Climate Risk and Credit Risk

Theory and Empirics

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1. Introduction

It is nowadays univocal that climate change poses a major challenge for all of humankind and life on earth. The number of extreme weather events increases year by year and temperatures have risen at a rapid rate. The summer of 2023 has been the hottest summer on record globally (EEA, 2023) and given the current temperature trajectory, this probably was not the last summer of its kind. On the other hand, intergovernmental institutions and governments all over the world implement different legislation to curb the emission of carbon and achieve the goal of being carbon-neutral by 2050. In response to these developments, people are adjusting their behavioral patterns and mindsets. From a financial perspective, which will be the main scope of this thesis, all these events display severe risks which can incur significant costs for firms.

Typically, the financial risks associated with the climate change events outlined above materialize through three main channels: physical risk, transition risk and carbon risk. Physical risk comprises risks due to physical changes in climate such as droughts, wildfires or temperature rise. Transition risk refers to the risks associated with the low-carbon transition pathway, while carbon risk, as a subcategory of transition risk, incorporates only the risks related to emissions. From a firm's perspective, all risk types can profoundly affect business models and generate sizable costs. Unquestionably, these costs could significantly affect firms' cash flows and valuations, undermining their ability to service and repay their debt, and eventually leading to higher probabilities of default and higher credit risks (Aiello and Angelico, 2022; BIS, 2021; Carbone et al., 2021; Reznick and Viehs, 2018; Virgilio et al., 2022; Billio and Giacomelli, 2022; Caicedo, 2022). Hence, it is of utter importance for firms to understand how these climate risks translate financially and contribute to their credit risk.

Given these observations, it is important to have theoretical frameworks at hand which are able to capture these effects. This is where we make our first contribution. Building on the seminal, structural Merton (1974a) model, we propose a new model that introduces a random growth adjustment factor in the firm value dynamics to reflect the depreciation due to climate risks. Within this model, we find that higher exposure to climate risk implies higher probabilities of default and, ultimately, higher credit spreads. In addition, we also provide a comprehensive overview of competing structural credit models. Different approaches on how to incorporate climate risk in structural models of credit have already been suggested. Bouchet and Guenedal (2020) investigate the sensitivity to transition risk by transmitting carbon price shocks to the firm value process. Kölbel et al. (2022) and Agliardi and Agliardi (2021) acknowledge the unpredictability of some climate risk types and argue for the incorporation of a jump-type component. Last, Le Guenedal and Tankov (2022) introduce a Bayesian approach in a first-passage-time credit model to account for scenario uncertainty.

Empirical literature establishing the link between climate change and credit risk is growing as well. Looking at the physical risk channel, various studies examine the effect of natural disasters on different credit instruments (Rajhi and Albuquerque, 2017, Kölbel et al., 2022, Bats et al., 2023). The vast majority finds evidence of deteriorating effects for firms vulnerable to physical climate events. On the transitional dimension, several researchers have investigated the effects 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., 2023 Seltzer et al., 2022), distance-to-default (Capasso et al., 2020), options (Ilhan et al., 2020) and credit default swaps (Kölbel et al., 2022, Barth et al., 2022, Christ et al., 2022; Zhang and Zhao, 2022). The overall consensus is that firms more exposed to the risks associated with the low-carbon pathway exhibit higher financing and protection costs than firms well prepared for the transition.

Despite the comprehensive evidence on the relationship between climate risk and credit, most of the used climate risk proxies in these existing studies are insufficient. This is because most of them rely on historical information when it comes to quantifying climate risk. Climate risks, however, are future risks and hence relying on past data is usually not the appropriate choice. Instead, it is important to incorporate the forward-looking aspect of climate risk into the measurement. We contribute on this dimension by proposing a market-based, frequently observable risk metric that incorporates this important characteristic. For that, we concentrate on the measurement of carbon risk in this thesis, recognizing the relative prominence of carbon among transition risks, and given its wide coverage across countries, markets and sectors.

Motivated by the theoretical models, we utilize the information contained in the spreads of Credit Default Swap (CDS) contracts to construct a *market-implied, forward-looking* carbon risk (CR) factor. CDSs offer several advantages over other commonly used credit risk measures, such as corporate bonds (or ratings). First, CDSs respond more quickly to changes in market conditions than alternative financial debt and credit products, because CDS contracts are traded on standardized terms (Blanco et al., 2005; Zhu, 2006; Norden and Weber, 2009). Second, CDSs are usually more liquid than corporate bonds (Longstaff et al., 2005; Ederington et al., 2015). Third, since there are CDS contracts with varying tenors up to 30 years, they allow us to incorporate lenders' collective forward-looking considerations.

The carbon risk factor is constructed as the daily difference between the median CDS spreads of high emission intensity (polluting) firms and low emission intensity (clean) firms. This difference is used to identify shocks that affect polluting and clean firms differently. When policy changes (e.g. announcement of tighter regulations) trigger a rise in carbon risk, lenders to more (less) exposed firms demand increased (decreased) protection, widening the CDS wedge, i.e. the distance between the price of default protection for polluting and clean firms. Conversely, if a loosening of regulation is expected, there is a narrowing of the wedge (or even a negative wedge). The CR thereby represents changes in perceived exposure to carbon risk. It mimics the dynamics of a lending portfolio in which default protection is bought for a polluting firm and sold for a clean firm. We also utilize various adaptations of the CR factor to assess exposure to carbon risk within sectors, countries, and across different term structures. Additionally, we introduce a generalized version of the CR, the carbon tail risk (CTR), designed to comprehensively capture the entire distribution of carbon risk, with a particular emphasis on its extreme parts.

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

We conduct further analyses to test for geographical, regulatory and sectoral dependencies. While an increase in the perceived carbon risk exposure is generally associated with an increased cost of default protection, the size of this positive effect differs significantly across regions. In Europe, where climate policies are more stringent, there is a very strong positive relationship, whereas the effect is comparatively weaker in North America, which has generally had more ambiguous climate policy signals in recent years. Employing data from the Carbon Disclosure Project (CDP), we discover additional evidence indicating that the significance of carbon risk is contingent upon the extent to which firms fall under the purview of an Emissions Trading Scheme (ETS). Firms that are subject to an ETS and whose regulated emissions are a substantial part of their total emissions experience more pronounced effects than their non-regulated counterparts. On a sectoral level, we find that carbon-intensive sectors (e.g. Energy) are more affected than less carbon-intensive industries (e.g. Healthcare). This suggests that the market recognizes which sectors are better positioned for a transition to a low-carbon economy.

We also find that the effect of carbon risk on CDS contract prices is even stronger during times of heightened public attention to climate change. Lenders appear to be more sensitive to carbon risk when market-wide concern about climate change risk is elevated.

Finally, we provide a comprehensive analysis of the temporal dimension of the effect of carbon risk. Using information from the entire CDS spread curve, we show that a shift in the expected temporal materialization of carbon risk positively affects the steepness of the CDS curve slope. In Europe, the effect on the CDS term structure is particularly salient for shorter time horizons, suggesting that the market perceives carbon risk to be a short- to medium-term risk.

The remainder of this thesis is organized as follows. Chapter 2 introduces the different types of climate risk: physical risk, transition risk and carbon risk. We focus on the financial, particularly credit-related, impact of these risk types and describe common ways to measure them. In Chapter 3, we continue with an introduction to credit risk. We specifically introduce relevant credit products and sketch their pricing via structural credit models. The chapter closes with a presentation of multiple climate-adjusted models that incorporate the risk stemming from climate change. Serving as a foundation for the remaining parts of this thesis, Chapter 4 describes the relevant data (CDS spreads, control variables) as well as our methodological framework necessary to investigate the effects of carbon risk on credit. Chapter 5 presents our approach in quantifying the exposure to carbon risk. Particularly, we review the literature on existing metrics and introduce the CR factor. Aside from the general CR, we also propose various different alternative CRs that identify exposures at the sectoral, geographical, term structure and distributional level. In Chapter 6, we present the empirical results of the effect of carbon risk on CDS spread returns. We investigate the general impact, but also conduct further analyses to examine the effects with respect to different geographies, regulatory frameworks, sectors, attention regimes and term structures. Additionally, we run a multitude of robustness checks to substantiate our findings. Last, in Chapter 7, we resume our findings and outline possible future research paths.

2. Climate risk

Climate risk encapsulates all risks that can be attributed to alterations resulting from climate change. Generally, these risks materialize through three main channels: the physical risk channel, the transition risk channel and the carbon risk channel. In the following, all risk types, their financial impact as well as their measurement will be described in more detail. In our exposition, we will mainly follow Hellmich and Kiesel (2021).

2.1. Physical risk

Physical risks pertain to alterations in the climate's physical characteristics, resulting in shifts in climate patterns and variations in the frequency and intensity of extreme weather events. In general, physical risks stem from two major sources. The first refers to the potential harm caused by extreme weather events, such as heatwaves, droughts, floods, and storms. These events can have a wide range of consequences for human communities and natural ecosystems, including damage to infrastructure, loss of life, and disruption of food and water supplies. The second source comes from the gradual change of climate patterns over time, such as sea level rise or the expansion of deserts in dry regions. Former habitable regions like coastal areas could become uninhabitable making it impossible for firms to continue their production in the region and hence they need to relocate their business.

As illustrated in Figure 2.1, physical risks can have a significant impact on a firm's financial performance, as these risks can disrupt the normal operations of their business and lead to financial losses. For instance, a heatwave could cause a power outage that halts production at a factory, or a flood could damage a firm's supply chain and disrupt its ability to get products to market. Additionally, physical risks can also lead to increased costs for a business, such as higher insurance premiums or the need to invest in resilience measures like sea walls or cooling systems. Firms with high exposure to physical risks will also likely be assigned a higher credit risk by investors and lenders, as their operations and financial performance may be more vulnerable to disruption. This can make it more difficult for these firms to access capital sources, and could also lead to higher interest rates on loans or bonds. The following real-world example of the Californian utility PG&E illustrates the potentially severe and adverse effects physical risk can have for firms.

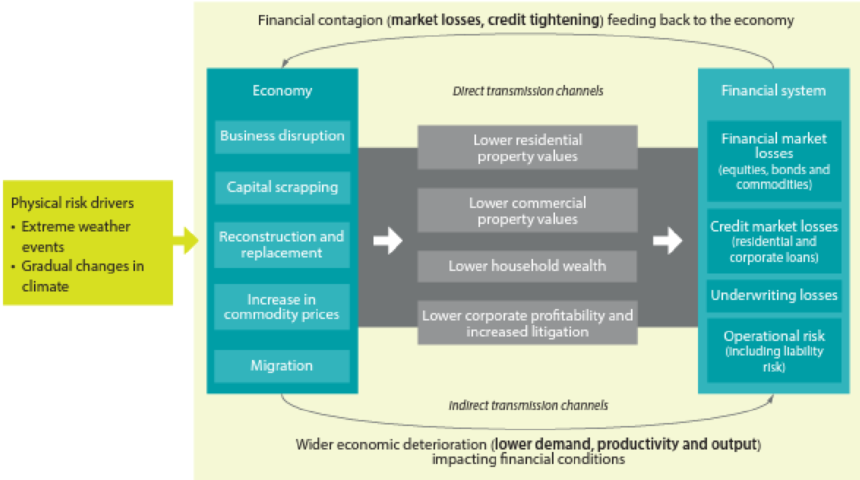

Figure 2.1.: Transmission channels of physical risk drivers. Source: NGFS (2021).

