 9th decile, and the mean. All estimates are scaled by factor 1000. **Right panels**: Graphic visualization of the ΔCR QR estimates for all nine deciles. The pink-shaded area indicates the 95% confidence interval. The blue dashed line represents the respective value of the OLS estimate.

firms, such as through compliance and operational adjustments, they do not have the same direct and immediate financial implications as an explicit carbon price. This difference in regulatory approach could be a significant factor in the weaker relationship between CDS spread returns and the CR factor in North America compared to Europe. Fundamentally, the direct carbon costs incurred by European companies under explicit pricing regulations might result in more noticeable changes in their exposure to carbon risk. This is reflected in CDS spreads. This contrasts with the more indirect financial impacts experienced by North American firms operating under non-explicit pricing regulations. The presence or absence of explicit carbon pricing, and its implications for credit risk perception, is the focus of our subsequent analysis.

4.2 Explicit carbon pricing matters

The disparity in the regulatory landscape between Europe and North America begs further investigation into how the scope and stringency of carbon policies differentially shape lenders' perceptions. To interrogate this, we make use of CDP (formerly the Carbon Disclosure Project) questionnaires. The CDP, a global disclosure system that enables companies to measure and manage their environmental impacts, has been instrumental in shedding light on how firms are affected by and respond to carbon pricing regulations. Originally capturing whether companies were subject to mandatory carbon pricing at the time of responding, the questionnaire has evolved over time to capture anticipated pricing regulation as well.



(a) Europe

(b) North America

Figure 6: Breakdown of North American (left panel) and European (right panel) firms, categorizing them by their exposure to carbon price regulation, versus those not subject to such regulation or who did not respond to the survey.

CDP questionnaire responses reveal that 25% of the North American firms, but 50% of the European firms, in our sample are subject to explicit carbon pricing, as illustrated in Figure 6. The significant difference in explicit carbon pricing coverage between Europe and North America underscores the varying scope of regulations.[39]

[39] In the context of carbon pricing, the scope of regulations refers to the range and extent of sectors and activities that are covered by carbon pricing mechanisms.

The difference between Europe and North America, in terms of the relationship between CDS spread returns and the CR factor, can potentially be explained by this difference in carbon pricing coverage, coupled with differing levels of regulatory pressure.[40] This observation forms the premise of Hypothesis 3. To test this hypothesis, we turn to question C11.1 of the CDP questionnaire, which inquires, "Are any of your operations or activities regulated by a carbon pricing system (i.e. Emission Trading System, Cap and Trade or Carbon Tax)?" This question not only captures the current scope of regulations but also anticipates future carbon policy changes. If companies respond positively to this question, they are then asked to identify the specific systems that apply to them. Utilizing this information, we can classify companies according to whether, and with what stringency, they are currently or expect to be regulated. We classify companies into four distinct categories. First, those that did not provide any feedback are labeled as "No response". Those who confirmed that they are not under any carbon regulation are categorized as "No". Companies that are not currently regulated, but expect to be in the future, we termed "No but anticipation". Finally, companies that are actively regulated or subject to emission pricing are grouped under "Yes". With this refined classification in hand, we re-estimate our baseline QR for each European and North American tenor. This enables us to investigate whether explicit carbon pricing can more accurately account for the observed variations in CDS spread returns. In particular, we estimate the following model:

$$\begin{aligned} Q_{s^m_{i,t}}(\tau|\boldsymbol{x}_{i,t}) = \alpha_{\tau,i} + \beta_{\tau,1} r_{i,t} + \beta_{\tau,2}\Delta\sigma_{i,t} + \beta_{\tau,3}\Delta\mathrm{MRI}^m_{i,t} + \beta_{\tau,4}\Delta\mathrm{CR}^m_t \\ + \sum_{j=5}^{7}\beta_{\tau,j}\mathrm{ETS}_i + \sum_{k=8}^{10}\beta_{\tau,k}(\Delta\mathrm{CR}^m_t \times \mathrm{ETS}_{i,t}) + \varepsilon_{i,t}, \end{aligned}$$

where $\mathrm{ETS}_{i,t}$ denotes firm i's response to question C11.1 from the CDP questionnaire at time t.

Figure 7 reports the coefficient estimates of the interaction terms for the 5-year model of the European sample.[41] Figure 7 reveals that being subject to direct carbon pricing matters. Firms not subject to carbon pricing regulations, or those who did not respond to the question, show reduced exposure to carbon risk, evidenced by a significantly weaker relationship between CDS spread returns and the CR factor. On the other hand, firms operating under explicit carbon pricing (ΔCR $\times$ ETS (Yes)) exhibit a markedly higher exposure to carbon risk. Their coefficient estimates are roughly twice as large as those for firms not governed by explicit price regulation. For firms under direct carbon pricing, a rise in the CR factor equates to an estimated additional annual cost of US\$0.35 million per US\$100 million of exposure, which is thrice the impact experienced by firms not under direct carbon pricing. This stark difference underscores the heightened financial implications these companies face, as they grapple with the tangible costs of explicit carbon pricing mandates. This holds across both Europe and North America, underscoring the marked influence of being subject to direct carbon pricing on perceived carbon risk. The lenders' market, in its characteristic

[40] In examining the bond market, Seltzer et al. (2024) finds a greater impact on the credit risk of firms operating in states with stricter environmental regulations.

[41] The estimation results for the remaining maturities do not differ qualitatively, as reported in Appendix G.

Europe				
5Y	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$	OLS
ΔCR $\times$ ETS (No response)	84.50***	27.48***	69.15***	1.24***
	(12.82)	(5.20)	(16.70)	(0.23)
ΔCR $\times$ ETS (No)	102.30***	30.80***	75.96***	1.03***
	(11.35)	(5.14)	(8.82)	(0.15)
ΔCR $\times$ ETS (No but anticipation)	34.48	8.16	1.11	0.25
	(37.67)	(14.54)	(22.80)	(0.27)
ΔCR $\times$ ETS (Yes)	184.25***	78.59***	177.04***	2.12***
	(5.00)	(5.10)	(14.49)	(0.17)

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

North America				
5Y	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$	OLS
ΔCR $\times$ ETS (No response)	19.55***	2.70***	40.07***	0.38***
	(1.70)	(0.61)	(5.77)	(0.07)
ΔCR $\times$ ETS (No)	13.44*	2.00***	31.18***	0.32***
	(5.72)	(0.52)	(7.30)	(0.06)
ΔCR $\times$ ETS (No but anticipation)	31.20***	2.44	60.29*	0.37***
	(5.56)	(1.63)	(28.96)	(0.07)
ΔCR $\times$ ETS (Yes)	36.04***	6.33***	77.27***	0.66***
	(1.68)	(1.60)	(9.56)	(0.09)

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

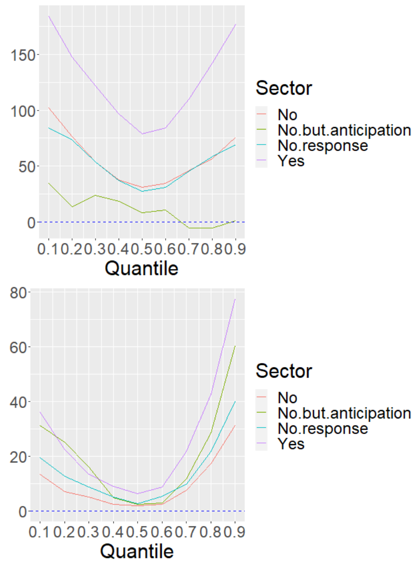


Figure 7: **Left panels**: Coefficient estimates of the ETS QR model as well as the respective mean (OLS) regression model for 5-year CDS spread returns in Europe (top) and North America (bottom). The sample comprises data for 119 European firms and 164 North American firms from 2013/01/01 to 2019/12/31 in daily frequency. Estimates and standard errors (in brackets) are reported for the 1st, 5th, and 9th decile, and the mean. All estimates are scaled by factor 1000. **Right panels**: Graphic visualization of all ETS interaction estimates for all nine deciles. The blue dashed line represents the zero line.

forward-looking manner, appears to be acutely sensitive to these differences in regulatory exposure, adjusting its perception of carbon risk accordingly.

The impact of explicit carbon pricing is evident, and transcends the binary existence or absence of regulation. The extent of a firm's affectedness, determined by the proportion of its direct emissions subject to these regulations and the stringency of the policy, are also important considerations. For example, two firms facing direct carbon pricing may be subject to differing levels of stringency within the regulation, leading to significantly different implications for their credit risk. This brings into focus the per-ton cost of carbon price regulation, which can provide a more accurate measure of a firm's exposure to carbon risk.[42] We examine this dimension through Hypothesis 4, aiming to elucidate the role of policy stringency – the proportion of a firm's direct emissions subject to regulation – as a crucial factor in carbon risk.

To that end, we compute the ratio of verified emissions to total direct emissions. Verified emissions are the officially measured, reported, and independently validated greenhouse gases emitted by a firm. We derive this data from the CDP questionnaire to reflect the share of a firm's emissions officially subject to carbon pricing. The firm's total emissions profile, drawn from Refinitiv LSEG data, provides information on Scope 1 emissions – those emitted directly from sources owned or controlled by the firm. By comparing verified emissions with total direct emissions, we can assess policy stringency and its effect on the credit risk faced

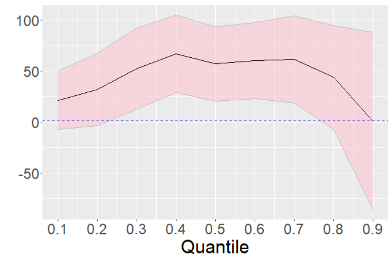
[42] This approach parallels the ECB and ESRB (2022) method of using the emission-to-allowance gap to gauge firms' exposure to transition risk.

5Y (Europe)	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$	OLS
ΔCR $\times$ ETS (No response)	84.41***	27.43***	69.15***	1.24***
	(12.66)	(5.19)	(16.70)	(0.23)
ΔCR $\times$ ETS (Yes) $\times$ ETS Share	21.18	57.10**	0.60	0.85
	(14.69)	(18.67)	(44.55)	(0.60)
ΔCR $\times$ ETS (No)	102.32***	30.80***	75.98***	1.03***
	(11.35)	(5.13)	(8.83)	(0.15)
ΔCR $\times$ ETS (No but anticipation)	32.95	8.40	1.12	0.25
	(38.66)	(14.60)	(22.80)	(0.27)
ΔCR $\times$ ETS (Yes)	175.34***	59.73***	176.75***	1.80***
	(7.52)	(6.79)	(25.34)	(0.24)

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

5Y (North America)	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$	OLS
ΔCR $\times$ ETS (No response)	19.56***	2.70***	40.09***	0.38***
	(1.71)	(0.60)	(5.79)	(0.07)
ΔCR $\times$ ETS (Yes) $\times$ ETS Share	69.49**	28.08*	84.85	0.36
	(26.77)	(14.14)	(216.73)	(0.85)
ΔCR $\times$ ETS (No)	13.44*	2.01***	31.14***	0.32***
	(5.75)	(0.52)	(7.31)	(0.06)
ΔCR $\times$ ETS (No but anticipation)	31.21***	2.44	60.29*	0.37***
	(5.48)	(1.63)	(28.95)	(0.07)
ΔCR $\times$ ETS (Yes)	31.54***	3.99*	70.18***	0.63***
	(4.56)	(1.55)	(17.10)	(0.10)

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



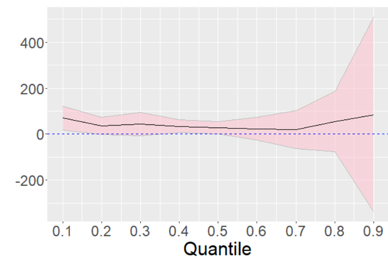


Figure 8: **Left panels**: Coefficient estimates of the ETS share QR model as well as the respective mean (OLS) regression model for 5-year CDS spread returns in Europe (top) and North America (bottom), respectively. The sample comprises data for 119 European firms and 164 North American firms from 2013/01/01 to 2019/12/31 in daily frequency. Estimates and standard errors (in brackets) are reported for the 1st, 5th, and 9th decile, and the mean. All estimates are scaled by factor 1000. **Right panels**: Graphic visualization of the ΔCR $\times$ ETS(Yes) $\times$ ETS share QR estimates for all nine deciles. The pink-shaded area indicates the 95% confidence interval. The blue dashed line represents the respective value of the OLS estimate.

by firms. Formally, our model reads

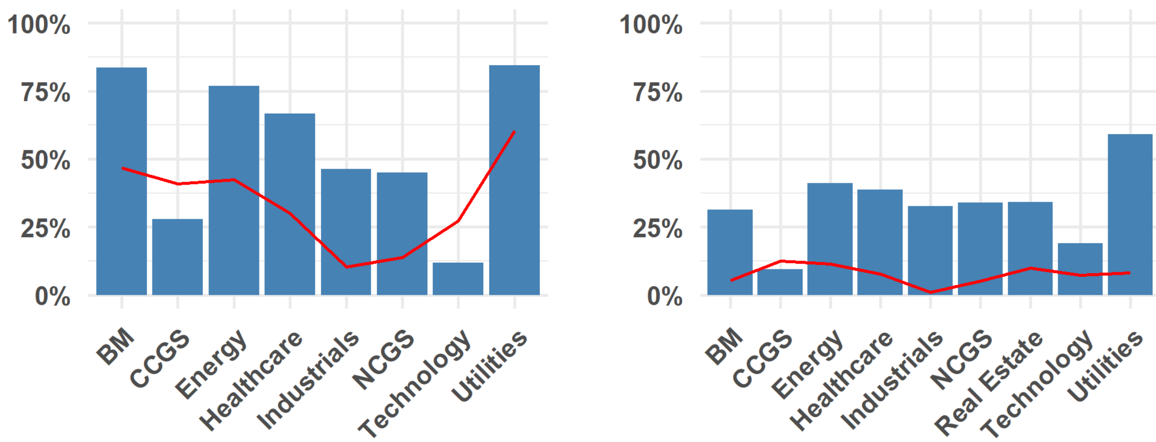
$$
\begin{aligned}
Q_{s_{i,t}^m}(\tau|\boldsymbol{x}_{i,t}) = \alpha_{\tau,i} + \beta_{\tau,1} r_{i,t} + \beta_{\tau,2}\Delta\sigma_{i,t} + \beta_{\tau,3}\Delta\mathrm{MRI}_{i,t}^m + \beta_{\tau,4}\Delta\mathrm{CR}_t^m \\
+ \sum_{j=5}^{7}\beta_{\tau,j}\mathrm{ETS}_i + \sum_{k=8}^{10}\beta_{\tau,k}(\Delta\mathrm{CR}_t^m \times \mathrm{ETS}_{i,t}) \\
+ \beta_{\tau,11}(\Delta\mathrm{CR}_t^m \times \mathrm{ETS(Yes)}_{i,t} \times \mathrm{ETS\ Share}_{i,t}) + \varepsilon_{i,t},
\end{aligned}
$$

where $\mathrm{ETS(Yes)}_{i,t}$ is a dummy that takes the value 1 if firm i is subject to an ETS at time t, and zero otherwise. ETS $\mathrm{Share}_{i,t}$ denotes firm i's share of regulated emissions to their total emissions at time t.