Example: The bankruptcy of Pacific Gas & Electric (PG&E)

On January 29, 2019, California's largest utility PG&E filed for Chapter 11 bankruptcy after facing $30 billion in potential liabilities from wildfires linked to their power lines. It is suspected that the fire originated from a PG&E power line coming into contact with nearby trees. Prior to the blaze's onset, PG&E had reported an outage on a transmission line in the vicinity. In the extensive burnt region, PG&E discovered power equipment and a fallen power pole, both of which exhibited bullet holes. Furthermore, a string of wildfires in 2017, many of which were attributed to PG&E, resulted in $10 billion in damages and claimed 44 lives. State investigators identified 11 of those fires where the firm had violated regulations pertaining to brush clearance around its power lines or committed related infractions. The bankruptcy of PG&E is widely considered the first climate change bankruptcy and highlights the importance for firms to thoroughly identify and mitigate vulnerabilities to physical climate risk events.


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EDITORS' PICK

PG&E Is Just The First Of Many Climate Change Bankruptcies

Chunka Mui Former Contributor

I focus on innovations aimed at making the world a much better place.

Jan 24, 2019, 10:14am EST

Figure 2.2.: Headline of the Forbes article "PG&E Is Just The First Of Many Climate Change Bankruptcies" from Jan 24, 2019. Source of photograph: Ross Stone (retrieved from Unsplash under the Unsplash license).

Empirical literature establishing the link between physical risks and financial risk is growing. In the realm of equity research, Hong et al. (2019) conduct a study to assess whether food stocks accurately account for the long-term drought risk. Their findings indicate that the prices of food stocks exhibit an insufficient reaction to climate change risks. Similarly, Gostlow (2022) employs a factor-based analysis and concludes that physical climate risks do not elucidate variations in stock returns. Additionally, utilizing a text-based factor approach, Faccini et al. (2021) fail to identify substantial evidence suggesting the integration of news concerning natural disasters into the market. Looking at the credit dimension, various studies examine the effect of natural disasters on different credit instruments (Rajhi and Albuquerque, 2017, Kölbel et al., 2022, Bats et al., 2023). The vast majority finds evidence of credit-deteriorating effects for firms vulnerable to physical climate events.

Measuring physical climate risk involves a multifaceted approach that combines observational data, climate modeling, and vulnerability assessments. The Intergovernmental Panel on Climate Change (IPCC) provides valuable guidelines and sources for understanding the methodology. Initial steps include collecting historical climate data from meteorological observations and satellite records. The World Meteorological Organization (WMO) and the National Oceanic and Atmospheric Administration (NOAA) offer comprehensive datasets for this purpose. Climate models, such as those developed by the National Center for Atmospheric Research (NCAR), simulate future climate scenarios based on various greenhouse gas emission trajectories. Vulnerability assessments consider the exposure, sensitivity, and adaptive capacity of physical assets and sectors, as outlined in the IPCC's assessment reports.

2.2. Transition / carbon risk

Transition risk refers to the risks associated with the transition to a more sustainable and low-carbon economy. These risks typically comprise three major components: regulatory risks related to changes in policy and legislation, technological risks associated with investing in new technologies and market risks due to changing demand preferences. Managing these risks involves careful planning and assessment, as well as the development of strategies to address potential challenges. Carbon risk, on the other hand, narrows the definition down to risks related to greenhouse gas (GHG) emissions. Typical examples comprise implemented policies to curb emissions, such as emission trading schemes or taxes. Additionally, past emissions of firms may also be subject to litigation risks if they fail to comply with their targets.

With transition risk affecting a firm's ability to generate revenue and profits in the future, it also represents a non-negligible driver of financial risk (see Table 2.3). If a firm's business model becomes less profitable or relevant in a low-carbon economy, the firm may struggle to meet its financial obligations, such as repaying debt or paying dividends to shareholders. This can lead to a downgrade in the firm's credit rating, making it more difficult and expensive for the firm to access capital markets. Additionally, if a firm is heavily reliant on fossil fuels and does not have a strategy to transition to cleaner energy sources, it may be at a higher risk of defaulting on its debt as regulations

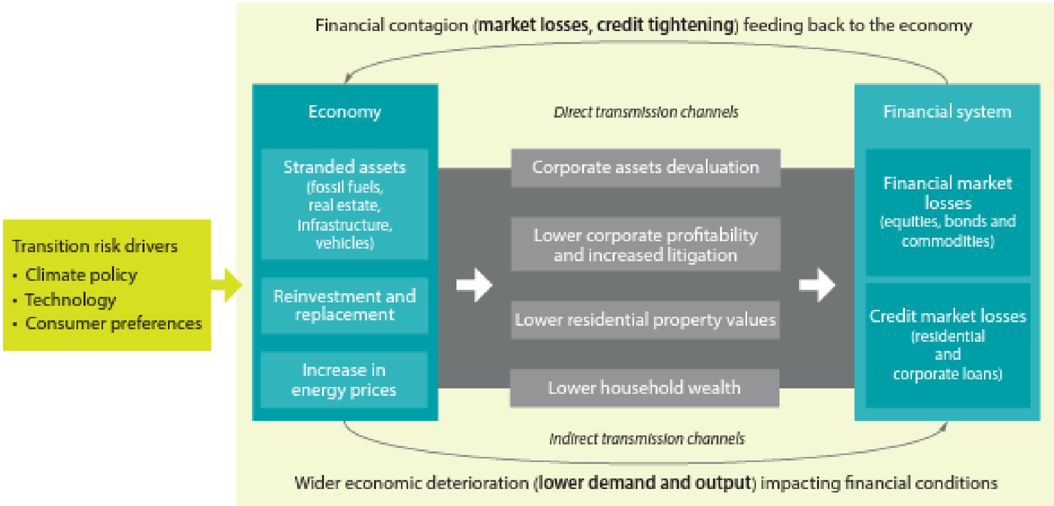


Figure 2.3.: Transmission channels of transition risk drivers. Source: NGFS (2021).

and policies aimed at reducing carbon emissions become more strict. However, firms that are able to proactively manage their transition risk by diversifying their revenue streams, investing in low-carbon technologies and aligning their strategy with the regulatory framework, may be seen as less risky and have more favorable credit conditions. The following example of the EU phaseout of combustion engine cars demonstrates how transition risk (specifically regulatory risk) can act on firms' credit state perception.

Example: EU phaseout of combustion engine cars

On July 14, 2021 the European Commission proposed an effective ban on the sale of new petrol and diesel cars from 2035 with the aim to speed up the transition to zero-emission electric vehicles. Although initially blocked by Germany demanding exceptions for hybrid vehicles, German environment minister Lemke eventually agreed to the plan on March 16, 2022. Following upon this, the EU's environment ministers finally struck a deal on the ban of combustion engine cars on June 29, 2022. As a result of these policy decisions, the costs of default protection for automotive manufacturers (proxied by their CDS spread) significantly went up. Figure 2.4 displays the daily evolution of 5-years CDS spreads of three major European automotive manufactures (BMW, Volvo and Volkswagen) from 2021 until 2022 as well as three vertical lines highlighting the relevant policy events outlined above. While the reaction to the EU

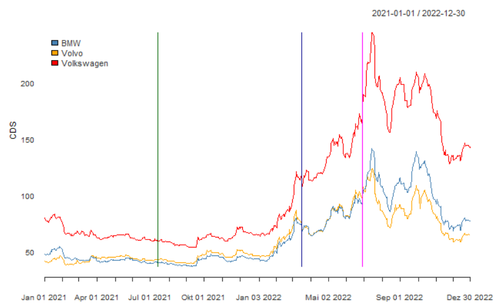


Figure 2.4.: Daily evolution of 5-year CDS spreads of BMW (blue), Volvo (orange) and Volkswagen (red) from Jan 1, 2021 until Dec 31, 2022. The vertical lines indicate the announcement of the EU proposal (darkgreen), Germany's decision to finally back up the phase out (darkblue) and the final EU agreement (magenta). Own illustration based on CDS data from Refinitiv.

proposal (darkgreen) is mild given the subsequent temporal blockade by Germany, the protection costs severely increased once the German government finally agreed to the phaseout (darkblue). With the final decision by the EU's environment ministers to implement the ban (magenta), these costs spiked to its maximum. Although the CDS spreads reverted back afterwards, the overall costs – starting from the first EU proposal – significantly leveled up, illustrating the influential effect of regulatory changes on firms credit risk.

Recent works have focused on the effect of a low-carbon transition on the equity market (Bolton and Kacperczyk, 2021; Cheema-Fox et al., 2020; Görgen et al., 2020; Hsu et al., 2022; Lioui, 2022) and the capital structure (Nguyen and Phan, 2020; Kleimeier and Viehs, 2018). Using firms' carbon emissions to codify their exposure to carbon risk, and the effort required to successfully transition to a low-carbon economy, these papers document that firms with an emissions-intensive business model have disproportionately higher transition costs than their low-carbon peers. There is an also growing body of empirical work investigating the effects of transition risk on credit risk through the lens of the cost of debt (Kleimeier and Viehs, 2018; Jung et al., 2018; Delis et al., 2018), corporate bonds (Duan et al., 2021; Seltzer et al., 2022), distance-to-default (Capasso et al., 2020), options (Ilhan et al., 2020), and CDSs (Barth et al., 2022; Christ et al., 2022; Kölbel et al., 2022; Zhang and Zhao, 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.

When it comes to quantifying a firm's exposure to carbon (and also transition) risk, the general strategy is to look at their total emissions. The simple rationale is that firms with more emissions need to undertake more measures to become a net-zero aligned firm compared to their low-carbon peers. The current standard of measuring total emissions is specified by the GHG Protocol, which was jointly established by the World Resources Institute (WRI) and the World Business Council for Sustainable Development (WBCSD). The GHG Protocol distinguishes between three sources of emissions:

- Scope 1 emissions cover direct emissions from establishments that are owned or controlled by the firm, 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 firm.

- Scope 3 emissions are caused by the operations and products of the firm but are generated by sources not owned or controlled by the firm.

One drawback of using total emissions is that it does not take into account the size of firms and with it their operational efficiency regarding emissions. To circumvent this issue and have a comparable metric, normalization by a firm-specific financial metric (usually from the balance sheet) is done. The Task Force on Climate Related Financial Disclosures (TCFD) recommends to use the following:

$$\text{Emissions intensity} = \frac{\text{Total emissions (in tonnes CO2e)}}{\text{Revenues (in mil. \$)}}.$$

While this metric allows to draw comparisons between firms, it may still be sensitive to the denominator, which, however, is not related to climate aspects whatsoever. Additionally, emissions intensities tend to be higher for larger firms, which can induce a bias towards those firms. Consequently, a sector-specific normalization may be preferable.

Another prominent measure to quantify exposure to carbon risk are ESG (Environmental, Social, and Governance) ratings. These ratings are a set of metrics and evaluations used by investors, firms, and other stakeholders to assess a firm's environmental, social, and governance performance. Their purpose is to provide an indication of how well a firm is managing its impact on the environment, its relationships with society, and the quality of its corporate governance. Focusing on the environmental part, these assessments apply not only to firms' carbon footprint, but also cover aspects such as environmental management, supply chain practices, innovation or stakeholder engagement. To conduct the assessment, vendors, like Refinitiv, MSCI, Sustainalytics and others, use a combination of publicly available data, firm disclosures, and proprietary methodologies to provide scores for each of those aspects. Afterwards, they use a weighted combination to come up with an aggregate rating that reflects a firm's performance in managing these risks.

3. Credit risk

The quantification of a firm's ability to fulfill its financial obligations lies at the heart of credit risk. In the following, we will provide an introduction to credit risk and present some of the most important credit instruments. Following upon that, we will introduce structural models of credit risk and sketch the pricing of the aforementioned instruments. Last, we will illustrate how these models can be augmented to account for the climate risk part.

3.1. A brief introduction

Credit risk incorporates all risks associated to credit-linked events of an entity. These events can include for example variations in the credit quality (rating upgrades or downgrades), changing (re)financing costs or the bankruptcy of the entity (default event). All these events can have financial consequences for the entity in question or an insurer assuring the entity. To rigorously introduce the concept of credit risk, it is thus important to quantify the expected costs associated to those events. For that, we first need a proper notion of (expected) loss. Typically, loss comprises three components: the probability of default (PD), the loss given default (LGD) and the exposure at default (EAD). Hence, we define the loss of an obligor as the random variable (see Bluhm et al., 2002)

$$\widetilde{\mathrm{L}} = \mathrm{EAD} \times \mathrm{LGD} \times \mathrm{L}, \tag{3.1}$$

where $\mathrm{L} = \mathbb{1}_{\mathrm{D}}$ is a Bernoulli-distributed random variable with $\mathbb{P}(\mathrm{D}) = \mathrm{PD}$. Following this definition, the expected loss (EL) is now naturally given by

$$\mathrm{EL} = \mathbb{E}[\widetilde{\mathrm{L}}] = \mathrm{EAD} \times \mathrm{LGD} \times \mathbb{P}(\mathrm{D}), \tag{3.2}$$

where we use $\mathbb{E}[\mathbb{1}_{\mathrm{D}}] = \mathbb{P}(\mathrm{D})$ and for simplicity assume that EAD and LGD are constant values.[1] In the following, we will describe each component of the expected loss in more detail.

The PD constitutes the likelihood that the obligor defaults on its debt within a prespecified time horizon. It is a crucial concept in the risk management of financial institutions, serving as a key component in credit risk analysis. The PD is expressed in percent and is typically calibrated from market data or credit ratings such as Standard & Poor's (S&P), Fitch or Moody's. A higher PD indicates a greater risk of default, and

[1] Equation (3.2) still holds if EAD and LGD are assumed to be random, but all components are jointly independent. In this case, EAD and LGD represent the expectations of the introduced random variables.

financial institutions use this metric to make informed decisions about lending, investment, and risk management.

The EAD quantifies the level of risk a bank faces from its borrowers. Typically, this exposure is comprised of two primary components: outstandings and commitments. Outstandings represent the portion of the exposure that the obligor has already utilized. In the event of the borrower's default, the bank is at risk for the entire outstanding amount. Commitments can be divided into two categories: undrawn and drawn, up until the point of default. The total commitments represent the amount that the bank has committed to lend to the obligor upon their request. Historical data reveals that borrowers often tap into their committed lines of credit during financial hardships. Consequently, in the event of obligor default, the commitments are also exposed to potential losses, but only the drawn portion of commitments prior to default contributes to the loan loss. The proportion of commitments divided into drawn and undrawn segments is a random variable, reflecting the optional nature of commitments. Hence, it is immediate to define the EAD as:

$$\text{EAD} = \text{Outstandings} + \xi \times \text{Commitments},$$

where $\xi \in [0, 1]$ is the expected portion of the commitments likely to be drawn prior to default.

The LGD quantifies the portion of loss the bank will really suffer in case of default. It represents the portion of the exposure that remains unrecovered after the default and subsequent recovery efforts, expressed as a percentage of the initial exposure. In essence, LGD provides insight into the severity of financial loss in a default scenario, taking into account factors like collateral, guarantees and recovery processes. A lower LGD indicates a higher likelihood of recovering a significant portion of the exposure, while a higher LGD implies a more substantial loss upon default, which is a crucial consideration in risk assessment, portfolio management, and capital provisioning for financial institutions.

3.2. Credit instruments

This section provides an overview of relevant credit instruments. We will focus on two main instruments: corporate bonds and credit default swaps (CDSs). Corporate bonds are the most commonly known credit product and serve as the main tool for firms to finance their business via debt. CDSs are popular default insurance products and will be comprehensively used later on in this thesis. In our exposition, we will mainly follow Bielecki and Rutkowski (2004) and Augustin et al. (2014).

3.2.1. Corporate bonds

Corporate bonds represent debt instruments issued by firms, constituting a fundamental component of a firm's capital structure. When a firm issues bonds, it commits to making predetermined payments to bondholders at specified future dates, charging a fee for this obligation. Nevertheless, a risk of default exists, wherein the firm may fail to fulfill its commitment, leading to a partial loss for bondholders. This default risk is relevant only during the bond's existence, spanning from its issuance to maturity.

A corporate bond exemplifies a defaultable claim, with its notional amount, or face value, set at F units of currency, such as US dollars, and a fixed maturity date denoted as T. Key elements of every bond are:

- Recovery rules: Recovery rules refer to the process by which bondholders may recover their investment in the event of a default by the issuer. Recovery is usually achieved through bankruptcy proceedings or asset liquidation. Recovery rules can vary widely between bonds and may be governed by the bond's indenture, which is a legal document outlining the terms and conditions of the bond.

- Safety covenants: Safety covenants are protective clauses included in the bond's indenture to safeguard bondholders' interests. They may include restrictions on the issuer's actions, such as limiting additional debt issuance, specifying financial reporting requirements, or defining collateral for secured bonds. Safety covenants enhance the security of the bond by reducing the risk of default.

- Credit spread: A credit spread quantifies the additional return offered by a corporate bond compared to an equivalent Treasury bond, assumed to be devoid of credit risk. Depending on the context, a credit spread can be expressed as the disparity between their respective yields to maturity or as the divergence between their corresponding instantaneous forward rates.

- Coupon: The coupon rate of a bond is the annual interest rate paid to bondholders. It is typically a fixed percentage of the bond's face value and determines the periodic interest payments. Coupons can be fixed, floating (adjusted periodically based on market interest rates), or zero-coupon (no periodic interest payments, with the entire return realized at maturity).

3.2.2. Credit default swaps (CDSs)

Introduced by J.P. Morgan in 1994 to transfer credit risk, credit default swaps (CDSs) are insurance contracts allowing the protection buyer to purchase insurance against a contingent credit event on an underlying reference entity. For the insurance, the buyer pays an annuity premium to the protection seller. The so-called CDS spread, is paid either until the reference entity defaults or the maturity of the contract. The spread is typically quoted as a percentage of the insured notional amount (basis points) and can be paid in quarterly or semi-annual schemes. If the reference entity is unable to meet its debt obligations, i.e. a credit event occurs, the protection seller is obliged to make a payment of the difference between the notional principal and the value of the underlying reference obligation (LGD) to the protection buyer. Figure 3.1 illustrates the basic features of a CDS contract with a simple example.

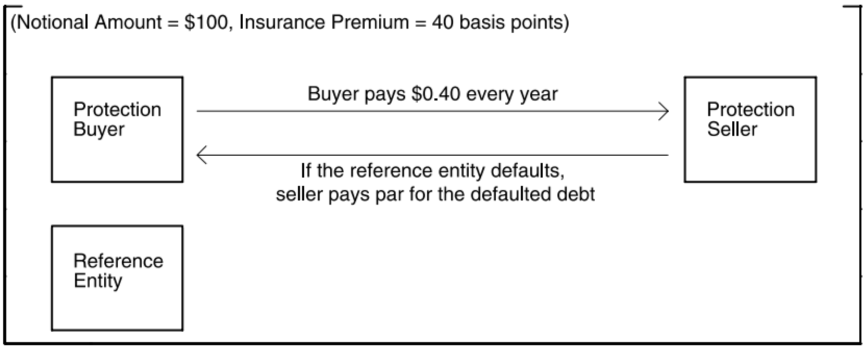


Figure 3.1.: Basic features of a CDS contract. Source: Bomfim (2005).

CDS contracts are traded over-the-counter (OTC) and set up in a standardized structure which was laid out by the International Swaps and Derivatives Association (ISDA) via master agreements. The reference entity can comprise obligors, such as firms, countries or an underlying credit product issued by the respective obligor (e.g. bonds). CDS contracts have different tenors ranging from 6 months up to 30 years with 5 years being the most commonly traded tenor in the market. Events that classify as a credit event in a CDS contract are typically the following:

- bankruptcy
- failure to pay
- obligation of default or acceleration
- repudiation or moratorium
- restructuring.

For the latter event, multiple tradable clauses exist:

- Full Restructuring (CR): Restructuring is defined as a credit event in its original form. Standard clause in the sovereign CDS market.
- Modified Restructuring (MR): Restructuring is still defined as a credit event, but the deliverable obligations are limited to those with tenors within 30 months of the CDS contract's remaining tenor. Standard clause in the North American CDS market until 2009.
- Modified-Modified Restructuring (MM): Restructuring is still defined as a credit event, but the deliverable obligations are restricted to those with tenors of up to 60 months within the CDS contract's remaining tenor for restructured debt, and 30 months for other obligations. Standard clause in the European CDS market.
- No Restructuring (XR): Restructuring is not defined as a credit event. Standard clause in the North American CDS market.

CDS contracts can be settled in two ways: cash settlement or physical delivery of a specific set of reference obligations. In a cash settlement scenario, the financial exchange only covers actual losses incurred, with the claimant retaining the debt claim on the reference entity's balance sheet. Conversely, in a physical delivery settlement, the claimant transfers the referenced obligation as per the contract to the insurer and, in return, receives the full notional amount of the underlying contract. Subsequently, the protection seller may seek to maximize the resale value of the received debt claim or choose to retain it.

3.3. Structural models of credit risk

The modeling of credit risk follows two main approaches: structural and reduced-form models. Structural models explicitly describe the firm value and define a credit event as an event triggered by movements of the firm value relative to some (random) default barrier. Reduced-form models instead represent credit events as a result of some exogenously specified jump process and disregard firm characteristics (value, capital structure) completely. In this thesis, we will focus on structural models as we want to understand the economic mechanism of climate risk on credit. Specifically, we present the original Merton model and discuss relevant extensions of it. In our exposition, we will mainly follow Bielecki and Rutkowski (2004) and Lando (2004).

3.3.1. Merton model

Structural credit models have been introduced by Merton (1974b) using a framework relying on the standard Black-Scholes assumptions. Here, the firm is financed by equity S_t and a single zero-coupon bond B_t with face value F and maturity T. Consequently, the total value of the firm's assets at time t is $V_t = S_t + B_t$. The risk-free interest rate is $r > 0$. Under an equivalent martingale measure $\mathbb{P}^*$, the firm value V_t is governed by the following dynamics

$$\mathrm{d}V_t = (r - \gamma)V_t \mathrm{d}t + \sigma_V V_t \mathrm{d}\widetilde{W}_t \tag{3.3}$$

with volatility $\sigma_V > 0$, constant dividend rate γ and $\widetilde{W}_t$ a Brownian motion under $\mathbb{P}^*$. Default only takes place at maturity T and happens if the the total firm value V_T is less than the face value of the bond F. For equity owners the terminal payoff is then

$$S_T = (V_T - F)^+ ,$$

whereas the terminal cash flow B_T received by the bond owner is

$$B_T = F - (F - V_T)^+ = \begin{cases} F, & \text{if } V_T \geq F \\ V_T & \text{if } V_T < F. \end{cases}$$

Consequently, equity can be viewed as a call option on the firm value and bonds can be viewed as a portfolio long a risk-free payment and short a put option on the firm value.