In Figure 8, we present the key coefficient estimates, specifically focusing on the interaction term ΔCR $\times$ ETS (Yes) and the double interaction term ΔCR $\times$ ETS (Yes) $\times$ ETS Share. We restrict the discussion to the 5-year model within the European and North American samples.[43] The coefficients reported in the table reveal that the greater the share of a firm's total direct (Scope 1) emissions are covered by carbon pricing regulation, the more pronounced the CR factor's impact becomes. Specifically, firms with a larger fraction of their emissions regulated by carbon pricing show increased sensitivity to CR factor fluctuations. This holds true for both the European and the North American samples, with the effect being significantly more marked in Europe. A 1% increase in the percentage of total emissions under regulation equates to an estimated additional annual cost of US$0.24 million per US$100 million of exposure in Europe and US$0.11 million per US$100 million of exposure in North America. This underscores the importance of accounting for carbon policy stringency, as it has a direct bearing on how the firm's credit profile responds to perceived carbon risks.

[43] The estimation results for the remaining maturities do not differ qualitatively, as reported in Appendix G.

So far, we have observed the exposure of the average firm in Europe and North America to carbon risk. However, carbon regulation frequently hinges on the specific emissions profile of an industry. Heavy manufacturing and energy production, for example, inherently involve processes that emit substantial amounts of carbon.[44] Consequently, companies in these industries are more likely to be subject to carbon pricing, as illustrated in Figure 9.



(a) Europe

(b) North America

Figure 9: The proportion of firms across sectors subject to carbon pricing is represented by bars, while the average share of emissions under regulation (verified against Scope 1 emissions) per sector is represented by the red line.

Hypothesis 5 proposes that lenders primarily base their assessment of carbon risk on industry categorizations, rather than on individual company characteristics, and may not perform a nuanced analysis of the diverse intrasectoral exposure. To test this hypothesis, we regroup the firms according to LSEG's nine sectors, as described in the Refinitiv Business Classification (RBC), and re-estimate our baseline QR.[45] We include sector dummies and interaction terms with our CR factor in the baseline regression:

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

where Sector_i indicates firm i's Refinitiv Business Classification.

Figure 10 reports the coefficient estimates of the interaction terms for the 5-year sector model of the European and North American samples, respectively.[46] Figure 10 reveals important sectoral differences. Specifically, the interaction term is both positive and highly significant for firms within the Basic Materials and Energy sectors. This indicates a strong and direct correlation between increased carbon risk and CDS spread returns in these sectors. Utilities

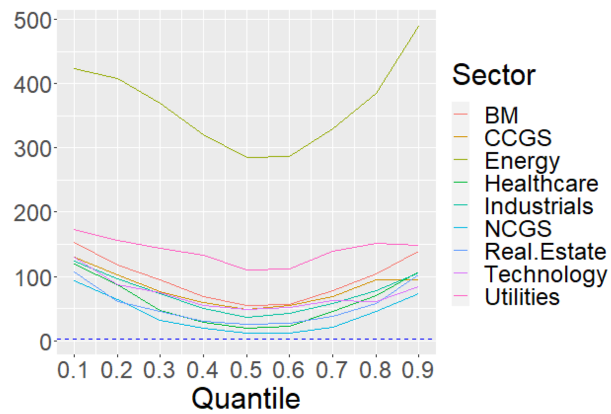
[44] A growing body of empirical literature identifies activities directly related to the production of energy and emissions-intensive goods, especially steel and cement (Dietz et al., 2020), as the most exposed categories.

[45] A detailed description of the Refinitiv Business Classification RBC is available here.

[46] The estimation results for the remaining maturities do not differ qualitatively, as reported in Appendix G.

5Y (Europe)	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$	OLS
BM × ΔCR	153.23***	54.34***	139.93***	1.73***
	(8.33)	(8.00)	(10.24)	(0.22)
CCGS × ΔCR	130.35***	47.96***	94.18***	1.35***
	(6.09)	(6.80)	(23.93)	(0.26)
Energy × ΔCR	423.46***	284.61***	489.91***	4.30***
	(29.68)	(34.37)	(46.42)	(0.35)
Healthcare × ΔCR	119.06***	19.59*	106.36***	1.04**
	(20.63)	(9.58)	(19.84)	(0.40)
Industrials × ΔCR	123.93***	36.34***	106.18***	1.42***
	(6.89)	(7.05)	(19.01)	(0.26)
NCGS × ΔCR	93.26***	11.95***	72.63***	0.89***
	(21.76)	(3.53)	(14.50)	(0.19)
Real Estate × ΔCR	107.29***	25.14$^{\cdot}$	102.42***	1.25*
	(9.82)	(13.19)	(12.62)	(0.49)
Technology × ΔCR	130.55***	47.87***	83.89***	1.18***
	(16.50)	(8.97)	(12.30)	(0.23)
Utilities × ΔCR	172.65***	110.75***	148.95***	2.56***
	(11.27)	(15.04)	(27.28)	(0.45)

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



5Y (North America)	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$	OLS
BM × ΔCR	46.05***	17.42***	97.91***	0.88***
	(4.47)	(5.07)	(9.91)	(0.14)
CCGS × ΔCR	19.72***	2.61***	44.03***	0.34***
	(2.61)	(0.75)	(9.88)	(0.07)
Energy × ΔCR	61.60***	19.12***	166.85***	1.19***
	(5.53)	(4.83)	(30.82)	(0.14)
Healthcare × ΔCR	13.57***	0.26	25.38	0.18**
	(2.24)	(0.64)	(17.86)	(0.06)
Industrials × ΔCR	12.34***	2.28**	31.77*	0.31**
	(1.24)	(0.75)	(14.42)	(0.10)
NCGS × ΔCR	5.79***	0.06	17.77*	0.24**
	(0.83)	(0.40)	(6.91)	(0.07)
Real Estate × ΔCR	44.66***	12.79	76.88***	0.81**
	(1.36)	(9.50)	(12.68)	(0.26)
Technology × ΔCR	7.68$^{\cdot}$	0.32	25.26***	0.17
	(4.16)	(0.91)	(5.78)	(0.12)
Utilities × ΔCR	34.86***	4.32	63.32***	0.60***
	(6.06)	(3.10)	(14.08)	(0.07)

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

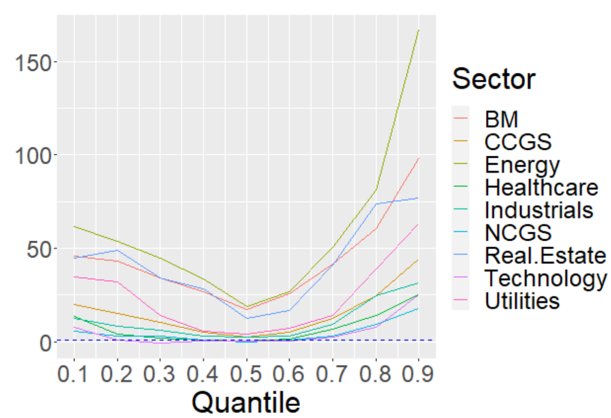


Figure 10: **Left panels**: Coefficient estimates of the sector QR model as well as the respective mean (OLS) regression model for 5-year CDS spread returns in Europe (top) and North America (bottom). The sample comprises data for 119 European firms and 164 North American firms from 2013/01/01 to 2019/12/31 in daily frequency. Estimates and standard errors (in brackets) are reported for the 1st, 5th, and 9th decile, and the mean. All estimates are scaled by factor 1000. **Right panels**: Graphic visualization of all sectoral interaction estimates for all nine deciles. The blue dashed line represents the zero line.

also exhibit this relationship, though to a slightly lesser degree. This indicates that industries such as Basic Materials, Energy, and Utilities are especially sensitive to carbon risk, leading to a heightened impact on CDS spread returns. This sensitivity is attributable to their operational characteristics and the regulatory landscape to which they are subjected. The pronounced effect observed in Europe can be attributed to the substantial portion of firms within these sectors that are subject to carbon pricing – about 50% as illustrated in Figure 9. The economic impact of these findings is significant: An increase in the CR factor translates to an additional estimated cost of US\$0.23 million for Basic Materials, with the effect being more than two times greater for Utilities (US\$0.52 million) and more than eight times greater for Energy (US\$1.94 million) per US\$100 million of exposure. These findings echo previous results in the equity market, highlighting that the economic impact of the carbon risk effect intensifies when accounting for industry-specific exposures (Bolton and Kacperczyk, 2021). However, we also quantify these impacts, providing a more detailed understanding.

4.3 Term structure

The earlier sections offer evidence of the dependency of firms' credit risk on the scope and stringency of carbon regulations. The regulatory environment is also an important determinant of the speed with which the economy will decarbonize, creating a link between carbon risk and the anticipated pace of transformation. We therefore shift our focus to examining lenders' expectations about how fast the transition to a low-carbon economy needs to be. For instance, if a new carbon regulation with a more pressing deadline is introduced, do lenders anticipate higher transition costs in the near term rather than the longer term? If so, this expectation is likely reflected in the term structure of CDS spreads. By comparing the adjustment in CDS spreads of shorter tenors against those with longer tenors, we can gauge lenders' projections regarding the pace of transition to a low-carbon economy. This comparison forms the basis of Hypothesis 6. To empirically test this, we examine how a change in the expected temporal materialization of carbon risk affects the term structure of a firm's credit risk. This involves leveraging the CR factor's slope, which represents the variation in carbon risk across different time horizons, to derive insights about carbon risk over specific periods. An upward shift in the CR slope suggests escalating default protection costs for longer-term tenors. 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 $\Delta\text{CRSlope}_{t}^{mn}$. We analyze the overall 10Y-1Y period, dividing it into a short-term slope (5Y-1Y) and a long-term slope (10Y-5Y). This division enables us to assess whether an accelerated transformation towards a low-carbon economy is manifested in a more rapid deterioration of credit quality in the near term compared to the long term. We thus estimate the model with the inclusion of the term structure control variables:

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

Figure 11 reports the estimation results for the entire period 10Y-1Y CR slope and for the 5Y-1Y and 10Y-5Y CR slopes for Europe and North America.[47]

[47] The results with the estimates for all control variables can be found in Tables 16 and 17 in Appendix G.

Europe	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$	OLS
		5Y-1Y		
ΔCRSlope	37.08^{***}	3.71^{***}	25.34^{***}	59.01^{***}
	(2.43)	(0.28)	(2.93)	(8.71)
		10Y-5Y		
ΔCRSlope	-1.34^{***}	-0.14^{***}	-0.43	-6.91^{**}
	(0.28)	(0.04)	(0.45)	(2.23)
		10Y-1Y		
ΔCRSlope	45.35^{***}	7.11^{***}	30.99^{***}	77.13^{***}
	(1.69)	(0.51)	(3.39)	(9.66)

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

North America	$\tau = 0.1$	$\tau = 0.5$	$\tau = 0.9$	OLS
		5Y-1Y		
ΔCRSlope	12.17^{***}	0.66^{***}	22.57^{***}	70.23^{***}
	(0.68)	(0.12)	(2.20)	(8.12)
		10Y-5Y		
ΔCRSlope	$-1.13^{\cdot}$	-0.00	-2.25^{**}	2.98
	(0.65)	(0.02)	(0.87)	(5.19)
		10Y-1Y		
ΔCRSlope	8.92^{***}	0.14^{**}	4.96^{***}	39.16^{***}
	(0.82)	(0.05)	(1.27)	(6.69)

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

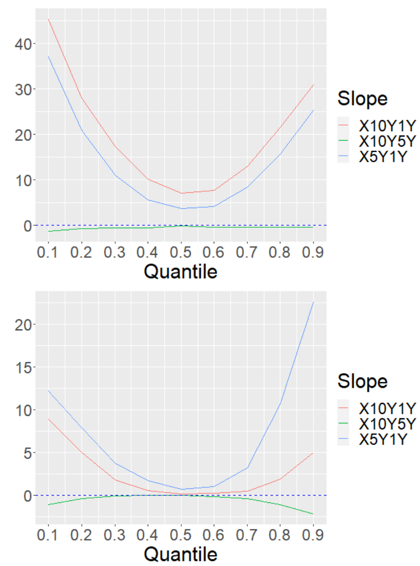


Figure 11: **Left panels**: Coefficient estimates of the term structure QR model as well as the respective mean (OLS) regression model for 5Y-1Y, 10Y-5Y, and 10Y-1Y CDS spread slope changes in Europe (top) and North America (bottom). The sample comprises data for 119 European firms and 164 North American firms from 2013/01/01 to 2019/12/31 in daily frequency. Estimates and standard errors (in brackets) are reported for the 1st, 5th, and 9th decile, and the mean. All estimates are scaled by factor 1000. **Right panels**: Graphic visualization of all three slope estimates for all nine deciles. The blue dashed line represents the zero line.

The findings presented in Figure 11 suggest that an overall rise in the CR slope leads to a steeper CDS curve across a decade, with this effect predominantly observed in the initial five years in both Europe and North America. This indicates a quicker deterioration in credit quality in the short term compared to the long term, reflecting lenders' anticipation of more immediate, significant financial impacts associated with an accelerated low-carbon transition. This analysis has significant policy implications, directly informing the debate on fiscal and monetary policies to mitigate the potential adverse effects of a disorderly transition, marked by sudden repricing risks and the possibility of assets becoming stranded. Our findings indicate that possible re-pricing activities, triggered by the potential acceleration of carbon reduction efforts, are more likely to manifest in the short term. This is especially relevant for central banks, given that collateral for monetary policy operations is often pledged for short periods. Consequently, if carbon risk poses predominantly short-term challenges, central banks might have a strong interest in closely monitoring carbon risk and its potential fallout.

5 Conclusions

The push towards net-zero carbon emissions necessitates a profound economic overhaul, with carbon emission regulations potentially imposing significant costs affecting business valuations. Recent studies highlight that firms with emissions-intensive models face greater carbon risk compared to their low-carbon counterparts. We extend and qualify these results, showing that the impact of carbon regulations on firm credit risk varies with the regulations' scope, stringency, and the pace at which they mandate carbon transformation. Our findings show that the influence of carbon regulations on credit risk is heavily contingent upon these dimensions, which collectively determine the true effect and fiscal consequences of carbon policies. This insight is essential for understanding how carbon emission regulations shape lenders' evaluation and pricing of firms' carbon risk exposure.

Using daily spreads of Credit Default Swap (CDS) contracts, we construct a market-implied, high-frequency, and forward-looking carbon risk (CR) factor that reflects the changing perceptions of overall carbon risk. This CR factor is defined by the differential in daily median CDS spreads between firms with high emission intensity (polluters) and those with low emission intensity (clean). This difference serves to gauge the lending market's perception of the relative carbon risk exposure of polluting versus clean firms.

We then study how carbon risk affects firms' creditworthiness using daily CDS data for more than 280 firms in Europe and North America for the period from 2013 to 2019. We find a positive relationship between lenders' perceived exposure to carbon risk – our CR factor – and firms' cost of default protection. Using quantile regression, we show that an increase in the CR factor leads to a doubling of its impact on the increase in CDS spread returns 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.

Carbon risk exposure shows significant differences across regions, reflecting the disparity in carbon regulations between Europe and North America. The impact of carbon risk on CDS spread returns is notably stronger in Europe, where explicit carbon pricing mechanisms are more prevalent, compared to North America. Despite regional differences, it is crucial to recognize that not every firm in our sample is subject to carbon pricing regulation. Firms that are currently subject to, or expect to be subject to, explicit carbon pricing experience a significantly higher exposure to carbon risk. This holds in both Europe and North America, highlighting the substantial impact that direct carbon pricing has on the perception of carbon risk. But the impact on firms goes beyond the mere existence or absence of regulation; the influence of carbon risk on CDS spread returns is also contingent upon the regulated proportion of a firm's direct emissions, evident in both Europe and North America. This highlights the critical role of carbon policy stringency, directly affecting a firm's credit profile in response to perceived carbon risks. Finally, we find that the degree of regulatory coverage over a sector's emissions amplifies the effect of carbon risk on CDS spread returns. Lenders view firms in the carbon-intensive sectors of Basic Materials, Utilities, and Energy as bearing increased risks. This perception is primarily due to these high-emission sectors frequently falling within the scope of carbon policies and facing more stringent regulations. Last, we find that carbon risk is shaped by more than just the scope and stringency of regulations; it is also affected by the anticipated pace of the transition to a low-carbon economy. When there is an increase in the CR factor, lenders anticipate higher costs for short-term transitions.

Overall, our results suggest that the lending market is keenly sensitive to variations in regulatory exposure. Essentially, a firm's carbon risk exposure is not solely determined by how much it emits or where it operates. Our findings indicate that lenders adjust their assessments of carbon risk based on the specific scope of the regulation, its stringency, and the pace at which carbon reduction is mandated, indicating the clearer consequences of direct carbon pricing on a firm's valuation. These findings have important policy implications.

First, explicit carbon pricing enables a more accurate evaluation of firm-level carbon and (the associated portion of) credit risks. This, in turn, aids lenders (and financial markets) in regulating carbon emissions by pricing both current and anticipated future carbon policies. A broader regulatory framework, and the resulting pricing, would also motivate firms to strategize more effectively regarding their carbon emissions. Second, the observed disparities in exposure within industries suggest that comparing emissions to those from previous years, or to emissions from peer firms, could be instrumental in evaluating firms' commitments to achieving net zero and other future carbon reduction pledges. This approach could ultimately pave the way for sustained reductions in emissions. Third, our findings related to term structure indicate that the market views carbon risk as a concern in the short to medium term. This insight holds significant implications for central banks, contributing to ongoing discussions about the time frame of carbon risk and the appropriateness of adjusting monetary policies in response.

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A Theoretical basis for varying effects of carbon regulation

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". The actual cost implied by the carbon tax rate is uncertain, reflecting the complexity of carbon regulation. This uncertainty is shaped by numerous factors, including changes in economic conditions and the varying expenses tied to strategies for reducing emissions. This contributes to the uncertainty in the transition path of each firm. We label the actual carbon tax rate δ. Our working assumption is that each firm, depending on their exposure to carbon risk, pays δ per unit of time, where $0 < \delta < r$.[48] 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:

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

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 actual 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) may incur greater costs compared to low-emitting firms (clean firms). For an unspecified value of the continuous

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

variable δ for clean and polluting firms, respectively, we can calculate the default probabilities (under uncertainty) by taking the default probability from Expression (2) and integrating it with respect to the relevant distribution of δ^C and δ^P:

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

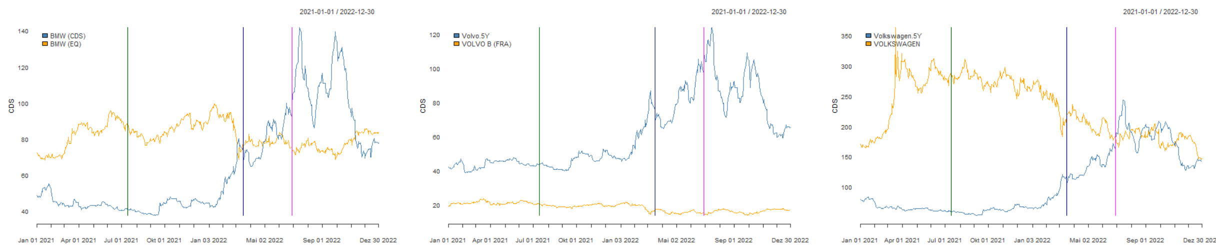
Naturally, $\delta^C \leq \delta^P$ and hence $F_P \geq F_C$. By stochastic dominance, we obtain $\mathrm{PD}^C \leq \mathrm{PD}^P$. Combining the relationship $\delta^C \leq \delta^P$ and the fact that the default probabilities have a monotonic relationship with the actual carbon tax rate, we retrieve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

B Carbon policy-related information transmission: the case of the automotive sector

The CDS market efficiently reflects changes in perceived carbon risk exposure through adjustments in credit spreads, owing to its high informational efficiency. This is exemplified by recent policy shifts in the European automotive sector.

In June 2021, the European Union (EU) unveiled a groundbreaking proposal that effectively signaled the end of new fossil-fuel cars by 2035. This ambitious plan aimed to accelerate the transition to zero-emission electric vehicles (EVs) as part of a broader strategy to achieve net-zero emissions in 2030. The European Commission, the EU's executive arm, proposed a 55% cut in carbon dioxide emissions from cars by 2030 – a significant increase from the existing target of a 37.5% reduction. Furthermore, a 100% cut in carbon dioxide emissions by 2035 would render the sale of new internal combustion engine (ICE) vehicles impossible within the 27-country bloc. The subsequent months saw a series of critical developments. Germany initially opposed this proposal – forming an alliance with Italy and some Eastern European countries – and refused to vote in favor, but eventually agreed when the European Commission made an exception for ICE cars that run on e-fuels.

We use these policy changes to visually illustrate that CDSs effectively reflect lenders' perceptions of shifting carbon risk exposure. Figure 12 plots the CDS spreads and equity movements for major car manufacturers like BMW, Volvo and Volkswagen, for which we have CDS data in our sample. The figure is marked by vertical lines representing the three pivotal events: the EU proposal announcement (dark green), Germany's support for the phase-out after initial opposition (dark blue), and the final EU agreement (magenta). While for Volkswagen, the responses of both CDS spreads and equity to the three events are closely aligned, for BMW and Volvo, these events seem to have little impact on equity, whereas their CDS spreads demonstrate significant responsiveness. This highlights the CDS as a forward-looking tool that offers prompt insights into market perception changes, especially regarding regulatory developments affecting companies' creditworthiness. This contrasts with equity, which reflects a broader range of factors.



(a) BMW (b) Volvo (c) VW

Figure 12: Daily evolution of 5-year CDS spreads (blue) and equity (orange) of BMW (top), Volvo (center) and Volkswagen (bottom) from Jan 1, 2021 until Dec 31, 2022. The vertical lines indicate the announcement of the EU proposal (dark green), Germany's decision to finally back up the phase-out (dark blue), and the final EU agreement (magenta).

In the automotive sector, the shift to EVs and the EU's aggressive carbon dioxide reduction targets are transforming the industry, and CDS spreads offer immediate insights into lenders' perceptions of how companies are positioned to navigate this transition. The differential response observed in the CDS spreads for each automotive company may be linked to specific factors related to their business models and strategies. While companies like Volvo have already set ambitious plans to become a fully electric car brand by 2030, others like BMW and Volkswagen have adopted a more gradual approach to electrification, aiming for a significant share of their sales to come from electric vehicles. Currently, Volvo's fully electric vehicle percentage stands at 22%, compared to 15% for BMW and 8% for Volkswagen. Therefore, companies with a higher proportion of electric or hybrid models may be perceived as better positioned to comply with new regulations, leading to narrower CDS spreads. Conversely, companies heavily reliant on traditional combustion engines may face wider spreads, reflecting higher perceived risk.

While we acknowledge that this case provides anecdotal evidence, it serves as a compelling illustration of how the CDS market's informational efficiency can be observed in real-world scenarios. By focusing on CDS, we can extract valuable insights for investors, regulators and industry analysts seeking to understand the evolving landscape of carbon risk exposure.

C Validation of the CR factor

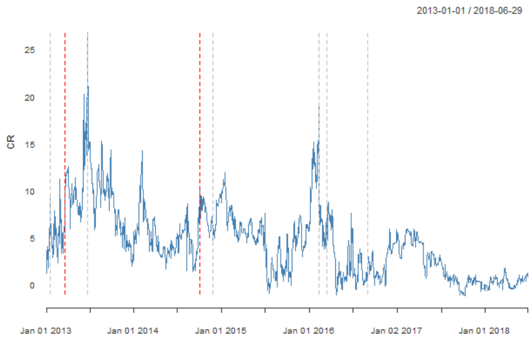
In Section 2.2, we illustrate that our CR factor responds to significant climate policy events, such as the Paris Agreement and the election of Donald Trump in the U.S. To validate the effectiveness of the proposed CR factor as a tool for tracking market responses to shifts in climate policy beyond these two selected events, we conduct a model-free event study. In particular, we utilize news data alongside the CR factor to demonstrate how relevant climate-related information is embedded in it.

We adopt the Transition Risk Concern (TRC) index of Bua et al. (2022) and the Media Climate Change Concerns (MCCC) index of Ardia et al. (2022) as our aggregated news measures for Europe and North America, respectively. The TRC index scans Reuters News for items with a European regional focus related to the introduction of new regulations to curb emissions or changes in regulations. The MCCC index generates an aggregate daily score based on the number of articles related to climate change in major US newspapers and their tone. Since the aggregate MCCC index includes news on physical climate risk, we use a variant that only incorporates topics under the superordinate themes "Financial and Regulation", "Agreement and Summit" and "Public Impact". This adjusted MCCC index provides daily information on the coverage and sentiment of North American carbon-related news while excluding any physical climate component. Finally, we normalize both indices to ensure they have comparable scales.

To identify relevant events captured by our CR factor, we analyze the joint behavior of news indices and our carbon risk metric. Specifically, we pinpoint dates where both the news index and the respective CR series (1Y, 3Y, 5Y, and 10Y) jointly deviate by 1.5 standard deviations from their respective means. Figure 13 illustrates these identified events (grey and red vertical lines) and plots the CR factors for all tenors in Europe and North America. In the interest of brevity, Table 2 provides descriptions of a subset of the identified events, specifically those corresponding to the red vertical lines in Figure 13. Each event described is a potential driver of carbon risk exposure, either through the implementation or non-implementation of climate policies (including their announcements) or through public pressure.
Let us consider two examples, one for Europe and one for North America. In September 2015, the European Commission established the Market Stability Reserve (MSR) as a measure to address potential imbalances between the demand and supply of emission allowances. The MSR mechanism allows the Commission to withhold allowances from the primary market or potentially cancel them at later stages. The MSR was planned to begin operating in January 2019, making it a relevant event for the longer tenors of 5Y and 10Y. This policy event highlights the advantage of our CR metric compared to other comparable metrics, as it allows us to extract risk exposures with respect to different horizons. Now, let us consider an example for North America: Barack Obama's announcement of a new climate plan in June 2013. This plan included new rules to cut carbon dioxide emissions from U.S. power plants and additional measures to promote renewable energy. The relevance of this decision is evident for the tenors of 3Y and 5Y, indicating that its impact is expected to materialize in the mid-term rather than within the very short term of one year. These two examples illustrate how our CR metric can discern the temporal horizon over which different policy measures are expected to influence carbon risk exposure.

Date	Event	Description
		Europe
Mar. 2013	2030 Framework Green Paper	The European Commission adopted the Green Paper on "A 2030 framework for climate and energy policies" to provide scientifically robust policy analysis on targeted issues within the debate on the post-2020 climate and energy policy framework.
Oct. 2014	EU Climate Deal	European leaders reached an agreement on a comprehensive climate change pact, committing the EU to reduce greenhouse gases by at least 40% by 2030.
Sep. 2015	Establishment of the MSR	Scheduled to take effect in 2019, the EU established the Market Stability Reserve (MSR) as a measure to address potential imbalances between the demand and supply of emission allowances by withholding allowances from the primary market and cancelling them at a later stage.
		North America
Jun. 2013	Obama's climate plan	President Barack Obama presented his new climate plan, which included new rules to cut carbon dioxide emissions from power plants, as well as additional measures to promote renewable energy.
Sep. 2014	People's Climate March	More than 310,000 people in New York, along with hundreds of thousands globally, rallied to pressure politicians to take action on climate change. The march also included several high-profile officials, such as then-UN Secretary General Ban Ki-moon and former U.S. presidential candidate Al Gore.
Oct. 2015	Limit on super GHGs	The U.S. announced plans to limit super greenhouse gases, with the Obama administration unveiling a series of executive actions and commitments from over a dozen companies to reduce their use.
Oct. 2017	Halt of trucks regulations	A federal appeals court halted the implementation of part of an Obama administration regulation that established emissions-reduction standards for truck trailers.

Table 2: Brief description of selected identified climate policy events.



(a) 1Y (Europe)

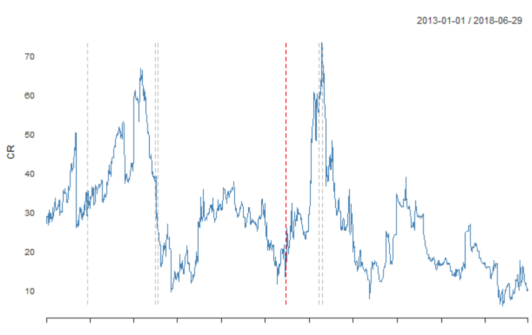
(b) 1Y (North America)

(c) 3Y (Europe)

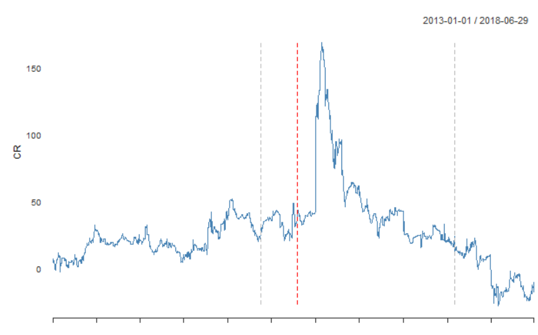
(d) 3Y (North America)

(e) 5Y (Europe)

(f) 5Y (North America)



(g) 10Y (Europe)



(h) 10Y (North America)

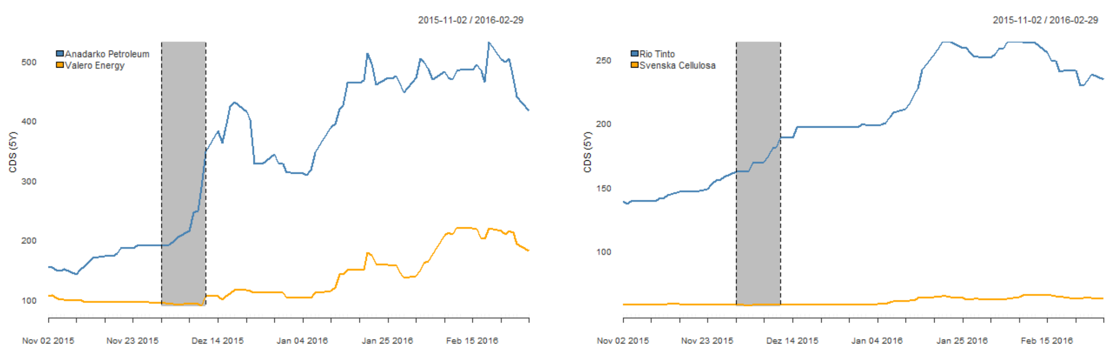
Figure 13: Evolution of CR factor over time for maturities 1Y (top), 3Y (top center), 5Y (bottom center) and 10Y (bottom) for Europe (left) and North America (right). The vertical solid lines indicate events where both the news index and the CR jointly deviate by a factor of 1.5 standard deviations from their respective means.

D 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 14 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 14: 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).

This figure exemplifies how the gap in CDS spreads expands following the Paris Agreement, underscoring the intuitive notion that lenders, in pursuit of greater protection, increase demand for the CDSs of firms more exposed to carbon risk (such as Anadarko Petroleum and Rio Tinto), leading to wider spreads.

E Constituents of clean & polluting class

Table 3 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 3: 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.

F 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 models) and find no significant differences. Results for these models are available upon request.

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.

F.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 4 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 4: 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 1000.