A straightforward calculation in the Black-Scholes-Merton framework then yields the value of equity

$$S_t = V_t e^{-\gamma(T-t)}\Phi(d_1) - Fe^{-r(T-t)}\Phi(d_2) \tag{3.4}$$

and the bond price

$$B_t = V_t e^{-\gamma(T-t)}\Phi\left(-d_1\right) + Fe^{-r(T-t)}\Phi\left(d_2\right) \tag{3.5}$$

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

$$d_1 = \frac{\log\left(V_t/F\right) + \left(r - \gamma + \sigma_V^2/2\right)(T-t)}{\sigma_V\sqrt{T-t}},$$
$$d_2 = d_1 - \sigma_V\sqrt{T-t}.$$

Risk-neutral probabilities of default (conditional on $\mathcal{F}_t$) are given by

$$p_t^* = \mathbb{P}^*(V_T < F|\mathcal{F}_t) = \Phi\left(-d_2\right). \tag{3.6}$$

Thus, we can give the following alternative representation for the bond price

$$B_t = Fe^{-r(T-t)}(1-p_t^*) + Fe^{-r(T-t)}p_t^*\delta_t^*,$$

where

$$\delta_t^* = \frac{\mathbb{E}^{\mathbb{P}^*}\left[V_T\mathbb{1}_{\{V_T<F\}}|\mathcal{F}_t\right]}{F\mathbb{P}^*(V_T<F|\mathcal{F}_t)} = \frac{V_t e^{-\gamma(T-t)}\Phi(-d_1)}{Fe^{-r(T-t)}\Phi(-d_2)}$$

is the conditional risk-neutral expected recovery rate upon default. The credit spread, defined as the difference between the yield of a defaultable bond and a default-free bond, is given by

$$y_t = -\frac{1}{T-t}\log\left(V_t e^{-\gamma(T-t)}\Phi(-d_1) + Fe^{-r(T-t)}\Phi(d_2)\right).$$

Typically, the time t firm value V_t and its volatility σ_V are unobservable. To overcome this issue and obtain these parameters, the nonlinear system of equations comprising equation (3.4) and the identity[2]

$$\sigma_S = \frac{\Phi(d_1)e^{-\gamma(T-t)}V_t\sigma_V}{S_t}, \tag{3.7}$$

with S_t and σ_S the observable equity value and its volatility, has to be solved. Once the tuple (V_t, σ_V) is known, we can obtain bond prices and (actual) probabilities of default. For the latter, let us assume that under the historical measure $\mathbb{P}$

$$\mathrm{d}V_t = (\mu - \gamma)V_t\mathrm{d}t + \sigma_V V_t\mathrm{d}W_t \tag{3.8}$$

[2] (3.7) is obtained by applying Itô's formula to obtain the stock price dynamics.

for some constant μ and W_t a $\mathbb{P}$-Brownian motion. The actual probability of default is then given by

$$\mathbb{P}(V_T < F|\mathcal{F}_t) = \Phi\left(-\mathrm{DD}_t\right), \tag{3.9}$$

where

$$\mathrm{DD}_t = \frac{\log\left(V_t/F\right) + \left(\mu - \gamma - \sigma_V^2/2\right)(T-t)}{\sigma_V\sqrt{T-t}}$$

is the distance-to-default. DD_t measures the distance of the expected total value of the firm's assets from the default point F at time t (scaled inversely by the volatility of the firm's assets).

3.3.2. Extensions

While the Merton model provides a very useful framework to think about implications and relations of the capital structure and defaultable bond prices, practical applications require to relax some of the model assumptions. For instance, the continuity of the value process V_t implies that credit spreads will either tend to zero or infinity as maturity approaches, which contradicts empirical evidence. Also, the capital structure of a firm is fixed in the Merton model and we obtain only the prices of equity and corporate bonds in a given capital structure. In practice, firms optimize their capital structure and models should accommodate this. Below, we will discuss these extensions. For further extensions, such as allowing default prior to maturity or stochastic interest rates, we refer to Bielecki and Rutkowski (2004) and Lando (2004).

Jump-diffusion models

As stated above, the continuity of the firm value process V_t prevents unexpected events (e.g. a sudden default) from happening. Thus, the Merton model cannot replicate the empirically observed positive credit spreads for very short-term maturities. To circumvent this problem, Zhou (2001) extends the firm value process to a jump-diffusion process.
For the jump component, they introduce a Poisson process N_t with intensity λ under the risk-neutral measure $\mathbb{P}^*$. Additionally, let $(\widetilde{Y}_i)_{i\geq 1}$ be a sequence of i.i.d. random variables with mean $\nu < \infty$ that will represent the jump sizes. Now, under $\mathbb{P}^*$ the dynamics of the firm value (with $\gamma = 0$) are given by

$$\mathrm{d}V_t = V_{t-}((r-\lambda\nu)\mathrm{d}t + \sigma_V \mathrm{d}\widetilde{W}_t + \mathrm{d}\widetilde{L}_t),$$

where

$$\widetilde{L}_t = \sum_{i=1}^{N_t} \widetilde{Y}_i$$

is a marked Poisson process that governs the discontinuous changes in the firm value. The processes $\widetilde{W}_t$, N_t and $(\widetilde{Y}_i)_{i\geq 1}$ are assumed to be mutually independent under $\mathbb{P}^*$. The firm value is now given by

$$V_T = V_t \exp\left(\left(r - \frac{1}{2}\sigma_V - \lambda\nu\right)(T-t) + \sigma_V(\widetilde{W}_T - \widetilde{W}_t)\right)\prod_{i=1}^{N_t}(1+\widetilde{Y}_i).$$

To obtain semi-analytic results, the jump size distribution is assumed to be log-normal[3], that is, $\log(Y_i + 1) \sim \mathcal{N}(\mu, \sigma^2)$. Then

$$\nu = \exp\left(\mu + \frac{1}{2}\sigma^2\right) - 1.$$

The risk-neutral probability of default is now given by

$$\mathbb{P}^*(V_T < F|\mathcal{F}_t) = \sum_{i=0}^{\infty} e^{-\lambda(T-t)}\frac{(\lambda(T-t))^i}{i!}\Phi(-d_{2,i}(V_t, T-t)), \tag{3.10}$$

where

$$d_{2,i}(V_t, T-t) = \frac{\log(V_t/F) + \mu_i(T-t)}{\sigma_i(T-t)}$$

with

$$\mu_i(T-t) = \left(r - \frac{1}{2}\sigma_V^2 - \lambda\nu\right)(T-t) + i\mu,$$
$$\sigma_i(T-t) = \sigma_V^2(T-t) + i\sigma^2.$$

With the introduction of the jump component in the firm value dynamics, the financial market at hand becomes incomplete and the specification of a market premium is required. Assuming no jump-risk premium, the bond price equals

$$\begin{aligned} B_t = Fe^{-r(T-t)}\Bigg\{1 &- \sum_{i=0}^{\infty} e^{-\lambda(T-t)}\frac{(\lambda(T-t))^i}{i!}\Phi\left(-d_{2,i}\left(V_t, T-t\right)\right) \\ &+ \frac{V_t}{F}\sum_{i=0}^{\infty} e^{\mu_i(T-t)+\sigma_i^2(T-t)/2-\lambda(T-t)}\frac{(\lambda(T-t))^i}{i!}\Phi\left(-d_{1,i}\left(V_t, T-t\right)\right)\Bigg\}. \end{aligned} \tag{3.11}$$

Optimal capital structure models

A straightforward approach to allow optimizing the capital structure is to include bankruptcy costs and tax advantages from issuing debt. The model needs to accommodate for a dynamic capital choice and default events are associated with the first passage time of some pre-specified barrier. In the following, we will focus on models suggested by

[3] An alternative is to use the double-exponential distribution advocated by Kou and Wang, 2004.

Leland (1994) and Leland and Toft (1996), in which stockholders choose a bankruptcy policy in such a way that the value of equity will be maximized (or, equivalently, the value of debt will be minimized).[4] To introduce a standard setting, assume that the firm has a stationary debt structure and issues a coupon bond with face value F, maturity T and constant coupon rate c. That is, the face value is uniformly distributed over $[t, T]$ and the firm constantly issues new bond principal at rate $f = F/T$ per year with coupon rate $c = C/T$ per year. Given the solvency of the firm, the total outstanding principal and the total coupon paid by all outstanding bonds are thus F and C per year, respectively. With that, the total debt service payments remain constant over time and equal $C + f$.

Default happens if the firm value falls below the constant default barrier $\bar{v}$. Hence, the default time is given by

$$\tau = \inf\{t \geq 0 : V_t \leq \bar{v}\}.$$

In case of default bondholders will receive a recovery payment at default of $\beta\bar{v}$, where $\beta \in [0, 1]$. Consequently, $(1 - \beta)\bar{v}$ represents the costs upon bankruptcy. Tax benefits arise from the tax-sheltering effects of debt financing. These benefits can be interpreted as constant coupon rate $\bar{c}$ which can be claimed as long as the firm does not default. Incorporating these two components yields the following total value of the firm at time t

$$T(V_t) = V_t + \frac{\bar{c}}{r}\left(1 - \left(\frac{\bar{v}}{V_t}\right)^{\frac{2r}{\sigma_{\bar{v}}^2}}\right) - (1 - \beta)\bar{v}\left(\frac{\bar{v}}{V_t}\right)^{\frac{2r}{\sigma_{\bar{v}}^2}}. \tag{3.12}$$

In the setting of the Merton model, the value of the firm's debt is then given by

$$B_t(V_t) = \frac{C}{r} + \frac{1}{r(T-t)}\left(F - \frac{c}{r}\right)\int_t^T e^{-ru} g(u)\mathrm{d}u + \frac{1}{T-t}\left(\beta\bar{v} - \frac{c}{r}\right)\int_t^T h(u)\mathrm{d}u,$$

where

$$g(u) = \Phi\left(k_1(u)\right) - \left(\frac{\bar{v}}{V_t}\right)^{2\widetilde{a}}\Phi\left(k_2(u)\right),$$
$$h(u) = \left(\frac{\bar{v}}{V_t}\right)^{\widetilde{a}+\widetilde{\zeta}}\Phi\left(g_1(u)\right) + \left(\frac{\bar{v}}{V_t}\right)^{\widetilde{a}-\widetilde{\zeta}}\Phi\left(g_2(u)\right)$$

with

$$\widetilde{\nu} = r - \gamma - \frac{1}{2}\sigma_V^2, \qquad \widetilde{a} = \widetilde{\nu}\sigma_V^{-2}, \qquad \widetilde{\zeta} = \sigma_V^{-2}\sqrt{\widetilde{\nu}^2 + 2\sigma_V r},$$

[4]These models build on Black and Cox (1976) and require the calculation of various functionals of Brownian motion.

and

$$k_1(u) = \frac{\log(V_t/\bar{v}) + \tilde{\nu}u}{\sigma_V\sqrt{u}}, \qquad k_2(u) = \frac{\log(\bar{v}/V_t) + \tilde{\nu}u}{\sigma_V\sqrt{u}},$$
$$g_1(u) = \frac{\log(\bar{v}/V_t) + \tilde{\zeta}\sigma_V^2 u}{\sigma_V\sqrt{u}}, \qquad g_2(u) = \frac{\log(\bar{v}/V_t) - \tilde{\zeta}\sigma_V^2 u}{\sigma_V\sqrt{u}}.$$

The optimal default barrier v^* can now endogenously be determined by maximizing the equity value $S_t(V_t)$. Observing that $S_t(V_t) = T(V_t) - B_t(V_t)$ and invoking the smooth-pasting condition $\frac{\partial S_t}{\partial V_t}|_{V_t=v^*} = 0$ yields

$$v^* = \frac{\frac{C}{r}\left(\frac{A}{r(T-t)} - B\right) - \frac{AF}{r(T-t)} - \frac{\bar{c}(\tilde{a}+\tilde{\zeta})}{r}}{1 + \tilde{a}(\tilde{a}+\tilde{\zeta}) - (1-\tilde{a})B},$$

where

$$\begin{aligned}
A &= 2\tilde{a}e^{-r(T-t)}\Phi\left(\tilde{a}\sigma_V\sqrt{T-t}\right) - 2\tilde{\zeta}\Phi\left(\tilde{\zeta}\sigma_V\sqrt{T-t}\right) \\
&\quad - \frac{2}{\sigma_V\sqrt{T-t}}\phi\left(\tilde{\zeta}\sigma_V\sqrt{T-t}\right) + \frac{2e^{-r(T-t)}}{\sigma_V\sqrt{T-t}}\phi\left(\tilde{a}\sigma_V\sqrt{T-t}\right) + \tilde{\zeta} - \tilde{a}, \\
B &= -\left(2\tilde{\zeta} + \frac{2}{\tilde{\zeta}\sigma_V(T-t)}\right)\Phi\left(\tilde{\zeta}\sigma_V\sqrt{T-t}\right) - \frac{2}{\sigma_V\sqrt{T-t}}\phi\left(\tilde{\zeta}\sigma_V\sqrt{T-t}\right) \\
&\quad + \tilde{\zeta} - \tilde{a} + \frac{1}{\tilde{\zeta}\sigma_V(T-t)},
\end{aligned}$$

where $\phi(\cdot)$ denotes the density function of the standard normal distribution. Finally, it is now possible to determine the optimal leverage ratio that maximizes the firm value for different debt maturities.

3.4. Climate-adjusted models of credit risk

In order to analyze and model the impact of climate change risks (physical, transition and carbon risk), standard credit models are adjusted to include climate risk. In the following, we introduce a model to incorporate these risks. Furthermore, we outline and comment on various alternative approaches brought forward in the literature.

3.4.1. Growth adjustment

As climate risks (and opportunities) will affect the value of a firm, a straight-forward way to incorporate climate risk is to adjust the growth rate of the value process. This can explicitly be done in the structural model by introducing a growth adjustment factor δ_t. Depending on a firm's exposure (or opportunities) the factor adjusts the dynamics of the value process and allows to assess the effect of climate risk on the credit risk of a firm. Let us illustrate the effect in terms of calculations regarding the distance-to-default process[5] of a firm.

Including a growth factor, the dynamics of the firm value are given by

$$\mathrm{d}V_t = V_t \left((r - \delta_t)\mathrm{d}t + \sigma_V \mathrm{d}W_t^{(1)} \right), \tag{3.13}$$

where $W_t^{(1)}$ is a Brownian motion. In the case of a constant carbon rate ($\delta_t = \delta$), the formulation is equivalent to the Merton model with dividend rate $\gamma = \delta$ and all the results coincide with the ones obtained in Section 3.3.1. However, we may also assume that δ_t itself follows a random process

$$\mathrm{d}\delta_t = \mu_\delta \mathrm{d}t + \sigma_\delta \mathrm{d}W_t^{(2)},$$

for some constants $\mu_\delta, \sigma_\delta > 0$ and $W_t^{(2)}$ another Brownian motion with $\mathrm{d}W_t^{(1)}\mathrm{d}W_t^{(2)} = \rho \mathrm{d}t$. Hence, we allow the growth adjustment factor to increase over time due to rising climate risk exposure.

In this framework, the bond price and credit spread are now given by

$$B_t = V_t e^{-\frac{1}{2}\left(\mu_\delta (T-t) - \frac{1}{3}\sigma_\delta^2 (T-t)^2 - \frac{2}{\sqrt{3}}\sigma_V \sigma_\delta \rho\right)(T-t)} \Phi\left(-d_1\right) + F e^{-r(T-t)} \Phi\left(d_2\right) \tag{3.14}$$

resp.

$$y_t = -\frac{\log\left(V_t e^{-\frac{1}{2}\left(\mu_\delta (T-t) - \frac{1}{3}\sigma_\delta^2 (T-t)^2 - \frac{2}{\sqrt{3}}\sigma_V \sigma_\delta \rho\right)(T-t)} \Phi(-d_1) + F e^{-r(T-t)} \Phi(d_2) \right)}{T-t},$$

where

$$d_1 = \frac{\log(V_t/F) + \left(r - \left(\mu_\delta (T-t) + \sigma_V^2\right)/2 + \sigma_T^2\right)(T-t)}{\sigma_T \sqrt{T-t}}, \; d_2 = d_1 - \sigma_T \sqrt{T-t},$$

with

$$\sigma_T = \sqrt{\sigma_V^2 + \frac{1}{3}\sigma_\delta^2 (T-t)^2 + \frac{2}{\sqrt{3}}\sigma_V \sigma_\delta \rho (T-t)}.$$

Assuming the same $\mathbb{P}$-dynamics as in (3.8) the distance-to-default in the model reads

$$\mathrm{DD}_t = \frac{\log\left(V_t/F\right) + \left(\mu - \left(\mu_\delta (T-t) + \sigma_V^2\right)/2\right)(T-t)}{\sigma_T \sqrt{T-t}},$$

[5] The distance-to-default is a measure based on the relation of the value process and the default boundary and widely used in variants of the Merton model, see Lando, 2004 for further discussion.

and it is easy to see that

$$\frac{\partial \mathrm{DD}_t}{\partial \mu_\delta} = -\frac{(T-t)^{3/2}}{2\sigma_T} < 0.$$

That is, the distance of the expected firm value from the default point decreases with a steeper slope in the growth adjustment factor which makes the occurrence of default more likely.

The continuity of the adjustment of the firm value relates nicely to the incorporation of transition risks. A firm's exposure to transition risk is usually related to the size of its CO2 emissions (sometimes in relation to its sector). The rationale is that high-emitting firms have to take significantly more measures to reduce their emissions and hence comply with climate policies than their low-carbon counterparts. Therefore, the growth adjustment reflects the adjustment costs of a firm either directly in terms of a direct carbon price, which materializes via a trading scheme or a tax rate, or indirectly through higher energy cost, supply costs, changed costumer behavior or related factors. Observe, that the latter may well be opportunities (new low-carbon products or technologies).

3.4.2. Shocking the value process

Of course, it is possible to be more specific about the nature of the growth adjustment. A possibility is to define an exogenous shock that affects the growth-rate of the value process of the firm. This approach was developed by Bouchet and Guenedal (2020) which we will now discuss in detail.

Assume k different policy scenarios where C_t^k represents the scenario-dependent costs that will materialize in scenario k. Further, let $k = 0$ be the baseline scenario in which no additional costs for the firm accrue. The shock on the value process is given by

$$\xi_t^k = \frac{C_t^k}{V_0}, \tag{3.15}$$

which is then transmitted to the value process as follows

$$V_t^k = (1 - \xi_t^k) V_0. \tag{3.16}$$

Once the adjusted firm value is determined, bond prices and default probabilities can be calculated within a Merton model framework. Identification of the initial values for V_0 and σ_V is done similarly to the Merton model and independent of scenario k. Thus one can calculate the following scenario-adjusted distance-to-default

$$\mathrm{DD}_t^k = \frac{\log\left(\frac{(1-\xi_t^k)V_0}{F} + \left(\mu - \gamma - \frac{\sigma_V}{2}\right)(T-t)\right)}{\sigma_V \sqrt{T-t}} \tag{3.17}$$

and actual probability of default (PD)

$$\mathrm{PD}_t^k = \mathbb{P}(V_T < K|\mathcal{F}_t) = \Phi\left(-\mathrm{DD}_t^k\right). \tag{3.18}$$

In their original form, Bouchet and Guenedal (2020) use this approach to investigate the impact of transition risk. Following the same narrative as above, a firm's exposure to transition risk is commonly quantified in the literature in terms of emissions (intensity). Here, the approach is to use the carbon price directly and incorporate its effect on the firm value for each transition scenario k using the firm value adjustment.

Formally, let $\mathrm{CE}_t(j)$ be the firm's emitted CO2 emissions in region j at time t. Each region j is assumed to have a representative carbon price $\mathrm{CP}_t^k(j)$ for each scenario k under consideration. The baseline scenario $k = 0$ now refers to the case of a non-changing carbon price, i.e. $\mathrm{CP}_t^0(j) = \mathrm{CP}_0^0(j)$. The firm's carbon costs (CC) at time t in scenario k are then

$$\mathrm{CC}_t^k = \sum_{j\in\mathcal{M}} \mathrm{CE}_t(j) \times \mathrm{CP}_t^k(j),$$

where $\mathcal{M}$ is the set of regions the firm has reported direct emissions. Bouchet and Guenedal (2020) model the impact on the cash flow (EBITDA) and relate it to the firm value adjustment.[6] Incorporating these costs hence yields a shock to EBITDA

$$\xi_t^k = \frac{\mathrm{CC}_t^k}{\mathrm{EBITDA}_0}.$$

This shock is now transmitted to the firm value analogously to (3.16) and credit metrics of interest can be obtained accordingly. Additionally, in order to better understand how vulnerable a firm is to the level of a specific carbon price, an average price corridor or margin can be determined depending on the probability of default. This so-called carbon price margin (CPM) is the model-driven maximum average emission price at which the firm's default probability does not exceed a certain threshold S:

$$\mathrm{CPM}_t = \max\left\{\mathrm{CP}_t : \mathrm{PD}_t \leq S\right\}.$$

Solving Equation (3.18) for CP then yields

$$\mathrm{CPM}_t = \left[1 - \exp\left(\sigma_V\sqrt{T-t}\,\Phi^{-1}(1-S) - \left(\mu - \gamma - \frac{\sigma_V^2}{2}\right)(T-t)\right)\frac{F}{V_t}\right]\frac{\mathrm{EBITDA}_0}{\mathrm{CE}_t},$$

where CE_t denotes the firm's average emissions and we assume that the total emissions are uniformly distributed across all regions.

Although the approach at hand has initially been introduced to investigate the effect of transition risks on credit, it may also be applied to examine the impact of physical risks. For that purpose, the firm-specific costs of physical events such as natural disasters have to be integrated into the shock from (3.15). These may be retrieved from economic damage projections that depend on the physical severity of scenario k.

[6] Using the EBITDA relies on the assumption that the proportionality to the firm value stays constant over time.