F.2 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, 2023; 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 factor 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 factor with the new CR factor in the base model from Section 4.1 to check the robustness of our baseline CR factor.

F.2.1 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 factor 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 5 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 5: 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 1000.

F.2.2 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). The literature notes a trend where firms with higher pollution levels are more frequently classified as value firms, while those with lower emissions are often seen as growth firms. In particular, Huij et al. (2021) observe that the most polluting firms typically align with value firms, whereas cleaner firms align with growth firms. Similarly, Pastor et al. (2021) find a negative correlation between their green factor and the value factor, indicating that value stocks are more likely to be associated with higher emissions than green stocks. Furthermore, Bauer et al. (2023) suggests that returns on a portfolio differential between high-emission (brown) and low-emission (green) firms positively correlate with the value factor. This implies that firms with higher emissions tend to be value stocks, while those with lower emissions tend to be categorized as growth stocks. 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 6 shows again that, using the B/M-adjusted CR factor, 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 6: 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 1000.

F.2.3 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 7 displays the results of the base model using the leverage-adjusted CR factor for Europe and North America, respectively. Again, using the leverage-adjusted CR factor 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 7: 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 1000.

G Online appendix

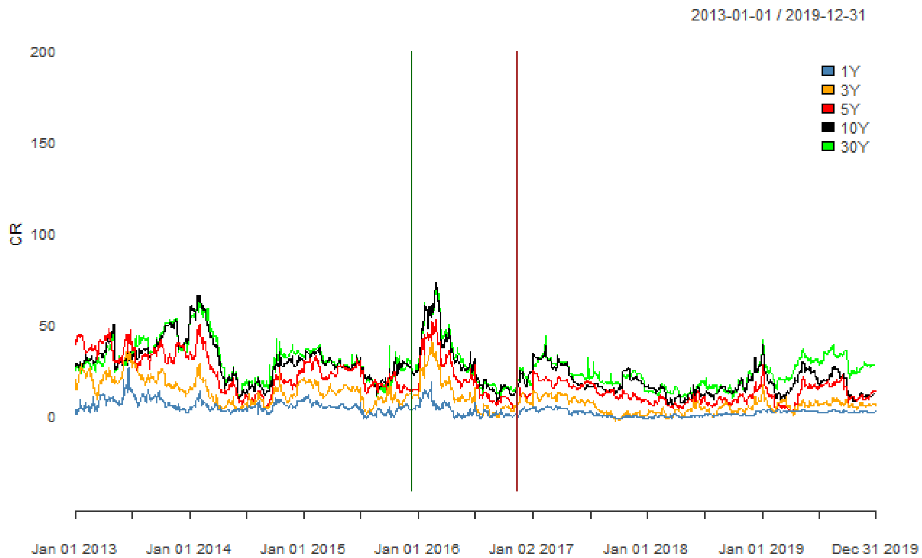
This section provides the complete list and description of figures and tables.

G.1 Additional figures

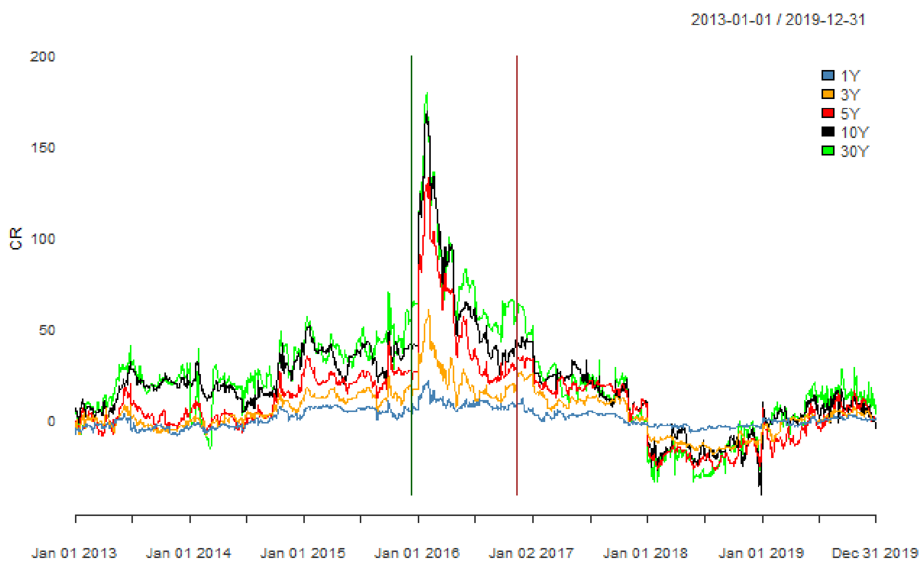
Figure 15 depicts the evolution of the CR factor for all tenors (1Y, 3Y, 5Y, 10Y, 30Y) in Europe (top) and North America (bottom). Figure 16 displays the evolution of the CR slope for all considered slopes (5Y-1Y, 10Y-5Y, 10Y-1Y) in Europe (top) and North America (bottom).

G.2 Additional tables

Table 8 and Table 9 present the estimates of the base model from Section 4.1 for all deciles and tenors in Europe and North America, respectively. Table 12 and Table 13 comprise the results of the ETS model from Section 4.2 for the remaining tenors 1Y, 3Y, 10Y, and 30Y in Europe and North America, respectively. Similarly, Table 14 and Table 15 depict the remaining ETS models but with the additional inclusion of the ETS share variable. Table 10 and Table 11 report the estimates of the interaction terms of the sector model for the remaining tenors 1Y, 3Y, 10Y and 30Y in Europe and North America, respectively. Finally, Table 16 and Table 17 report all coefficient estimates of the term structure model from Section 4.3 for all considered slopes in Europe and North America, respectively.

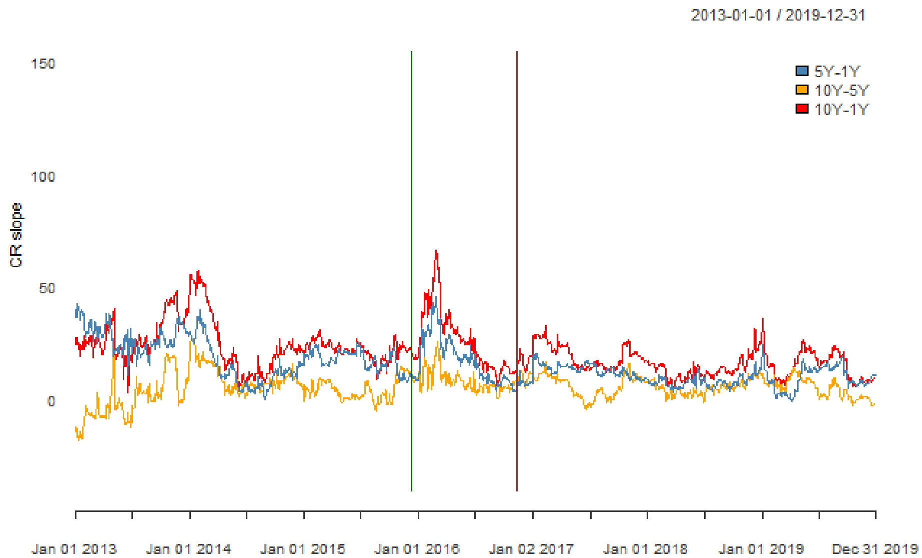


(a) Europe

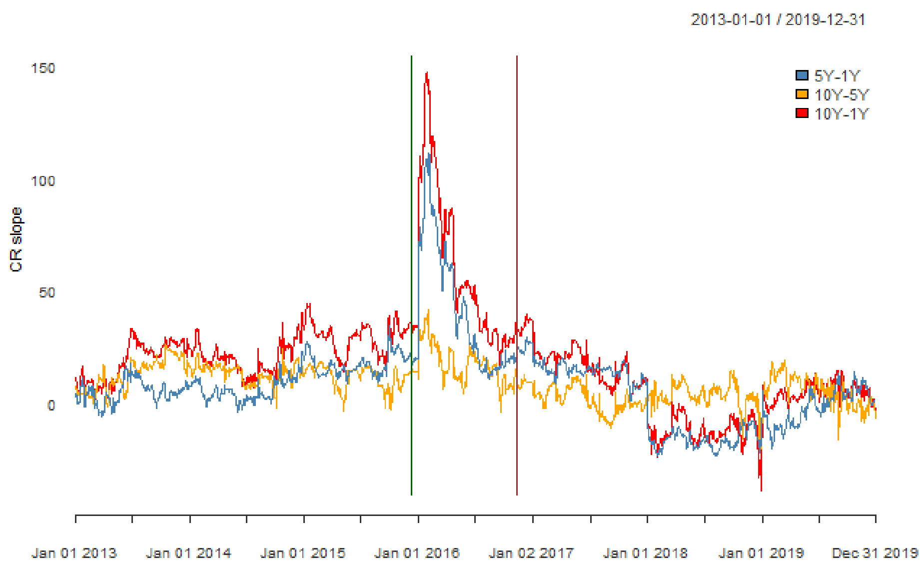


(b) North America

Figure 15: Evolution of the CR factor 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.



(a) Europe



(b) North America

Figure 16: Evolution of the CR slope over time for the slopes 5Y-1Y (blue), 10-5Y (orange), and 10Y-1Y (red) 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
					1Y				
StockReturn	−414.24***	−322.80***	−222.27***	−138.52***	−81.90***	−120.54***	−216.05***	−338.64***	−436.19***
	(14.24)	(8.91)	(6.64)	(4.62)	(3.36)	(4.06)	(6.08)	(13.07)	(23.71)
ΔVolatility	−581.53***	−448.71***	−285.46***	−103.03***	35.82*	308.53***	648.21***	930.61***	1106.00***
	(32.27)	(51.32)	(44.53)	(21.77)	(13.98)	(25.95)	(28.33)	(28.28)	(37.66)
ΔMRI	1608.99***	1619.83***	1543.03***	1471.78***	1433.21***	1454.27***	1561.10***	1699.73***	1831.08***
	(34.20)	(27.59)	(37.30)	(38.38)	(36.27)	(35.56)	(35.82)	(53.97)	(92.70)
ΔCR	349.28***	273.19***	217.40***	158.56***	126.31***	147.87***	207.46***	310.97***	445.79***
	(22.10)	(12.86)	(11.69)	(8.60)	(7.97)	(9.33)	(11.93)	(19.79)	(29.92)
					3Y				
StockReturn	−305.04***	−255.72***	−196.62***	−130.76***	−82.06***	−114.10***	−192.59***	−266.42***	−362.10***
	(8.06)	(5.98)	(5.17)	(4.27)	(3.23)	(3.53)	(4.64)	(8.50)	(15.23)
ΔVolatility	−500.54***	−370.70***	−250.35***	−96.80***	33.27*	285.55***	541.77***	715.75***	948.30***
	(59.56)	(41.39)	(30.33)	(23.46)	(14.55)	(18.82)	(12.34)	(27.28)	(30.33)
ΔMRI	638.54***	666.60***	668.00***	658.14***	645.99***	646.32***	676.72***	720.08***	748.49***
	(17.32)	(13.37)	(15.22)	(14.82)	(15.23)	(14.76)	(16.43)	(22.72)	(40.51)
ΔCR	271.37***	210.12***	159.27***	114.01***	87.44***	99.78***	141.18***	186.62***	239.89***
	(8.67)	(5.86)	(5.22)	(5.12)	(4.67)	(5.31)	(7.07)	(10.22)	(18.22)
					5Y				
StockReturn	−198.54***	−161.76***	−125.51***	−83.69***	−52.32***	−69.32***	−117.57***	−170.56***	−231.51***
	(4.95)	(3.82)	(3.25)	(2.64)	(2.00)	(2.08)	(2.82)	(4.77)	(9.14)
ΔVolatility	−335.62***	−224.24***	−153.43***	−66.25***	16.11·	166.52***	351.50***	502.85***	650.17***
	(20.04)	(21.60)	(18.36)	(13.06)	(8.43)	(11.68)	(11.26)	(9.29)	(11.76)
ΔMRI	379.33***	396.39***	396.99***	391.09***	388.15***	390.04***	405.07***	426.01***	447.97***
	(9.78)	(9.03)	(8.61)	(9.08)	(8.96)	(8.95)	(8.82)	(11.43)	(15.03)
ΔCR	132.63***	102.25***	80.67***	61.81***	50.97***	56.28***	73.61***	95.10***	115.18***
	(3.61)	(3.45)	(3.53)	(3.50)	(3.32)	(3.30)	(3.60)	(5.11)	(6.19)
					10Y				
StockReturn	−135.14***	−106.90***	−81.91***	−57.44***	−38.63***	−49.99***	−79.49***	−114.32***	−159.59***
	(3.35)	(2.48)	(2.18)	(1.75)	(1.44)	(1.56)	(1.90)	(3.23)	(6.46)
ΔVolatility	−234.11***	−169.29***	−110.08***	−50.62***	7.00·	101.25***	217.68***	334.65***	436.88***
	(13.59)	(13.91)	(13.26)	(8.67)	(4.00)	(8.16)	(6.93)	(6.24)	(7.88)
ΔMRI	264.37***	276.60***	275.59***	271.50***	270.45***	270.47***	279.03***	292.65***	304.63***
	(5.32)	(4.61)	(5.30)	(5.50)	(5.76)	(5.51)	(5.02)	(6.13)	(7.65)
ΔCR	80.74***	59.10***	48.20***	40.98***	34.46***	37.64***	48.25***	61.73***	76.91***
	(2.18)	(1.88)	(1.86)	(1.87)	(1.82)	(2.00)	(2.45)	(3.00)	(4.72)
					30Y				
StockReturn	−126.32***	−98.60***	−76.87***	−55.49***	−41.14***	−50.12***	−75.75***	−104.57***	−147.31***
	(3.55)	(2.48)	(2.01)	(1.67)	(1.49)	(1.54)	(2.04)	(3.20)	(6.74)
ΔVolatility	−244.66***	−168.41***	−101.83***	−40.59***	14.10*	103.93***	220.91***	304.64***	422.24***
	(23.54)	(14.65)	(14.64)	(9.32)	(6.17)	(7.51)	(8.30)	(6.16)	(7.54)
ΔMRI	289.35***	284.03***	278.48***	277.44***	277.52***	277.53***	284.71***	302.47***	326.61***
	(5.80)	(5.48)	(5.63)	(5.38)	(5.70)	(5.91)	(6.81)	(8.01)	(10.02)
ΔCR	53.77***	43.88***	35.92***	27.19***	21.41***	22.15***	29.17***	40.51***	48.73***
	(3.57)	(2.15)	(1.66)	(1.36)	(1.49)	(1.47)	(2.37)	(2.90)	(4.70)

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

Table 8: 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 119 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 1000.

	1	2	3	4	5	6	7	8	9
					1Y				
StockReturn	−257.76***	−150.49***	−99.87***	−56.37***	−18.97***	−46.77***	−89.46***	−154.38***	−274.10***
	(12.91)	(6.27)	(4.70)	(2.70)	(1.15)	(2.20)	(4.44)	(8.69)	(17.54)
ΔVolatility	−603.47***	−324.42***	−155.45***	−45.12***	6.69	138.80***	335.85**	621.86***	961.42***
	(35.80)	(37.56)	(19.47)	(9.99)	(4.39)	(7.72)	(114.31)	(30.31)	(100.12)
ΔMRI	768.00***	555.93***	362.05***	239.11***	136.48***	222.62***	373.83***	630.52***	1040.43***
	(42.05)	(29.46)	(23.18)	(16.64)	(11.85)	(17.43)	(26.55)	(38.02)	(74.67)
ΔCR	11.97	14.99***	12.90***	7.10***	1.79**	3.62**	11.52***	32.39***	76.53***
	(9.70)	(4.02)	(2.54)	(1.43)	(0.68)	(1.15)	(2.96)	(6.61)	(16.13)
					3Y				
StockReturn	−228.51***	−158.11***	−120.23***	−76.37***	−40.72***	−62.32***	−108.28***	−145.56***	−224.44***
	(7.07)	(4.45)	(4.04)	(2.84)	(1.63)	(2.13)	(3.25)	(5.94)	(10.94)
ΔVolatility	−378.54***	−244.02***	−144.90***	−60.46***	6.65	159.13***	322.92***	492.85***	742.54***
	(27.89)	(25.33)	(17.55)	(8.98)	(4.68)	(10.94)	(13.25)	(8.04)	(27.34)
ΔMRI	286.68***	272.58***	249.08***	212.44***	176.04***	204.91***	264.95***	326.87***	417.01***
	(10.64)	(10.83)	(11.32)	(10.55)	(7.47)	(9.41)	(10.37)	(12.68)	(15.79)
ΔCR	24.83***	13.59***	8.09***	4.30***	1.44**	0.43	2.64$^{\cdot}$	10.65***	23.55***
	(3.45)	(2.39)	(1.75)	(0.80)	(0.48)	(0.67)	(1.44)	(3.01)	(6.05)
					5Y				
StockReturn	−186.54***	−133.56***	−104.55***	−70.71***	−39.26***	−57.13***	−93.71***	−121.01***	−182.94***
	(4.94)	(3.50)	(3.34)	(2.61)	(1.60)	(1.97)	(2.74)	(4.66)	(6.66)
ΔVolatility	−326.67***	−210.57***	−125.13***	−50.43***	13.24*	149.31***	287.39***	421.39***	630.46***
	(14.61)	(19.41)	(14.78)	(9.92)	(5.70)	(11.15)	(10.07)	(5.34)	(8.88)
ΔMRI	205.82***	197.96***	187.41***	169.39***	156.34***	165.91***	196.38***	229.51***	283.21***
	(7.27)	(5.55)	(6.12)	(6.15)	(5.72)	(5.85)	(5.57)	(6.23)	(8.86)
ΔCR	18.27***	13.42***	8.71***	5.01***	2.64***	5.08***	10.85***	20.72***	37.96***
	(1.28)	(1.21)	(0.97)	(0.72)	(0.31)	(0.78)	(1.08)	(1.98)	(4.20)
					10Y				
StockReturn	−137.33***	−98.33***	−74.46***	−49.24***	−25.89***	−39.73***	−67.68***	−92.26***	−138.23***
	(3.33)	(2.62)	(2.34)	(1.91)	(1.14)	(1.44)	(2.11)	(3.69)	(5.83)
ΔVolatility	−232.67***	−158.29***	−88.52***	−34.26***	9.83*	107.87***	218.29***	316.94***	469.83***
	(12.97)	(11.45)	(10.38)	(8.26)	(4.05)	(6.98)	(8.39)	(3.07)	(10.83)
ΔMRI	128.02***	114.51***	102.64***	86.58***	72.55***	82.56***	104.78***	129.88***	168.73***
	(4.28)	(3.51)	(3.42)	(3.53)	(3.89)	(3.63)	(3.12)	(4.34)	(7.43)
ΔCR	10.61***	6.69***	4.33***	1.99***	0.61***	0.95***	1.46**	3.71***	8.41***
	(0.86)	(0.65)	(0.46)	(0.25)	(0.12)	(0.25)	(0.53)	(0.98)	(1.90)
					30Y				
StockReturn	−135.20***	−95.36***	−70.29***	−44.71***	−25.30***	−37.47***	−62.87***	−89.31***	−134.70***
	(3.79)	(2.60)	(2.28)	(1.68)	(1.08)	(1.38)	(1.95)	(3.48)	(5.20)
ΔVolatility	−250.30***	−158.14***	−89.52***	−33.64***	9.65*	102.11***	202.44***	308.35***	452.04***
	(3.49)	(6.72)	(11.28)	(6.94)	(4.17)	(7.27)	(6.61)	(6.37)	(5.88)
ΔMRI	94.95***	81.80***	71.09***	58.72***	48.48***	56.00***	74.73***	96.92***	128.66***
	(2.81)	(2.34)	(1.81)	(2.59)	(2.55)	(2.53)	(2.42)	(3.30)	(4.96)
ΔCR	4.89***	2.47***	1.78***	1.04***	0.41***	0.62**	1.30***	2.36***	5.66***
	(0.77)	(0.56)	(0.36)	(0.21)	(0.12)	(0.20)	(0.39)	(0.69)	(1.61)

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

Table 9: 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 164 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 1000.

	1	2	3	4	5	6	7	8	9	OLS
					1Y					
BM × ΔCR	293.26***	249.19***	176.74***	153.50***	111.95***	130.80***	171.07***	228.41***	364.07***	3.47**
	(28.95)	(30.40)	(22.44)	(17.68)	(17.48)	(20.47)	(23.00)	(42.74)	(59.14)	(1.08)
CCGS × ΔCR	243.55***	194.71***	166.33***	122.09***	94.54***	108.52***	162.88***	281.33***	357.80***	3.74***
	(28.86)	(38.88)	(31.40)	(20.93)	(18.93)	(20.70)	(33.61)	(53.14)	(86.13)	(1.08)
Energy × ΔCR	1179.29***	913.71***	742.05***	561.67***	488.17***	538.07***	621.18***	896.09***	1252.43***	14.01***
	(77.80)	(57.07)	(61.53)	(58.41)	(64.55)	(79.76)	(70.62)	(80.23)	(308.58)	(1.93)
Healthcare × ΔCR	78.08*	22.43	23.01	41.56·	19.59	27.44	51.43	145.61	386.37*	3.83·
	(38.42)	(88.98)	(32.43)	(24.13)	(15.67)	(21.60)	(42.36)	(123.16)	(189.00)	(2.29)
Industrials × ΔCR	326.33***	288.04***	229.64***	176.36***	135.68***	162.68***	222.92***	336.63***	503.82***	5.01***
	(59.65)	(29.01)	(27.08)	(22.13)	(18.35)	(24.23)	(26.30)	(37.23)	(60.98)	(1.15)
NCGS × ΔCR	225.36***	169.66***	110.55**	67.78***	40.47*	67.08**	109.21**	203.57*	322.13***	3.23***
	(62.66)	(49.71)	(36.12)	(19.99)	(17.44)	(22.05)	(38.36)	(82.37)	(58.46)	(0.75)
Real Estate × ΔCR	405.47***	298.54***	214.53**	147.78***	113.23*	134.34*	176.49**	340.55	598.63***	5.18***
	(113.50)	(78.21)	(70.25)	(30.94)	(49.25)	(63.54)	(62.29)	(208.80)	(180.36)	(0.68)
Technology × ΔCR	167.45	177.47***	168.90***	113.57***	93.49**	113.84***	151.22***	163.89*	207.61	1.01
	(111.30)	(40.63)	(45.94)	(28.75)	(28.86)	(34.21)	(43.13)	(74.39)	(169.20)	(0.96)
Utilities × ΔCR	783.37***	573.33***	467.30***	378.24***	326.59***	367.29***	482.21***	637.74***	766.52***	10.71***
	(80.79)	(61.17)	(44.67)	(42.89)	(40.50)	(50.08)	(58.92)	(81.79)	(198.56)	(1.78)
					3Y					
BM × ΔCR	302.68***	224.63***	164.49***	119.88***	87.59***	100.78***	143.08***	189.46***	259.34***	2.87***
	(21.08)	(13.70)	(12.36)	(12.23)	(9.88)	(11.47)	(13.56)	(22.82)	(45.84)	(0.49)
CCGS × ΔCR	220.22***	195.77***	142.11***	109.08***	83.13***	89.55***	118.42***	173.69***	216.36***	2.37***
	(28.72)	(17.96)	(12.43)	(11.90)	(10.34)	(12.02)	(16.84)	(19.14)	(62.53)	(0.55)
Energy × ΔCR	822.12***	763.24***	663.93***	539.73***	478.05***	493.70***	597.52***	768.69***	798.58***	7.65***
	(23.76)	(30.71)	(36.31)	(39.61)	(42.51)	(39.41)	(40.56)	(44.64)	(66.03)	(0.72)
Healthcare × ΔCR	243.61***	157.01***	93.93***	46.87**	26.28*	31.50*	55.74*	116.69***	217.83***	1.73*
	(26.82)	(28.28)	(23.53)	(17.73)	(12.65)	(15.65)	(21.72)	(32.53)	(57.62)	(0.87)
Industrials × ΔCR	251.88***	193.53***	139.21***	97.35***	72.57***	84.59***	120.06***	177.28***	242.40***	3.10***
	(32.45)	(19.05)	(12.48)	(12.41)	(10.39)	(12.01)	(14.42)	(19.76)	(50.35)	(0.57)
NCGS × ΔCR	175.56***	128.63***	86.59***	41.70***	22.07**	27.86***	48.73***	87.91**	118.40**	1.86***
	(26.42)	(19.45)	(11.10)	(8.43)	(7.47)	(8.16)	(12.26)	(28.36)	(36.78)	(0.40)
Real Estate × ΔCR	301.17***	177.27***	118.77***	74.05***	42.78*	52.51**	103.70***	181.36***	266.46***	2.92**
	(14.14)	(11.08)	(15.51)	(15.29)	(16.99)	(19.50)	(21.01)	(20.28)	(42.65)	(1.10)
Technology × ΔCR	205.85***	142.53***	119.68***	82.57***	57.15***	73.13***	95.19***	118.85***	184.08***	1.87***
	(18.87)	(17.22)	(14.97)	(13.06)	(12.14)	(14.75)	(17.34)	(29.53)	(27.87)	(0.48)
Utilities × ΔCR	362.32***	335.06***	316.88***	267.07***	212.86***	234.88***	298.31***	333.01***	372.49**	5.45***
	(34.59)	(29.72)	(27.84)	(27.08)	(22.68)	(24.10)	(29.76)	(44.72)	(114.18)	(0.91)
					10Y					
BM × ΔCR	93.60***	71.63***	55.16***	45.45***	39.26***	44.07***	56.17***	68.20***	92.32***	1.22***
	(4.95)	(5.98)	(4.53)	(4.48)	(5.04)	(5.47)	(4.17)	(7.11)	(7.43)	(0.14)
CCGS × ΔCR	86.06***	61.58***	47.07***	42.68***	34.20***	38.71***	49.27***	66.30***	82.63***	0.96***
	(4.55)	(4.16)	(3.91)	(4.08)	(4.09)	(5.25)	(6.07)	(9.05)	(8.84)	(0.16)
Energy × ΔCR	279.69***	280.96***	250.26***	218.01***	197.83***	198.38***	222.27***	267.21***	314.60***	2.94***
	(21.25)	(31.24)	(24.89)	(27.86)	(25.97)	(30.27)	(27.10)	(22.24)	(27.80)	(0.16)
Healthcare × ΔCR	82.32***	60.32***	50.36***	32.24***	29.10**	35.07***	39.39***	54.98***	77.63***	0.98***
	(6.82)	(7.27)	(9.93)	(9.58)	(9.22)	(8.45)	(11.97)	(16.03)	(16.77)	(0.23)
Industrials × ΔCR	71.96***	50.36***	41.48***	31.92***	28.34***	31.77***	42.04***	54.71***	60.72**	0.84***
	(9.50)	(5.12)	(3.52)	(4.32)	(5.10)	(4.20)	(4.83)	(7.26)	(23.57)	(0.18)
NCGS × ΔCR	44.40***	28.18***	18.58***	12.60***	7.94***	9.98**	17.36***	20.83***	35.30**	0.38*
	(5.21)	(6.55)	(3.60)	(2.32)	(2.30)	(3.21)	(3.34)	(6.23)	(11.47)	(0.15)
Real Estate × ΔCR	65.74**	30.80***	22.15***	14.61*	12.50**	16.07·	16.61*	28.56*	64.66·	0.80**
	(22.47)	(5.30)	(4.48)	(6.86)	(3.90)	(8.47)	(6.52)	(11.60)	(33.79)	(0.26)
Technology × ΔCR	73.78***	47.75***	40.23***	31.71***	24.90***	27.50***	32.97***	39.11***	47.08***	0.78***
	(5.80)	(4.75)	(4.68)	(3.55)	(3.07)	(3.87)	(4.62)	(10.30)	(4.32)	(0.13)
Utilities × ΔCR	103.31***	87.89***	85.59***	76.75***	68.16***	73.45***	88.03***	100.57***	114.53***	1.82***
	(6.82)	(6.76)	(12.19)	(9.86)	(9.96)	(10.17)	(12.50)	(16.39)	(30.19)	(0.28)
					30Y					
BM × ΔCR	82.11***	60.36***	45.06***	37.05***	29.26***	28.89***	38.60***	50.88***	62.07***	0.52***
	(6.51)	(3.68)	(2.99)	(3.49)	(3.56)	(4.16)	(6.14)	(6.37)	(7.96)	(0.15)
CCGS × ΔCR	43.45***	41.60***	36.65***	27.81***	20.07***	21.86***	27.76***	39.33***	45.82**	0.05
	(11.60)	(5.49)	(3.30)	(3.08)	(3.25)	(3.02)	(5.10)	(5.04)	(14.69)	(0.16)
Energy × ΔCR	164.56***	138.24***	127.73***	111.04***	99.81***	100.51***	119.28***	149.84***	195.08***	1.33***
	(10.03)	(18.33)	(26.58)	(20.06)	(18.57)	(18.71)	(21.42)	(26.65)	(31.21)	(0.21)
Healthcare × ΔCR	90.72***	54.16***	35.24***	22.59***	15.87***	17.59**	29.47**	44.34**	57.78***	0.20*
	(7.39)	(6.61)	(9.54)	(5.78)	(4.55)	(5.55)	(9.74)	(16.37)	(12.97)	(0.10)
Industrials × ΔCR	24.46***	31.67***	26.26***	20.33***	14.72***	16.16***	19.44***	29.23***	33.60*	−0.24
	(4.94)	(4.27)	(4.67)	(4.11)	(2.68)	(3.08)	(4.97)	(7.73)	(15.76)	(0.20)
NCGS × ΔCR	15.16*	17.08***	13.77***	9.47***	5.88*	5.84·	8.24·	12.95	24.01*	−0.31
	(5.89)	(4.58)	(4.11)	(2.71)	(2.69)	(3.39)	(4.94)	(8.93)	(11.36)	(0.23)
Real Estate × ΔCR	46.10***	33.47***	24.56***	11.87*	14.49**	13.19	17.14*	21.90	57.14**	−0.12
	(5.99)	(4.51)	(5.86)	(5.74)	(4.61)	(10.08)	(7.63)	(26.09)	(20.91)	(0.10)
Technology × ΔCR	11.71	23.08*	22.71***	17.27***	11.30**	11.13*	11.02·	8.76	12.11	−0.51**
	(20.71)	(10.60)	(6.11)	(3.72)	(4.21)	(5.43)	(5.72)	(8.20)	(14.93)	(0.17)
Utilities × ΔCR	81.66***	66.92***	54.01***	47.75***	42.01***	46.62***	59.14***	67.39***	78.00**	0.91***
	(5.88)	(6.50)	(5.64)	(9.82)	(8.22)	(8.04)	(9.82)	(8.78)	(24.91)	(0.23)

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

Table 10: This table reports the coefficient estimates of the interaction terms of the sector panel quantile and mean regression model for 1-year (top), 3-year (upper center), 10-year (lower center), and 30-year (bottom) CDS spread returns in Europe. The sample comprises data from 119 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 1000.