3.4.3. Discontinuous climate impacts

The setting of section 3.3.2 allows to incorporate abrupt changes in the value process motivated by physical climate risk, e.g. extreme weather events disturbing production or supply chains. Kölbel et al. (2022) and Agliardi and Agliardi (2021) argue for the incorporation of climate-related risks that can cause significant adjustments in corporate earnings resulting in a revaluation of the firm. While Kölbel et al. (2022) adopt precisely the framework presented in Section 3.3.2, Agliardi and Agliardi (2021) relate the jumps to transition risk (through a rapidly changing regulatory framework) and feed the jump-diffusion model in a Leland-type (Leland, 1994) structure to analyze the effects on framework bond prices. As we discuss a variant of the Leland model below, we focus on the former approach.

The model setup of Kölbel et al. (2022) is the same as in Section 3.3.2, but now the jump component solely models abrupt firm value changes arising from climate risks. Consequently, default probabilities and credit spreads can be directly read off from Equations (3.10) and (3.11). Using Equation (3.10), we can further see that

$$\frac{\partial \mathbb{P}^*(V_T < F|\mathcal{F}_t)}{\partial \mu} < 0$$

and

$$\frac{\partial \mathbb{P}^*(V_T < F|\mathcal{F}_t)}{\partial \lambda}\Big|_{\mu<0} > 0.$$

Hence, the severity of climate risks can be modeled through both the magnitude and frequency of the jumps. For the physical risk channel, different jump size distributions and intensities may be determined using cost projections associated with the physical state of the scenario under consideration. For the transition risk channel, this approach can be used as well. An example of it will be provided in the next subsection.

3.4.4. Climate scenario uncertainty

While the use of scenarios is a straightforward way to analyze the impact of different climate pathways on firms' credit profile, it suffers from the inherent static nature that comes with each scenario. That is, in applications, a finite number of scenarios with known trajectories is assumed. Ex-ante, however, it is far from clear which scenario will eventually materialize and different scenarios may be assigned different probabilities of occurrence. Additionally, the static approach usually also omits any updating and hence the incorporation of new information arriving in the market. For that purpose, Le Guenedal and Tankov (2022) introduce a Bayesian approach that accounts for both the uncertainty and updating feature of scenario analysis.

Let V_t be the value of the firm that will be impacted by the economic consequences associated with different scenarios. Similar to Section 3.3.2 and 3.4.3, we model the costs originating from these scenarios by a jump process which reads

$$L_t = \sum_{i=1}^{N_t} Y_i,$$

where N_t is now a doubly stochastic Poisson process with a scenario-dependent intensity and $(Y_i)_{i\geq 1}$ is a sequence of i.i.d. random variables that are independent from N_t. The additional layer of stochasticity in the Poisson process models the uncertainty regarding the true scenario. For that purpose, let us assume that there are n scenarios with increasing environmental stringency and let $I \in \{1, \ldots, n\}$ be the unobservable random variable representing the true scenario unknown to the agent. The varying degrees of stringency are incorporated by allowing for scenario-dependent intensities $0 < \lambda_1 < \ldots < \lambda_n$ making the process jump more frequently for more economically severe scenarios. Conditional on I the process N_t is hence a Poisson process with intensity λ_I. However, as the true scenario is unknown to the agent, the intensity will be a mixture of multiple scenario intensities weighted by their respective probability of occurrence. For model tractability, the jump sizes $(Y_i)_{i\geq 1}$ are assumed to exhibit the same distribution in every scenario. That is, the impact of climate risks is only modeled through the frequency of events, but not their magnitude.

The firm value dynamics are now given by

$$\mathrm{d}V_t = V_{t-}\left(r\mathrm{d}t + \sigma\mathrm{d}W_t - \mathrm{d}L_t\right),$$

where W_t is a Brownian motion independent from I and N_t, and $(Y_i)_{i\geq 1}$ is a sequence of i.i.d. random variables with mean $\nu < \infty$ that are independent from W_t, I and N_t.

To integrate the Bayesian learning, let $\mathcal{F}_t = \sigma(\widetilde{W}_s, N_s, s \leq t)$ be the observation filtration that contains all the information about the trajectories of the firm value and jump process until t. Further, we denote by $\widehat{p}_t^i = \mathbb{E}[I = i|\mathcal{F}_t]$ the posterior probability of the occurrence of scenario i given the available information at time t. With that, the intensity of N_t is given by

$$\widehat{\lambda}_t^N = \sum_{i=1}^{n} \lambda_i \widehat{p}_t^i$$

with the filtered probabilities

$$\widehat{p}_t^{i,N} = \frac{e^{-\lambda_i t}\lambda_i^{N_t}\widehat{p}_0^i}{\sum_j e^{-\lambda_j t}\lambda_j^{N_t}\widehat{p}_0^j}$$

which gives

$$\widehat{\lambda}_t^N = \frac{\sum_i e^{-\lambda_i t}\lambda_i^{N_t+1}\widehat{p}_0^i}{\sum_j e^{-\lambda_j t}\lambda_j^{N_t}\widehat{p}_0^j}.$$

We now consider a simplified version of the model from Section 3.3.2 without any bankruptcy costs and tax benefits. Further, we are not interested in the optimal structure, but only want to determine bond prices and the optimal default barrier for a fixed capital structure. Considering a coupon bond with face value F, constant coupon rate c and maturity T, the value of the firm at time t is given by

$$\begin{aligned}\widehat{V}_t &= \mathbb{E}\left[\int_t^\infty e^{-r(s-t)} V_s \mathrm{d}s\right] \\ &= \sum_{i=1}^n \mathbb{P}\left[I = i \mid \mathcal{F}_t\right] \mathbb{E}\left[\int_t^\infty e^{-r(s-t)} V_s \mathrm{d}s \Big| \mathcal{F}_t, I = i\right] \\ &= V_t \sum_{i=1}^n \frac{\hat{p}_t^i}{r + \nu\lambda_i - \mu} = V_t \alpha_t^{N_t},\end{aligned}$$

where

$$\alpha_t^N := \sum_{i=1}^n \frac{1}{r + \nu\lambda_i - \mu} \frac{e^{-\lambda_i t} \lambda_i^N \hat{p}_0^i}{\sum_j e^{-\lambda_j t} \lambda_j^N \hat{p}_0^j}.$$

The equity value at time t, provided that default resp. restructuring did not happen before t, is given by

$$\begin{aligned}U^N(t, V) = \sup_{\tau \in \mathcal{T}([t,T])} \mathbb{E}\Bigg[\int_t^{\tau\wedge T} & e^{-r(s-t)} \left(V_s^{t,V,N} - c\right) \mathrm{d}s \\ & + e^{-r(T\wedge\tau - t)} \left(\widehat{V}_{T\wedge\tau}^{t,V,N} - K\right)^+\Bigg],\end{aligned}$$

where the superscript t, V, N means that the Markov process (V_s, N_s) is started at time t with initial values (V_t, N_t), and $\mathcal{T}([t, T])$ is the set of $(\mathcal{F}_t)$-stopping times in $[t, T]$ with respect to the filtration generated by $(V_s^{t,V,N}, N_s^{t,V,N})_{s\geq t}$.

The optimal default resp. restructuring time at time t is now defined as

$$\tau^* = \inf\left\{s \geq t : S_t^{N_s^{t,N}}\left(V_s^{t,V,N}\right) = \left(V_s^{t,V,N} - F\right)^+\right\},$$

and the bond price equals

$$B_t = \mathbb{E}\left[\int_t^{\tau^*\wedge T} e^{-r(s-t)} c\mathrm{d}s + e^{-r(\tau^*\wedge T - t)} \widehat{V}_{\tau^*\wedge T}^{t,V,N} \wedge F\right].$$

Alternatively, using $V_t = S_t + B_t$, we can also represent the bond price as follows

$$\begin{aligned}B_t &= V_t \alpha_t^N - \sup_{\tau \in \mathcal{T}([t,T])} \mathbb{E}\Bigg[\int_t^{\tau\wedge T} e^{-r(s-t)} \left(V_s^{t,V,N} - c\right) \mathrm{d}s \\ &\qquad\qquad + e^{-r(T\wedge\tau - t)} \left(\widehat{V}_{T\wedge\tau}^{t,V,N} - K\right)^+\Bigg] \\ &= \inf_{\tau \in \mathcal{T}([t,T])} \mathbb{E}\left[\int_t^{\tau\wedge T} e^{-r(s-t)} c\mathrm{d}s + e^{-r(T\wedge\tau - t)} \widehat{V}_{T\wedge\tau}^{t,V,N} \wedge K\right].\end{aligned}$$

This last equation can be used to approximate the bond price. For that two (integro-differential) variational inequalities have to be solved, see Sections 3 and 4 of Le Guenedal and Tankov (2022) for details.

Le Guenedal and Tankov (2022) use the model to implement transition risks. For that, they assume L_t to be a carbon price process C_t that randomly jumps over time depending on different possible climate policies. To calibrate, they first match the deterministic carbon price trajectories in each scenario with their stochastic model. In particular, they first pre-specify the jump size ΔC and estimate the scenario-dependent intensity for the time period $[T_1, T_2]$ as

$$\widehat{\lambda}_i = \frac{C^i_{T_2} - C^i_{T_1}}{\Delta C(T_2 - T_1)}.$$

For the scenario probabilities a uniform prior is assumed, although a different prior may be assigned if more information about future regulation is available. To use the model for physical risks, a similar calibration to the one outlined in Section 3.4.3 may be applied. However, the assumption of scenario-independent jump size distribution (and hence the sole calibration based on frequency) seems hard to justify here.

4. Data and methodological framework

In this section, we describe the data and methodological framework that will be used in the upcoming Chapters 5 and 6. First, we describe the CDS data and its characteristics. Second, we introduce known CDS determinants that have been identified in the literature. Third, we report some summary statistics for the variables of interest. Last, we introduce our panel quantile regression approach.