	1	2	3	4	5	6	7	8	9	OLS
					1Y					
BM × ΔCR	456.23***	223.27***	105.22***	46.42***	14.87***	30.19***	77.72***	208.26***	509.26***	5.35***
	(74.93)	(23.45)	(16.54)	(7.15)	(3.53)	(5.90)	(16.46)	(40.86)	(143.50)	(0.96)
CCGS × ΔCR	−118.49**	−49.06·	−16.16	−2.79	−1.35	−7.08*	−21.60*	−16.83	−53.49	−1.30
	(36.24)	(26.51)	(10.83)	(3.93)	(1.87)	(3.50)	(10.22)	(17.60)	(52.53)	(0.89)
Energy × ΔCR	415.18***	197.99***	112.11***	53.68***	17.91***	36.99***	76.64***	199.57***	474.54***	3.99***
	(78.37)	(26.58)	(11.41)	(7.85)	(3.79)	(5.91)	(12.45)	(34.39)	(101.72)	(1.21)
Healthcare × ΔCR	−147.04**	−39.87**	−10.71·	−1.25	−0.02	−0.27	−3.81	0.05	42.50	−0.25
	(49.89)	(13.33)	(6.21)	(2.81)	(1.56)	(2.36)	(5.94)	(14.96)	(56.88)	(0.58)
Industrials × ΔCR	99.84**	29.94·	18.70*	8.16·	2.22	4.55	23.64**	60.82*	157.84·	2.38***
	(31.08)	(18.15)	(7.93)	(4.38)	(1.87)	(2.95)	(9.08)	(25.44)	(81.83)	(0.65)
NCGS × ΔCR	−38.99	−3.29	−0.79	−0.18	−0.18	0.56	4.39	21.28	74.18·	1.44*
	(24.09)	(10.90)	(4.74)	(2.02)	(1.07)	(1.85)	(5.03)	(14.37)	(41.79)	(0.56)
Real Estate × ΔCR	72.93*	−81.87**	−9.59	7.18	2.61	9.83	14.82	107.87*	124.35	0.98
	(30.32)	(25.52)	(10.62)	(9.30)	(5.19)	(8.32)	(19.14)	(45.88)	(216.43)	(1.54)
Technology × ΔCR	−128.44***	−32.16·	−6.84	−0.38	−0.05	−2.46	−7.44	−0.84	1.69	−1.36
	(29.64)	(18.29)	(7.92)	(2.51)	(1.37)	(2.56)	(8.99)	(22.67)	(89.35)	(1.13)
Utilities × ΔCR	465.22***	150.10***	45.13***	18.99***	5.78*	12.47*	27.48*	141.75**	330.75**	3.13*
	(27.78)	(41.91)	(10.74)	(5.23)	(2.77)	(5.53)	(11.78)	(46.96)	(102.71)	(1.23)
					3Y					
BM × ΔCR	145.18***	90.11***	54.99***	29.54***	14.72***	18.96***	47.62***	91.20***	169.47***	1.79***
	(11.50)	(11.32)	(8.74)	(4.80)	(3.66)	(4.77)	(8.61)	(18.53)	(39.58)	(0.36)
CCGS × ΔCR	−20.28*	−10.89	−11.79*	−4.95·	−2.16	−4.95**	−14.51**	−8.22	−0.70	−0.03
	(8.28)	(10.22)	(5.26)	(2.66)	(1.32)	(1.61)	(5.55)	(6.62)	(15.80)	(0.16)
Energy × ΔCR	169.18***	107.83***	66.51***	37.47***	15.47***	21.16***	44.92***	81.74***	186.76***	1.75***
	(11.72)	(10.85)	(8.78)	(5.53)	(3.58)	(5.00)	(7.70)	(15.20)	(33.86)	(0.29)
Healthcare × ΔCR	12.10	2.70	0.28	−0.29	−0.55	−2.50	−3.23	2.84	15.88	0.18
	(12.25)	(6.24)	(4.34)	(1.84)	(1.10)	(1.56)	(3.71)	(8.33)	(17.09)	(0.16)
Industrials × ΔCR	22.74	11.90	9.33*	5.21*	1.17	0.22	2.45	8.07	26.24	0.32*
	(14.50)	(7.44)	(3.62)	(2.41)	(1.47)	(2.15)	(5.02)	(13.66)	(31.16)	(0.16)
NCGS × ΔCR	20.64**	13.55***	5.68*	2.75*	0.57	−0.46	0.95	4.94	20.23	0.57***
	(7.14)	(3.20)	(2.56)	(1.24)	(0.97)	(1.12)	(2.21)	(8.42)	(16.14)	(0.13)
Real Estate × ΔCR	21.14	12.86	−19.59	−4.68	0.92	−1.54	−3.02	29.68	−30.21	0.74
	(40.95)	(35.25)	(21.16)	(11.46)	(5.69)	(7.10)	(23.74)	(46.47)	(44.66)	(0.51)
Technology × ΔCR	−17.55	−6.60	−5.80	−0.66	−0.29	−1.86	−3.70	0.55	−9.83	0.03
	(15.24)	(7.02)	(5.40)	(2.20)	(1.08)	(1.83)	(3.21)	(8.07)	(18.62)	(0.30)
Utilities × ΔCR	58.20	45.39***	12.30**	2.74	1.85	0.13	−2.29	15.44	56.51	0.44*
	(53.27)	(12.99)	(4.66)	(2.40)	(1.32)	(1.88)	(6.21)	(14.37)	(61.66)	(0.20)
					10Y					
BM × ΔCR	28.53***	17.69***	12.61***	7.88***	4.11***	5.53**	12.68***	25.80***	48.14***	0.54***
	(1.27)	(2.03)	(2.55)	(1.82)	(1.03)	(1.88)	(3.20)	(4.69)	(9.41)	(0.11)
CCGS × ΔCR	16.38***	10.66***	6.40***	2.89***	0.84**	1.75**	3.51·	6.45*	13.79·	0.14***
	(1.04)	(0.71)	(0.47)	(0.48)	(0.29)	(0.68)	(2.04)	(2.70)	(7.25)	(0.04)
Energy × ΔCR	33.91***	23.15***	13.15***	7.52***	3.95***	5.95**	11.94***	31.39***	77.81***	0.63***
	(1.28)	(2.79)	(3.12)	(1.51)	(0.79)	(1.91)	(3.50)	(5.17)	(10.60)	(0.10)
Healthcare × ΔCR	−2.52	−0.56	−0.33	−0.02	0.00	−0.27	−0.88	−1.27	−4.37**	−0.01
	(4.78)	(2.63)	(1.16)	(0.47)	(0.18)	(0.30)	(0.60)	(1.51)	(1.41)	(0.04)
Industrials × ΔCR	6.13***	3.52·	2.35*	0.72	0.29	0.04	0.20	1.70	−3.63	0.11**
	(1.33)	(2.08)	(1.11)	(0.44)	(0.26)	(0.40)	(1.10)	(3.68)	(6.14)	(0.04)
NCGS × ΔCR	−5.73***	−1.44	0.60	0.20	0.02	−0.26	−0.48	−0.63	−2.70	−0.01
	(0.92)	(1.70)	(0.41)	(0.26)	(0.16)	(0.25)	(0.59)	(0.93)	(6.67)	(0.05)
Real Estate × ΔCR	23.17***	11.86***	12.63***	3.98	1.67	3.28·	8.56*	17.43***	11.05·	0.43***
	(0.58)	(0.90)	(2.64)	(5.57)	(2.37)	(1.96)	(4.10)	(4.82)	(5.79)	(0.07)
Technology × ΔCR	3.25	1.04	0.56	0.45	0.23	−0.19	−1.00	−1.13	−1.28	−0.00
	(3.44)	(3.51)	(1.10)	(0.40)	(0.29)	(0.28)	(0.77)	(1.04)	(1.94)	(0.09)
Utilities × ΔCR	19.10***	9.86***	4.46***	2.64·	1.47·	2.16·	3.63***	11.97*	49.64***	0.32***
	(0.43)	(1.91)	(0.78)	(1.50)	(0.89)	(1.16)	(0.93)	(5.12)	(6.68)	(0.08)
					30Y					
BM × ΔCR	26.09***	17.68***	11.50***	6.71***	4.35***	6.13***	11.42***	19.23***	38.57***	0.56***
	(1.67)	(3.07)	(2.12)	(1.12)	(0.90)	(1.03)	(2.44)	(3.23)	(5.66)	(0.09)
CCGS × ΔCR	−1.54	0.05	0.16	0.11	0.32	0.23	0.61	1.23	0.36	−0.02
	(3.14)	(1.94)	(0.92)	(0.56)	(0.27)	(0.39)	(1.04)	(2.37)	(4.25)	(0.04)
Energy × ΔCR	41.53***	21.13***	12.00***	6.67***	4.10***	4.99***	10.78***	22.91***	56.20***	0.53***
	(2.78)	(2.96)	(2.25)	(1.47)	(1.15)	(1.10)	(2.27)	(3.83)	(5.46)	(0.12)
Healthcare × ΔCR	−3.00·	−1.55	−1.12	−0.93·	−0.31	−0.77·	−1.56	−5.63**	−8.15***	−0.04
	(1.69)	(1.58)	(1.30)	(0.55)	(0.34)	(0.46)	(1.16)	(1.91)	(1.54)	(0.07)
Industrials × ΔCR	2.80	0.69	1.92**	0.71	0.07	−0.21	0.30	1.47	4.85	0.14**
	(4.43)	(3.07)	(0.74)	(0.52)	(0.34)	(0.47)	(1.31)	(2.53)	(6.57)	(0.05)
NCGS × ΔCR	1.11	0.60	0.34	0.22	0.13	−0.02	0.07	0.02	−1.54	0.02
	(2.72)	(1.29)	(0.75)	(0.35)	(0.22)	(0.26)	(0.63)	(1.68)	(6.06)	(0.08)
Real Estate × ΔCR	8.93***	−9.10·	−5.79	−3.73	−0.57	−0.57	−2.88	−4.83	−19.65	0.14*
	(0.62)	(5.36)	(3.66)	(2.61)	(2.01)	(1.59)	(3.15)	(7.63)	(19.43)	(0.06)
Technology × ΔCR	−3.02	−3.32*	−0.05	0.33	0.14	0.12	0.04	0.93	2.91	−0.10
	(2.18)	(1.59)	(1.34)	(0.70)	(0.31)	(0.38)	(1.13)	(1.33)	(4.92)	(0.13)
Utilities × ΔCR	14.10	5.15·	2.68·	1.08·	0.34	−0.07	2.06	7.71*	22.84***	0.12**
	(14.74)	(2.66)	(1.44)	(0.56)	(0.36)	(0.44)	(2.00)	(3.17)	(5.84)	(0.04)

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

Table 11: This table reports the coefficient estimates of the interaction terms of the sector panel quantile and mean regression model for 1-year (top), 3-year (upper center), 10-year (lower center), and 30-year (bottom) CDS spread returns in North America. The sample comprises data from 164 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 1000.

	1	2	3	4	5	6	7	8	9	OLS
					1Y					
ΔCR $\times$ ETS (No response)	108.39**	141.01***	134.07***	99.73***	74.85***	86.67***	127.42***	174.30**	304.91**	3.15**
	(34.19)	(31.07)	(21.60)	(16.52)	(15.84)	(16.59)	(24.75)	(54.43)	(95.00)	(1.01)
ΔCR $\times$ ETS (No)	187.61***	171.87***	137.42***	88.58***	77.38***	92.09***	133.45***	196.71***	281.48**	2.29***
	(33.26)	(32.24)	(30.51)	(18.42)	(16.01)	(19.40)	(24.20)	(48.03)	(90.16)	(0.68)
ΔCR $\times$ ETS (No but anticipation)	202.67	102.45***	187.90***	142.12***	132.36***	181.16**	260.57***	302.82**	103.91	4.05***
		(23.98)	(49.21)	(39.97)	(38.70)	(60.75)	(78.58)	(116.80)	(170.81)	(1.23)
ΔCR $\times$ ETS (Yes)	569.94***	421.10***	315.40***	229.10***	180.19***	214.36***	295.08***	455.17***	647.81***	6.96***
	(41.30)	(21.32)	(17.56)	(13.70)	(12.88)	(16.24)	(22.54)	(26.50)	(50.30)	(0.73)
					3Y					
ΔCR $\times$ ETS (No response)	135.33***	132.91***	114.63***	75.59***	51.11***	59.60***	90.05***	120.36***	112.13***	2.21***
	(21.60)	(14.34)	(11.10)	(9.87)	(8.90)	(9.32)	(15.02)	(23.14)	(28.64)	(0.46)
ΔCR $\times$ ETS (No)	188.75***	128.01***	94.26***	63.26***	44.67***	56.00***	80.63***	117.39***	160.78***	1.80***
	(15.40)	(15.78)	(10.66)	(8.12)	(6.87)	(8.87)	(11.14)	(17.82)	(28.03)	(0.30)
ΔCR $\times$ ETS (No but anticipation)	8.26	53.24	40.75	25.61	28.39	33.87	13.35	57.88	91.29**	0.68
	(38.95)	(44.04)	(25.79)	(18.90)	(19.63)	(21.37)	(23.53)	(37.22)	(31.41)	(0.42)
ΔCR $\times$ ETS (Yes)	398.49***	306.94***	234.88***	177.74***	135.57***	147.95***	209.75***	281.86***	386.74***	4.11***
	(13.35)	(9.64)	(9.11)	(9.63)	(8.09)	(8.18)	(11.30)	(15.36)	(27.12)	(0.36)
					10Y					
ΔCR $\times$ ETS (No response)	58.08***	46.32***	35.46***	28.39***	22.55***	24.50***	33.53***	40.52***	48.05***	0.86***
	(6.89)	(3.07)	(3.14)	(3.47)	(2.58)	(3.58)	(4.74)	(7.21)	(6.08)	(0.16)
ΔCR $\times$ ETS (No)	56.30***	38.11***	32.79***	26.87***	22.61***	23.08***	28.87***	36.45***	48.31***	0.66***
	(8.72)	(3.77)	(2.50)	(2.40)	(1.71)	(2.25)	(3.14)	(6.16)	(4.64)	(0.10)
ΔCR $\times$ ETS (No but anticipation)	5.70	18.28***	19.75	8.25	0.57	8.78	8.64	3.58	-27.82^{***}	0.32$^{\cdot}$
	(3.88)	(3.74)	(14.06)	(11.49)	(7.30)	(8.34)	(8.35)	(11.66)	(6.15)	(0.17)
ΔCR $\times$ ETS (Yes)	113.10***	87.93***	73.37***	60.54***	51.28***	56.12***	69.01***	89.16***	117.23***	1.42***
	(3.61)	(3.44)	(3.96)	(3.59)	(3.39)	(3.54)	(3.66)	(6.27)	(6.58)	(0.12)
					30Y					
ΔCR $\times$ ETS (No response)	23.31***	25.61***	23.29***	18.52***	12.71***	12.95***	16.43***	20.64***	19.94	-0.14
	(6.21)	(5.50)	(3.64)	(3.16)	(2.41)	(3.10)	(4.20)	(5.57)	(18.08)	(0.16)
ΔCR $\times$ ETS (No)	16.72***	23.53***	23.40***	17.14***	11.61***	12.25***	14.56***	19.75**	25.85**	-0.27
	(4.92)	(4.38)	(3.99)	(2.58)	(2.72)	(2.99)	(3.07)	(6.31)	(8.16)	(0.18)
ΔCR $\times$ ETS (No but anticipation)	-15.02	-3.22	-3.00	-9.85	-6.99	-5.54	-8.89	-24.43	-38.16	-0.57
	(9.31)	(9.38)	(13.19)	(18.89)	(10.18)	(8.45)	(14.76)	(18.96)	(38.20)	(0.35)
ΔCR $\times$ ETS (Yes)	86.22***	63.24***	49.08***	37.98***	32.17***	34.97***	46.50***	59.54***	76.51***	0.51***
	(3.25)	(2.47)	(2.18)	(2.31)	(2.64)	(3.09)	(3.37)	(3.75)	(4.84)	(0.12)

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

Table 12: This table reports the coefficient estimates of the interaction terms of the ETS panel quantile and mean regression model for 1-year (top), 3-year (upper center), 10-year (lower center), and 30-year (bottom) CDS spread returns in Europe. The sample comprises data from 119 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 1000.

	1	2	3	4	5	6	7	8	9	OLS
1Y										
ΔCR × ETS (No response)	38.39	21.37*	11.51*	6.74**	1.56	4.06*	11.80*	48.51**	103.27*	0.24
	(35.05)	(10.17)	(4.89)	(2.29)	(1.22)	(2.04)	(5.59)	(15.89)	(43.68)	(0.76)
ΔCR × ETS (No)	−66.54**	−17.25$^{\cdot}$	2.32	1.31	0.04	−1.29	−0.80	6.87	29.63	0.32
	(23.46)	(9.97)	(3.90)	(2.01)	(0.96)	(1.72)	(4.64)	(12.51)	(44.52)	(0.62)
ΔCR × ETS (No but anticipation)	29.55	58.34	33.64*	20.17***	5.42	12.60*	40.19*	114.14**	270.31**	2.03**
	(198.52)	(61.01)	(16.53)	(6.07)	(3.41)	(5.77)	(16.00)	(42.44)	(99.15)	(0.76)
ΔCR × ETS (Yes)	177.26***	60.61***	32.45***	14.62***	4.08**	9.56***	28.27***	85.08***	214.07*	3.03***
	(48.99)	(14.55)	(7.30)	(3.46)	(1.47)	(2.70)	(6.49)	(19.38)	(104.40)	(0.63)
3Y										
ΔCR × ETS (No response)	26.32**	25.32***	12.18***	4.68**	1.26	−0.01	2.59	11.57*	27.92*	0.46**
	(8.03)	(5.96)	(3.15)	(1.44)	(0.87)	(1.18)	(3.12)	(4.84)	(11.19)	(0.16)
ΔCR × ETS (No)	2.65	4.51	1.30	0.95	0.03	−1.54	−0.67	4.66	8.91	0.25$^{\cdot}$
	(7.94)	(4.56)	(3.09)	(1.23)	(0.68)	(1.12)	(2.47)	(5.74)	(15.72)	(0.15)
ΔCR × ETS (No but anticipation)	64.39***	48.01*	17.63	5.86	2.41	−0.91	0.64	19.19	76.73***	0.44
	(12.55)	(20.21)	(11.06)	(3.62)	(2.48)	(2.95)	(9.26)	(14.52)	(14.51)	(0.43)
ΔCR × ETS (Yes)	87.75***	36.32***	18.32***	6.84***	2.95**	3.91**	11.15*	30.95***	68.99*	0.93***
	(17.24)	(7.37)	(4.32)	(1.72)	(0.92)	(1.37)	(4.72)	(8.27)	(27.21)	(0.19)
10Y										
ΔCR × ETS (No response)	15.77***	9.55***	5.88***	2.75***	0.78***	0.90*	1.81	4.93***	9.52*	0.19***
	(1.60)	(0.98)	(0.49)	(0.43)	(0.23)	(0.42)	(1.14)	(1.25)	(3.78)	(0.04)
ΔCR × ETS (No)	4.14***	2.32*	1.58**	0.91**	0.44**	0.51$^{\cdot}$	0.47	1.26	5.16	0.09*
	(0.90)	(0.99)	(0.60)	(0.30)	(0.17)	(0.26)	(0.53)	(1.95)	(4.13)	(0.04)
ΔCR × ETS (No but anticipation)	18.10***	9.30***	5.53***	2.09*	1.34	1.54	3.39	9.90$^{\cdot}$	22.66	0.19***
	(1.00)	(1.20)	(1.26)	(1.07)	(0.97)	(1.16)	(4.96)	(5.53)	(15.10)	(0.05)
ΔCR × ETS (Yes)	19.53***	10.06***	6.08***	2.62***	1.00**	1.84**	4.26***	10.54***	22.49**	0.30***
	(1.03)	(1.23)	(0.53)	(0.58)	(0.34)	(0.62)	(0.90)	(3.14)	(8.72)	(0.06)
30Y										
ΔCR × ETS (No response)	9.14***	5.92***	4.00***	2.03***	0.70**	1.46***	2.80***	5.97***	13.33***	0.15**
	(1.44)	(1.10)	(0.83)	(0.41)	(0.25)	(0.39)	(0.70)	(1.20)	(2.25)	(0.05)
ΔCR × ETS (No)	0.86	−0.31	0.32	−0.00	0.08	−0.07	0.08	−0.17	−1.54	−0.02
	(1.96)	(0.98)	(0.73)	(0.37)	(0.19)	(0.29)	(0.55)	(1.27)	(2.71)	(0.06)
ΔCR × ETS (No but anticipation)	19.36	8.50	3.38	1.30	0.43	0.32	0.59	2.53	14.73	0.22*
	(13.61)	(8.83)	(4.30)	(1.38)	(0.80)	(1.04)	(2.99)	(2.98)	(20.96)	(0.11)
ΔCR × ETS (Yes)	8.78***	4.41**	3.29***	1.46**	0.52*	1.08*	2.20*	5.48**	10.67*	0.22***
	(1.48)	(1.70)	(0.72)	(0.45)	(0.23)	(0.42)	(1.03)	(1.75)	(4.68)	(0.06)

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

Table 13: This table reports the coefficient estimates of the interaction terms of the ETS panel quantile and mean regression model for 1-year (top), 3-year (upper center), 10-year (lower center), and 30-year (bottom) CDS spread returns in North America. The sample comprises data from 164 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 1000.

	1	2	3	4	5	6	7	8	9	OLS
1Y										
ΔCR $\times$ ETS (No response)	108.59**	140.94***	134.19***	99.71***	75.08***	86.68***	127.42***	174.26**	304.95**	3.15**
	(34.01)	(31.00)	(21.55)	(16.52)	(15.84)	(16.59)	(24.76)	(54.35)	(95.02)	(1.01)
ΔCR $\times$ ETS (Yes) $\times$ ETS Share	15.52	−54.43	65.67	106.48**	107.50*	128.19**	102.62	4.95	50.19	2.78
	(117.61)	(63.83)	(55.24)	(40.12)	(45.59)	(46.41)	(75.33)	(92.60)	(187.80)	(2.32)
ΔCR $\times$ ETS (No)	187.73***	171.86***	137.45***	88.70***	77.32***	92.07***	133.21***	197.19***	281.18**	2.29***
	(32.97)	(32.23)	(30.52)	(18.43)	(16.00)	(19.46)	(24.16)	(48.27)	(90.00)	(0.68)
ΔCR $\times$ ETS (No but anticipation)	202.65	102.53***	187.75***	142.14***	132.38***	181.17**	260.39***	302.99**	104.66	4.05***
		(24.00)	(49.20)	(39.95)	(38.69)	(60.72)	(78.64)	(117.59)	(170.71)	(1.23)
ΔCR $\times$ ETS (Yes)	563.55***	441.83***	285.42***	188.53***	140.83***	166.74***	255.39***	454.10***	636.31***	5.95***
	(83.26)	(37.07)	(28.18)	(20.68)	(17.82)	(22.62)	(30.58)	(35.54)	(66.48)	(0.93)
3Y										
ΔCR $\times$ ETS (No response)	135.33***	132.82***	114.85***	75.60***	51.20***	59.60***	90.04***	120.37***	112.78***	2.22***
	(21.60)	(14.34)	(11.12)	(9.86)	(8.91)	(9.29)	(15.00)	(23.14)	(28.26)	(0.46)
ΔCR $\times$ ETS (Yes) $\times$ ETS Share	4.06	41.38	63.90*	108.72***	103.61***	112.94***	114.73***	57.57	4.08	1.24
	(39.93)	(27.08)	(29.06)	(31.97)	(26.13)	(26.86)	(32.14)	(38.13)	(85.46)	(1.11)
ΔCR $\times$ ETS (No)	188.63***	128.13***	94.12***	63.56***	44.88***	55.72***	80.39***	117.39***	160.58***	1.80***
	(15.42)	(15.74)	(10.65)	(8.12)	(6.89)	(8.85)	(11.10)	(17.78)	(28.07)	(0.30)
ΔCR $\times$ ETS (No but anticipation)	8.14	53.01	41.65	25.70	28.12	33.61	13.27	57.62	91.16**	0.69
	(38.84)	(44.05)	(26.16)	(18.88)	(19.63)	(21.46)	(23.57)	(37.67)	(31.24)	(0.42)
ΔCR $\times$ ETS (Yes)	396.92***	291.43***	211.89***	138.37***	99.12***	109.85***	167.71***	261.61***	385.34***	3.64***
	(18.29)	(13.36)	(11.68)	(12.24)	(10.72)	(11.03)	(13.91)	(18.83)	(40.03)	(0.49)
10Y										
ΔCR $\times$ ETS (No response)	58.31***	46.32***	35.47***	28.37***	22.53***	24.53***	33.62***	40.50***	47.77***	0.86***
	(7.14)	(3.06)	(3.14)	(3.46)	(2.58)	(3.59)	(4.74)	(7.21)	(5.60)	(0.16)
ΔCR $\times$ ETS (Yes) $\times$ ETS Share	37.92*	39.86***	47.37***	54.84***	53.10***	52.68***	50.90***	37.17*	37.45	0.88*
	(14.82)	(11.78)	(12.36)	(11.84)	(10.06)	(10.46)	(12.40)	(15.15)	(25.33)	(0.39)
ΔCR $\times$ ETS (No)	56.43***	38.12***	32.89***	26.89***	22.59***	23.06***	28.92***	36.51***	48.23***	0.66***
	(8.83)	(3.78)	(2.52)	(2.39)	(1.71)	(2.24)	(3.15)	(6.13)	(4.65)	(0.10)
ΔCR $\times$ ETS (No but anticipation)	5.70	18.30***	19.68	8.27	0.56	8.75	8.59	3.60	−27.88***	0.32$^{\cdot}$
	(3.89)	(3.75)	(13.95)	(11.44)	(7.28)	(8.33)	(8.36)	(11.64)	(6.16)	(0.17)
ΔCR $\times$ ETS (Yes)	98.85***	74.05***	57.41***	42.11***	33.24***	37.84***	51.79***	77.09***	102.43***	1.09***
	(7.07)	(5.25)	(4.66)	(4.46)	(4.12)	(4.63)	(4.68)	(6.47)	(11.79)	(0.18)
30Y										
ΔCR $\times$ ETS (No response)	23.35***	25.64***	23.24***	18.48***	12.61***	12.95***	16.40***	20.62***	19.86	−0.14
	(6.08)	(5.55)	(3.64)	(3.15)	(2.43)	(3.10)	(4.20)	(5.55)	(18.06)	(0.16)
ΔCR $\times$ ETS (Yes) $\times$ ETS Share	13.10	18.84*	26.86***	27.85**	29.89***	32.37***	30.55**	21.68*	11.28	0.66*
	(15.92)	(7.45)	(7.32)	(8.60)	(8.62)	(8.37)	(9.95)	(10.30)	(19.74)	(0.34)
ΔCR $\times$ ETS (No)	16.76***	23.51***	23.40***	17.20***	11.71***	12.19***	14.56***	19.76**	25.84**	−0.27
	(4.95)	(4.38)	(3.98)	(2.58)	(2.71)	(2.98)	(3.07)	(6.31)	(8.19)	(0.18)
ΔCR $\times$ ETS (No but anticipation)	−14.95	−3.21	−2.99	−10.00	−7.10	−5.54	−8.87	−24.41	−38.17	−0.57
	(9.34)	(9.38)	(13.26)	(18.83)	(10.12)	(8.50)	(14.77)	(18.96)	(38.26)	(0.35)
ΔCR $\times$ ETS (Yes)	82.83***	57.30***	40.10***	28.91***	22.21***	22.79***	34.61***	51.79***	72.60***	0.25
	(6.03)	(3.44)	(2.83)	(2.86)	(2.85)	(3.65)	(4.69)	(5.34)	(11.09)	(0.19)

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

Table 14: This table reports the coefficient estimates of the interaction terms (incl. ETS share) of the ETS panel quantile and mean regression model for 1-year (top), 3-year (upper center), 10-year (lower center), and 30-year (bottom) CDS spread returns in Europe. The sample comprises data from 119 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 1000.