4.1. CDS spreads

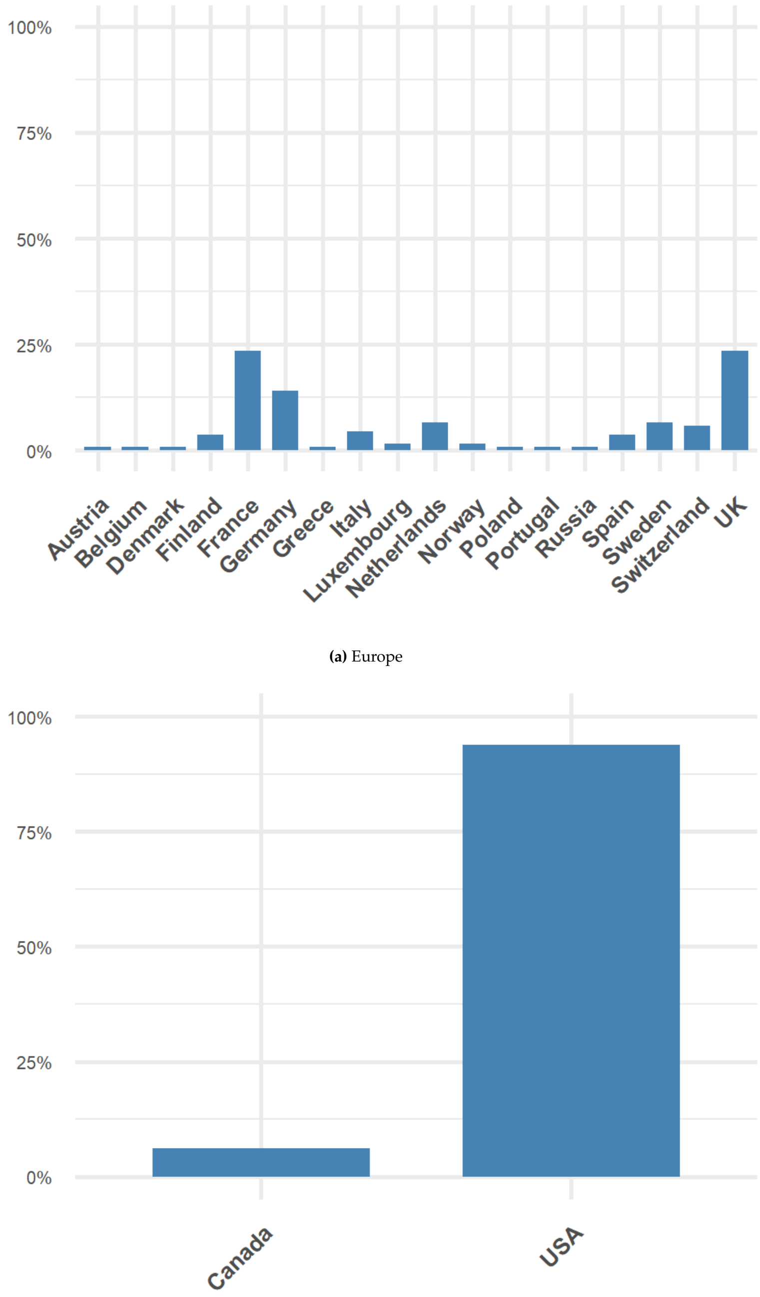
We obtain CDS spread data in daily frequency from Refinitiv for the period January 1, 2013 to December 31, 2020. The dataset covers single-name CDS spreads across tenors of 1, 3, 5, 10 and 30 years for publicly listed European[1] and North American (US & Canada) entities. Each CDS is denominated in US 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).[2] We exclude all firms that have defaulted during the sample period or that exhibit illiquid CDSs, but in general retain firms with large CDS spreads.[3] 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 227,294 European and 437,072 North American CDS spreads-day observations for an unbalanced panel covering 136 European and 275 North American firms, respectively.

In Figure 4.1, we depict the regional distribution of the firms in the European (top) and North American (bottom) sample. In Europe, the big three European countries France, the United Kingdom and Germany dominate the sample with a share of approx. 24%, 24% and 14%, respectively. On the other hand, countries like Austria, Belgium,

[1]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.

[2]As outlined already before, MM and XR represent the standard clauses within their respective region and as such provide the best coverage of CDSs.

[3]Illiquid CDSs are those contracts where no spread movement is recorded for a minimum of 245 consecutive trading days. We acknowledge that this condition is rather lax, but we still use it to ensure a significant number of entities in our samples. Appendix 6.3.2 applies a much more stringent filtering condition, and shows that for both Europe and North America, the results remain unchanged with respect to the baseline findings reported in the Results section. Some studies also exclude firms with CDS spreads exceeding specific thresholds (Zhang et al., 2009; Kölbel et al., 2022; Barth et al., 2022). Our robust modeling approach allows us to dispense with this exclusionary criterion by eliminating exclusively illiquid CDSs.

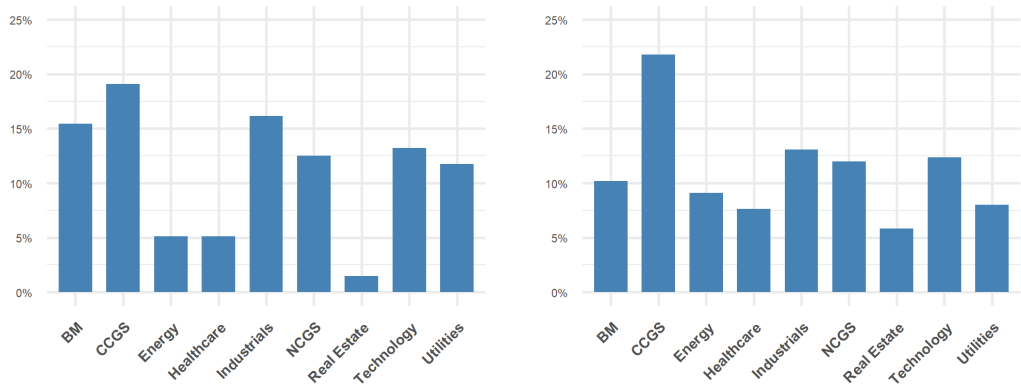


(a) Europe

(b) North America

Figure 4.1.: Regional distribution in the European (top) and North American (bottom) sample.

Denmark, Greece, Poland, Portugal and Russia are only represented once in the sample. In North America, the sample is heavily dominated by the United States of America (USA) with a share of approx. 94%, while Canada only has a share of approx. 6%.



(a) Europe

(b) North America

Figure 4.2.: Sector distribution in the European (left) and North American (right) sample.

Figure 4.2 shows the sectoral distribution (using Refinitiv's 9-sector business classification (RBC)) of the firms in the European (left) and North American (right) sample.[4] In Europe the sectors Consumer Cyclicals (CCGS), Industrials and Basic Materials (BM) dominate with a share of approx. 19%, 16% and 15%, respectively. Contrary, in North America, CCGS outweighs the rest by a margin with a share of approx. 22% followed by Industrials (13%) and Technology (12%). On the lower end in Europe, the sectors Real Estate (1.47%), Energy (5%) and Healthcare (5%) have the smallest shares. In North America, Real Estate also exhibits the smallest share (6%). Overall, the sectoral distribution in North America looks much more balanced than the European one.

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, so we analyze first-differences. Following Koutmos (2019), we thus calculate the daily CDS spread log returns as:

$$s^m_{i,t} = \log(\mathrm{CDS}^m_{i,t}) - \log(\mathrm{CDS}^m_{i,t-1}),$$

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

When investigating the term structure of CDS spreads, we consider the slope of the CDS curve. Namely, we first calculate the CDS slope as the difference between two CDS spreads of differing maturities $m \neq n$

[4] A detailed description of the sector classification of the Refinitiv Business Classification (RBC) is available here.

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

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

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

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

4.2. 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 (1974a), 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).[5] 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 also include information capturing the current state of the CDS market. Specifically, we include a market condition variable, the Median Rated Index (MRI), that captures

[5] 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.

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

Moving beyond CDS spreads, we consider the term structure of CDS spreads that reflects the shape of the conditional default probability over different time horizons (Han and Zhou, 2015). Following Collin-Dufresne et al. (2001) and Han and Zhou (2015), we include the risk-free interest rate (IR). Specifically, we measure the change in the 10-year constant maturity Treasury yield (ΔIR_t) using data collected from the St Louis Federal Reserve (FRED). Our initial 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.

4.3. Descriptive statistics

To gain more insights about the data under investigation, Table 4.1 presents descriptive statistics for all dependent and independent variables under consideration in both regions.[6] Average CDS spread returns are negative and slightly increase towards longer tenors. The corresponding standard deviations indicate a relatively large dispersion with values ranging between 1.6% and 7.3%. CDS spread returns with tenors ≥ 3 years exhibit large outliers with maximum (minimum) returns from 85% (-67%) to 300% (-220%). The shortest tenor of 1 year even reaches maximum (minimum) returns of over 550% (-550%) and 370% (-310%), for Europe and North America, respectively. The CDS spread return distributions are slightly right-skewed and characterized by heavy tails (with a kurtosis ranging from 47 to more than 1,000). These extreme CDS spread statistics are in line with those reported in the existing literature and illustrate the unconventional characteristics of CDS data (Pires et al., 2015).[7]

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

[7] 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

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

Table 4.1.: 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.

4.4. Methodology

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

Additionally, QR can mitigate some of the typical empirical problems frequently encountered in the CDS literature (e.g. the presence of outliers, non-normality), which also apply to our data. In particular, the descriptive measures in Table 4.1 illustrate that CDS returns tend to be interspersed by occasional influential outliers and their distributions are extremely heavy-tailed, making the normality assumption very problematic. While these empirical features would pose a threat to the validity of Ordinary Least Squared (OLS) estimates and their standard errors, QR is robust to these data characteristics and thus a viable option.

The use of QR is rather scant in the credit risk literature, although Pires et al. (2015) and Koutmos (2019) are notable exceptions. Since several researchers 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) show that the impacts of the explanatory variables on CDS 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

with many more outliers and move on a relatively larger scale in general.

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).[8] We follow Zhang et al. (2019) and implement a two-stage approach to estimate the parameter vector $\boldsymbol{\beta}_\tau$.[9] 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 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.[10]

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

[9] 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.

[10] 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.

5. Measuring carbon risk

Before investigating the financial impacts of carbon risk, it is important to have a proper quantification of the risk in question. In this chapter, we first provide a literature review of existing carbon risk metrics. Afterwards, we introduce our own carbon risk (CR) factor which utilizes the credit-linked and forward-looking information contained in CDS spreads. Last, we present a generalization of the CR – the carbon tail risk (CTR) factor – that also incorporates the tails of the carbon risk distribution.

5.1. Existing metrics

The quantification of carbon risks has traditionally been conducted using readily available data such as current emissions (intensities) or ESG metrics. The reasoning is that firms with high emissions and/or bad ESG ratings naturally face higher costs when policies accelerating the low-carbon transition are implemented. However, while these data are a natural proxy for exposure to carbon risk and are easy to access, they come with several drawbacks. First, emissions and ESG variables are typically only available in an annual frequency making it hard to assess the exposure intra-yearly. Second, both metrics, but especially ESG variables, have been shown to be dependent on the data vendor causing reliability issues when choosing a specific data provider (Busch et al., 2018; Berg et al., 2021; Berg et al., 2022). Third, emissions data and ESG scores mostly rely on past information that already realized, making it an backward-looking variable by construction. However, when trying to measure carbon risk and with it the financial impacts of the low-carbon transition, the exposure to future risks cannot be neglected. For this reason, a metric appropriately accounting for all these features is essential.

In general, the quantification of carbon risk can either be conducted on a firm level or even broader levels such as sectors, regions or entire markets. Whereas firm-specific metrics serve to depict the idiosyncratic risk of a firm to carbon, broader metrics such as a market-wide risk factor characterize the systemic carbon risk inherent to the market. Furthermore, carbon risk metrics can typically be divided into two main categories: textual metrics and market-based metrics. Textual metrics analyze publicly available textual data (e.g. newspaper articles, (legal) corporate documents, etc.) to extract information related to carbon aspects. Depending on the legal stringency of the documents as well as the coverage and tone used in the texts, a textual risk metric of carbon can then be constructed. Market-based metrics instead rely on assets traded on financial markets and extract the risk component from the observed prices. This approach implicitly assumes that market participants are able to incorporate the risk into the price formation process.