	1	2	3	4	5	6	7	8	9	OLS
					1Y					
ΔCR × ETS (No response)	38.80	21.36*	11.49*	6.74**	1.56	4.07*	11.78*	47.85**	103.45*	0.24
	(34.59)	(10.17)	(4.89)	(2.29)	(1.22)	(2.04)	(5.58)	(15.77)	(43.70)	(0.76)
ΔCR × ETS (Yes) × ETS Share	−311.18	38.22	43.36	19.63	27.59	7.83	−60.86	−315.38	−1256.27**	−6.99$^{\cdot}$
	(274.84)	(190.35)	(84.61)	(58.30)	(23.41)	(42.64)	(105.66)	(251.23)	(434.19)	(3.94)
ΔCR × ETS (No)	−66.35**	−17.27$^{\cdot}$	2.32	1.31	0.03	−1.31	−0.82	6.95	29.08	0.32
	(23.58)	(9.97)	(3.90)	(2.01)	(0.96)	(1.72)	(4.64)	(12.51)	(45.43)	(0.62)
ΔCR × ETS (No but anticipation)	30.02	58.26	33.67*	20.17***	5.42	12.56*	40.11*	114.44**	270.53**	2.03**
	(198.01)	(60.42)	(16.54)	(6.07)	(3.41)	(5.77)	(16.01)	(42.89)	(100.34)	(0.76)
ΔCR × ETS (Yes)	197.48***	57.09**	29.05**	13.73**	2.49	9.03*	33.05**	110.28***	328.36**	3.46***
	(36.45)	(21.24)	(10.69)	(5.00)	(1.94)	(3.98)	(11.12)	(26.90)	(102.86)	(0.77)
					3Y					
ΔCR × ETS (No response)	26.23**	25.45***	12.17***	4.65**	1.26	−0.03	2.60	11.73*	28.27*	0.46**
	(8.05)	(5.97)	(3.15)	(1.44)	(0.87)	(1.18)	(3.12)	(4.82)	(11.65)	(0.16)
ΔCR × ETS (Yes) × ETS Share	−47.20	−13.93	−71.25	−38.89	−8.64	−37.56	−103.58$^{\cdot}$	−213.69*	−165.09	−0.94
	(99.19)	(77.38)	(64.35)	(24.91)	(16.76)	(26.94)	(61.94)	(83.22)	(237.57)	(1.33)
ΔCR × ETS (No)	2.67	4.48	1.34	0.97	0.03	−1.54	−0.68	4.58	8.34	0.25$^{\cdot}$
	(7.95)	(4.56)	(3.10)	(1.23)	(0.68)	(1.12)	(2.46)	(5.73)	(15.60)	(0.15)
ΔCR × ETS (No but anticipation)	64.40***	48.00*	17.61	5.87	2.41	−0.93	0.64	19.20	76.79***	0.44
	(12.64)	(20.19)	(11.04)	(3.62)	(2.48)	(2.94)	(9.27)	(14.53)	(14.73)	(0.43)
ΔCR × ETS (Yes)	89.92***	37.32***	23.62***	10.01***	3.53*	6.49*	18.60**	43.51***	79.44**	0.99***
	(9.48)	(8.77)	(6.55)	(2.58)	(1.44)	(2.53)	(7.19)	(12.17)	(30.28)	(0.23)
					10Y					
ΔCR × ETS (No response)	15.78***	9.54***	5.87***	2.75***	0.78***	0.90*	1.81	4.93***	9.51*	0.19***
	(1.59)	(0.98)	(0.49)	(0.43)	(0.23)	(0.42)	(1.14)	(1.25)	(3.81)	(0.04)
ΔCR × ETS (Yes) × ETS Share	20.34	−9.06	1.32	6.19	4.18	0.56	1.85	−5.20	84.05	0.00
	(40.35)	(20.97)	(7.55)	(7.76)	(4.88)	(4.88)	(11.60)	(18.31)	(145.03)	(0.30)
ΔCR × ETS (No)	4.14***	2.32*	1.58**	0.91**	0.44**	0.51$^{\cdot}$	0.46	1.26	5.21	0.09*
	(0.91)	(0.99)	(0.60)	(0.30)	(0.17)	(0.26)	(0.53)	(1.95)	(4.11)	(0.04)
ΔCR × ETS (No but anticipation)	18.10***	9.30***	5.53***	2.09*	1.34	1.54	3.39	9.90$^{\cdot}$	22.77	0.19***
	(1.00)	(1.20)	(1.26)	(1.07)	(0.97)	(1.16)	(4.96)	(5.53)	(15.16)	(0.05)
ΔCR × ETS (Yes)	18.00***	10.42***	5.99***	2.26**	0.78*	1.74*	4.18**	11.07**	16.30	0.30***
	(2.61)	(1.04)	(0.73)	(0.74)	(0.40)	(0.79)	(1.32)	(4.04)	(11.27)	(0.07)
					30Y					
ΔCR × ETS (No response)	9.14***	5.92***	4.00***	2.03***	0.70**	1.46***	2.80***	5.97***	13.32***	0.15**
	(1.44)	(1.10)	(0.83)	(0.41)	(0.25)	(0.39)	(0.70)	(1.20)	(2.24)	(0.05)
ΔCR × ETS (Yes) × ETS Share	−0.49	−2.10	−0.26	−4.00	1.28	2.12	−3.63	8.83	−17.10	−0.17
	(31.43)	(9.87)	(8.86)	(6.30)	(4.22)	(3.83)	(12.54)	(20.18)	(31.33)	(0.42)
ΔCR × ETS (No)	0.86	−0.31	0.32	0.00	0.08	−0.07	0.08	−0.16	−1.54	−0.02
	(1.96)	(0.98)	(0.74)	(0.37)	(0.19)	(0.29)	(0.55)	(1.27)	(2.70)	(0.06)
ΔCR × ETS (No but anticipation)	19.36	8.50	3.36	1.30	0.42	0.32	0.59	2.53	14.76	0.22*
	(13.61)	(8.83)	(4.34)	(1.38)	(0.80)	(1.04)	(2.99)	(2.98)	(20.87)	(0.11)
ΔCR × ETS (Yes)	8.78*	4.57*	3.29**	1.73*	0.44	0.85$^{\cdot}$	2.40	4.77$^{\cdot}$	11.37*	0.23***
	(4.33)	(2.23)	(1.05)	(0.69)	(0.34)	(0.49)	(1.50)	(2.86)	(5.59)	(0.07)

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

Table 15: This table reports the coefficient estimates of the interaction terms (incl. ETS share) of the ETS panel quantile and mean regression model for 1-year (top), 3-year (upper center), 10-year (lower center), and 30-year (bottom) CDS spread returns in North America. The sample comprises data from 164 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 1000.

	1	2	3	4	5	6	7	8	9	OLS
					5Y-1Y					
ΔVolatility	−120.92***	−41.67***	−12.68**	−2.80	1.95	15.46***	49.60***	128.34***	258.45***	190.10*
	(16.61)	(11.48)	(4.15)	(1.80)	(1.23)	(1.61)	(3.09)	(3.82)	(4.30)	(80.03)
ΔMRISlope	204.32***	162.88***	112.27***	60.07***	37.07***	41.74***	77.23***	138.84***	216.07***	248.10***
	(6.81)	(6.18)	(6.47)	(4.62)	(3.06)	(3.18)	(4.77)	(6.29)	(10.25)	(25.04)
ΔIR	−3190.10***	−1896.44***	−989.93***	−52522***	−35431***	−39385***	−724.52***	−1706.95***	−3104.45***	−441871***
	(320.22)	(136.14)	(66.21)	(29.46)	(19.90)	(22.89)	(55.42)	(139.79)	(330.11)	(601.83)
ΔIR^2	−36151.01***	−1625818***	−565221***	123.80	121250***	233255***	1028293***	39620.72***	91466.84***	2485433**
	(3960.65)	(1305.16)	(589.48)	(167.25)	(125.11)	(234.26)	(877.71)	(2797.45)	(4770.73)	(8686.94)
ΔTerm	1922.24***	1128.15***	564.99***	298.39***	164.94***	140.41***	89.46*	−68.89	−586.25**	2356.29*
	(321.30)	(131.92)	(61.63)	(26.66)	(18.33)	(19.64)	(35.31)	(72.27)	(198.60)	(1128.85)
ΔCRSlope	37.08***	20.86***	11.13***	5.67***	3.71***	4.23***	8.43***	15.58***	25.34***	59.01***
	(2.43)	(1.08)	(0.79)	(0.45)	(0.28)	(0.35)	(0.75)	(1.55)	(2.93)	(8.71)
					10Y-5Y					
ΔVolatility	−22.75***	−12.68***	−7.93***	−4.75***	−0.54	−0.37	1.94*	6.49***	15.58***	−8.25
	(1.92)	(1.01)	(0.87)	(0.68)	(0.39)	(0.58)	(0.79)	(0.78)	(1.08)	(18.43)
ΔMRISlope	6.08***	1.57***	0.46*	0.39*	0.08	0.39·	0.49*	1.42***	4.95***	31.91***
	(0.90)	(0.33)	(0.21)	(0.20)	(0.11)	(0.20)	(0.21)	(0.34)	(0.63)	(4.19)
ΔIR	212.86***	261.68***	193.45***	205.16***	35.95***	156.55***	148.81***	238.60***	329.53***	801.69**
	(61.90)	(18.30)	(13.01)	(9.68)	(6.36)	(10.91)	(13.29)	(18.92)	(60.08)	(275.64)
ΔIR^2	−9435.17***	−3701.05***	−204174***	−115550***	−186771***	261.71***	792.14***	1993.90***	7951.49***	−116224
	(1125.27)	(230.61)	(109.11)	(83.47)	(56.40)	(55.23)	(80.21)	(178.90)	(624.12)	(1162.16)
ΔTerm	−324.44***	−233.83***	−172.28***	−20568***	−35.72***	−15859***	−139.30***	−221.02***	−356.87***	−876.57***
	(56.00)	(18.87)	(13.77)	(10.33)	(6.58)	(11.15)	(12.57)	(16.88)	(43.37)	(264.47)
ΔCRSlope	−1.34***	−0.75***	−0.60***	−0.59***	−0.14***	−0.45***	−0.34***	−0.42**	−0.43	−6.91**
	(0.28)	(0.13)	(0.07)	(0.06)	(0.04)	(0.07)	(0.08)	(0.14)	(0.45)	(2.23)
					10Y-1Y					
ΔVolatility	−138.44***	−60.94***	−20.22**	−4.81*	3.77*	20.89***	63.96***	143.19***	299.63***	171.27·
	(17.63)	(13.54)	(6.20)	(2.12)	(1.78)	(2.48)	(4.08)	(5.47)	(40.02)	(89.09)
ΔMRISlope	211.50***	170.76***	125.51***	81.70***	62.82***	67.38***	99.36***	156.06***	231.84***	214.74***
	(4.98)	(6.14)	(6.12)	(5.19)	(4.35)	(4.60)	(5.45)	(6.88)	(9.82)	(25.80)
ΔIR	−2281.39***	−1464.89***	−897.70***	−47928***	−27387***	−34359***	−673.25***	−1538.15***	−2696.23***	−267307***
	(274.27)	(156.07)	(81.70)	(45.82)	(31.76)	(38.77)	(70.90)	(156.87)	(424.47)	(639.64)
ΔIR^2	−44155.95***	−2201621***	−836782***	−41238	175308***	400182***	1401082***	40724.65***	92498.04***	2452849*
	(3138.06)	(1828.69)	(928.89)	(297.66)	(196.74)	(357.61)	(1141.41)	(2907.96)	(7572.63)	(9679.88)
ΔTerm	723.85**	512.78**	337.98***	155.76***	7.13	−29.10	−180.65***	−384.19***	−1005.07***	738.52
	(275.22)	(159.50)	(80.99)	(43.14)	(30.05)	(31.68)	(53.42)	(102.91)	(276.47)	(1207.35)
ΔCRSlope	45.35***	28.04***	17.44***	10.18***	7.11***	7.69***	13.00***	21.53***	30.99***	77.13***
	(1.69)	(1.22)	(0.94)	(0.64)	(0.51)	(0.65)	(1.09)	(1.53)	(3.39)	(9.66)

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

Table 16: This table reports the coefficient estimates of the term structure panel quantile and mean regression model for 5Y-1Y (top), 10Y-5Y (center), and 10Y-1Y (bottom) CDS spread slope changes in Europe. The sample comprises data from 119 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 1000.

	1	2	3	4	5	6	7	8	9	OLS
					5Y-1Y					
ΔVolatility	−229.70***	−85.44***	−16.74***	−1.78	3.80***	27.71***	81.94***	230.33***	467.91***	223.83*
	(15.35)	(9.26)	(4.06)	(1.26)	(1.11)	(2.31)	(4.30)	(2.76)	(6.78)	(91.75)
ΔMRISlope	148.11***	109.77***	67.74***	35.94***	20.46***	27.73***	60.89***	121.86***	209.88***	228.89***
	(7.26)	(5.44)	(4.39)	(2.43)	(1.34)	(1.75)	(3.54)	(6.29)	(9.88)	(23.98)
ΔIR	−3431.36***	−2266.93***	−1190.82***	−598.17***	−383.49***	−577.40***	−1394.54***	−3022.07***	−4812.75***	−9049.97***
	(180.56)	(96.38)	(63.05)	(29.64)	(17.65)	(23.83)	(67.10)	(143.32)	(240.43)	(911.52)
ΔIR^2	−37945.17***	−16861.92***	−4008.03***	912.22***	1115.50***	1560.99***	8359.40***	32860.72***	79186.38***	18314.84***
	(2320.35)	(847.56)	(338.09)	(89.87)	(57.60)	(85.21)	(647.01)	(2025.26)	(5123.16)	(3296.11)
ΔTerm	1752.86***	1241.34***	728.15***	397.16***	240.89***	352.79***	692.95***	1132.72***	1576.24***	5096.48***
	(163.02)	(95.03)	(57.41)	(27.63)	(16.14)	(19.49)	(36.46)	(77.52)	(154.40)	(810.24)
ΔCRSlope	12.17***	7.84***	3.75***	1.67***	0.66***	0.96***	3.20***	10.58***	22.57***	70.23***
	(0.68)	(0.71)	(0.46)	(0.22)	(0.12)	(0.17)	(0.42)	(1.09)	(2.20)	(8.12)
					10Y-5Y					
ΔVolatility	−70.70***	−32.79***	−11.51***	−3.11***	0.02	5.41***	18.44***	58.95***	137.47***	155.69*
	(4.45)	(5.01)	(1.73)	(0.83)	(0.27)	(0.99)	(1.31)	(4.66)	(15.45)	(71.02)
ΔMRISlope	22.80***	10.91***	4.28***	2.17***	0.52***	1.88***	3.45***	9.56***	22.59***	44.60***
	(1.31)	(0.77)	(0.27)	(0.16)	(0.11)	(0.17)	(0.28)	(0.96)	(3.01)	(10.59)
ΔIR	−233.16**	−118.06**	−17.95	−2.22	0.05	−3.17	−59.98***	−350.32***	−822.91***	−1292.35**
	(86.40)	(43.51)	(15.14)	(8.73)	(4.08)	(6.45)	(12.43)	(43.43)	(143.83)	(426.46)
ΔIR^2	−8531.71***	−2332.12***	−463.62***	−232.73***	1.04	184.93***	572.73***	3881.06***	13238.57***	−672.90
	(1109.50)	(354.31)	(80.79)	(36.81)	(16.19)	(37.40)	(83.63)	(615.12)	(2790.68)	(2208.02)
ΔTerm	246.96**	117.21*	31.77*	13.03	0.04	7.84	54.67***	193.14***	425.06***	1424.17**
	(82.69)	(45.95)	(15.03)	(8.62)	(4.17)	(6.39)	(11.85)	(31.58)	(96.78)	(481.43)
ΔCRSlope	−1.13·	−0.43·	−0.07	−0.05	−0.00	−0.14***	−0.38***	−1.10***	−2.25**	2.98
	(0.65)	(0.22)	(0.09)	(0.05)	(0.02)	(0.04)	(0.10)	(0.25)	(0.87)	(5.19)
					10Y-1Y					
ΔVolatility	−301.18***	−105.34***	−18.32***	−1.63	6.73***	34.60***	110.30***	323.27***	643.91***	379.68***
	(33.64)	(12.59)	(3.46)	(1.82)	(1.85)	(2.24)	(5.31)	(7.54)	(28.11)	(98.41)
ΔMRISlope	148.74***	111.55***	59.98***	29.54***	18.92***	25.38***	52.15***	113.26***	187.12***	220.61***
	(7.39)	(5.08)	(3.61)	(1.71)	(1.12)	(1.18)	(2.61)	(6.10)	(11.42)	(18.16)
ΔIR	−4275.02***	−2553.68***	−1221.46***	−555.18***	−354.13***	−541.34***	−1320.07***	−3529.48***	−5370.23***	−9504.29***
	(233.47)	(122.58)	(72.39)	(32.36)	(22.43)	(27.47)	(71.64)	(180.20)	(310.15)	(1058.84)
ΔIR^2	−48310.11***	−21505.34***	−5533.23***	340.50**	745.04***	1348.84***	7906.08***	40237.09***	83478.28***	14977.38***
	(2308.46)	(1206.78)	(441.27)	(126.47)	(65.70)	(108.14)	(648.44)	(2453.49)	(5046.16)	(3464.79)
ΔTerm	2371.39***	1431.34***	776.09***	392.74***	247.09***	365.46***	714.46***	1297.53***	1851.56***	5474.72***
	(247.89)	(121.79)	(69.54)	(31.85)	(21.27)	(24.41)	(48.35)	(109.97)	(225.50)	(924.08)
ΔCRSlope	8.92***	4.99***	1.74***	0.53***	0.14**	0.18*	0.44*	1.87*	4.96***	39.16***
	(0.82)	(0.49)	(0.28)	(0.11)	(0.05)	(0.08)	(0.21)	(0.83)	(1.27)	(6.69)

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

Table 17: This table reports the coefficient estimates of the term structure panel quantile and mean regression model for 5Y-1Y (top), 10Y-5Y (center), and 10Y-1Y (bottom) CDS spread slope changes in North America. The sample comprises data from 164 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 1000.