Textual metrics first arose with the work from Engle et al. (2020). Using articles from the Wall Street Journal, they build a monthly index that tracks the market-wide attention towards climate change. However, as one of the first metrics of this kind, it does not distinguish between the multiple facets of climate risk. Improving on this, Ardia et al. (2022) extract information from major U.S. newspapers to construct various theme-dependent metrics (available in daily frequency) that account for the different components of climate risk (incl. carbon risk). In a similar vein, Bua et al. (2022) provide a corresponding risk metric for Europe. Another strand of literature focuses on the incorporation of textual analysis to measure the exposure to carbon risk on a firm level. Here, a firm-specific climate risk metric is constructed that builds on the extraction of relevant keywords from earnings call transcripts (Sautner et al., 2023; Li et al., 2023).

For the market-based metrics, the concept of a carbon risk factor has been thoroughly investigated in the equity literature. Adopted from the classical asset pricing approach, the idea is to build a market-wide environmental factor that captures the difference in returns of firms with high versus low exposure to carbon. Famous examples of such factors include the pollution premium (Hsu et al., 2022), the pollutive-minus-clean (PMC) factor (Huij et al., 2021) and the brown-minus-green (BMG) factor (Görgen et al., 2020). Whereas the division of firms into high versus low carbon exposure is based on corporate emissions for the first two factors, the latter relies on ESG scores to assign firms to these groups. Building upon these factors, a metric of firm-specific exposure to carbon risk can also be extracted by regressing individual stock returns on these environmental factors (see e.g. Faccini et al., 2021 and Huij et al., 2021).

While the literature on the construction of an appropriate factor in the equity space has been growing in recent years, the measurement of carbon risk via credit instruments is still scant. To the best of the authors knowledge, no such carbon risk metric has been proposed yet. Such a factor, however, would be of importance in order to quantify the credit-deteriorating effects of carbon risk. The risk metric we propose in the next subsection will be a factor based on the general, market-wide perception of carbon risk. However, following the approach suggested by Faccini et al. (2021) and Huij et al. (2021) this factor could also be extended to a firm-level metric.

5.2. Carbon risk (CR) factor

In this section, we introduce the construction of our carbon risk factor. First, we build the general factor that proxies for the market-wide perception of carbon risk. Afterwards, we construct several variants that also account for risk exposures on a sectoral, regional and temporal dimension.

5.2.1. Market-wide perception of carbon risk

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

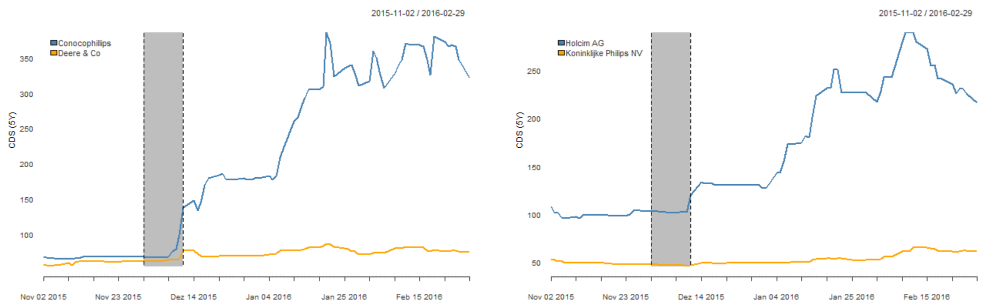
Motivated by the theoretical relationship between carbon risk and credit spreads, our approach to measuring carbon risk relies on analyzing the changes in the credit spreads, which reflect the evolution in the market's perception of carbon risk. To do this, we utilize the information contained in the spreads of CDS contracts. CDS contracts have three crucial advantages. First, they are typically traded on standardized terms, eliminating distortions due to differences in contractual arrangements or liquidity concerns (Longstaff et al., 2005; Ederington et al., 2015).[1] Furthermore, CDS spreads respond quickly to changes in credit and market (and arguably policy) conditions (Blanco et al., 2005; Zhu, 2006; Norden and Weber, 2009). Finally, since there are CDS contracts with varying tenors up to 30 years, they allow us to (i) incorporate the collective forward-looking considerations of lenders, and (ii) shed light on the expected degree of carbon risk within distinct time horizons. As such, CDS spreads provide a unique window for viewing the effect of carbon risk through the lens of lenders' perceptions.

This is clearly illustrated in Figure 5.1, where we plot the evolution of the CDS spreads for two pairs of firms (with the same credit rating) before and after the Conference Of the Parties in Paris in 2015 (COP21), which culminated in the landmark Paris Agreement. In this figure, we provide data on two exemplary polluting firms (ConocoPhillips and Holcim AG) and two exemplary clean firms (Deere & Company and Philips NV) in North America and Europe. Beginning with the North American examples, ConocoPhillips is a multinational firm 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 firm that has effected emissions reductions through increased use of renewable energy.

Figure 5.1 illustrates that the difference in CDS spreads is approximately constant until the occurrence of a policy-relevant event. Post-Paris Agreement, however, the spreads diverge, which we interpret as the result of lenders expecting higher carbon impacts for high-emitting firms. They seek higher protection, demanding more of the CDSs of relatively more carbon-exposed firms (in this example, ConocoPhillips and Holcim), ultimately paying higher spreads. 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-related

[1] Standard contractual characteristics include pre-specified maturity, default event and debt seniority. Corporate bonds, for example, may be embellished with additional idiosyncrasies such as embedded options or specific guarantees.

aspects (especially climate regulations) that can impact firms' credit risk profiles.[2]



(a) North America **(b)** Europe

Figure 5.1.: Evolution of the 5Y-CDS spreads of ConocoPhillips (blue) and Deere & Co (orange) on the left diagram, and Holcim AG (blue) and Koninklijke Philips NV (orange) on the right diagram. The time period spans from 02 November 2015 to 29 February 2016. The gray-shaded area indicates the time period of COP21 (30th Nov 2015 – 12th Dec 2015).

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

As with this literature, we construct firms' carbon profiles using yearly emissions intensities (Scope 1 & 2 emissions normalized by revenue) from Refinitiv as our primary dataset.[3] In order to avoid a look-ahead bias, we use emission intensities lagged by one year as emission data are typically only available at the end of the fiscal year. Emissions are estimated where no actual emissions were reported. These data have been shown to be sufficiently consistent across different data providers (Busch et al., 2018). The emissions of firms in our CDS sample account for a significant fraction – approximately 30% – of the total emissions in the universe of firms represented in the Refinitiv database. We chose firms' emission because other prominent metrics (e.g. environmental ratings provided by Asset4, MSCI, etc.) have been shown to deliver mixed signals, seriously weakening their reliability in terms of constructing the carbon risk classification (Görgen et al., 2020; Berg et al., 2021; Berg et al., 2022; Dimson et al., 2020).

Our approach to constructing a carbon risk factor relies on tracking how firms' expo-

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

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

sure to carbon risk changes. This change reflects one of two things: changes in lenders' expectations about the carbon exposure of different firms or changes in lenders perception of carbon risk for a specific firm over time. To that end, we follow the standard approach used in empirical asset pricing for factor construction (Fama and French, 1992). Specifically, we partition the universe of firms into quintiles according to the one-year lagged emission intensity profile of each firm.[4] We use the groups to form portfolios meant to mimic the underlying risk factor in returns related to carbon.[5] In fact, this grouping allows us to capture the gradient of carbon intensity per unit of revenue while retaining a sufficient number of firms within each group. We then define firms below the first quintile as "clean" and gather their CDS spreads in the set $\mathcal{C}_t^m$. Analogously, we define firms above the last quintile as "polluting" and gather their CDS spreads in the set $\mathcal{P}_t^m$.

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

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

where $\mathrm{Med}(\cdot)$ denotes the median function. Table 5.1 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 is in the Industrials sector with a share of approximately 35% of the sample, while the majority of polluting firms comes from the Basic Materials and Utilities sectors, respectively, with a share of 40% each. In North America, the majority of clean firms is in the Consumer Cyclicals (CCGS) sector with a share of approximately 38% of the sample, while the majority of polluting firms comes from the Utilities sector with a share of approximately 29%.

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

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

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

[4] We perform numerous robustness checks by extending the univariate portfolio sorts (based on emission characteristics) to bivariate sorts that also consider size, book-to-market ratio, and leverage. See Section 6.3.4 for details.

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

Europe	
Polluting	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	
Polluting	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 5.1.: This table displays all firms that were constituents of the polluting resp. clean 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.

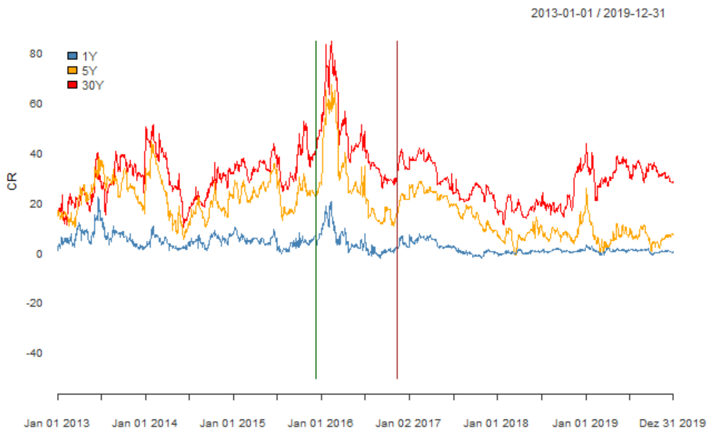
clean firm.[6] When policy events trigger a rise in carbon risk (e.g. expectation of a tighter future regulatory framework), the demand for protection of more (less) exposed firms increases (decreases), resulting in a widening of the wedge. Conversely, if the market expects a loosening of the regulatory framework, there is a narrowing of the wedge (or possibly even a negative wedge).[7] These changes in perceived exposure to carbon risk are aptly represented by the behavior of CR. As such, we consider CR to be an observable proxy for lenders' perception of carbon risk exposure.

To illustrate the relevance of CR, we examine its behavior in response to events that affect firms' exposure to carbon risk. Figure 5.2 displays the evolution of the CR over time, for tenors of 1, 5 and 30 years for the universe of CDS of firms listed in Europe (top) and North America (bottom), respectively.[8] In these graphs we also identify two

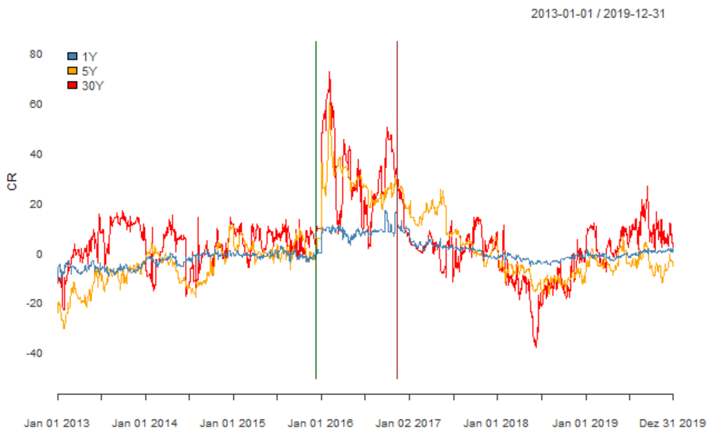
[6] A long-short portfolio is similarly constructed in Meinerding et al. (2020) by sorting firms on their carbon footprints. Combined with a climate news index, Meinerding et al. (2020) use these portfolios to identify the differential effect of carbon risk. Essentially, portfolios are used to identify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

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

[8] We relegate to Figure A.1 in Appendix A.1 that plots all available tenors (including 3Y and 10Y).



(a) Europe



(b) North America

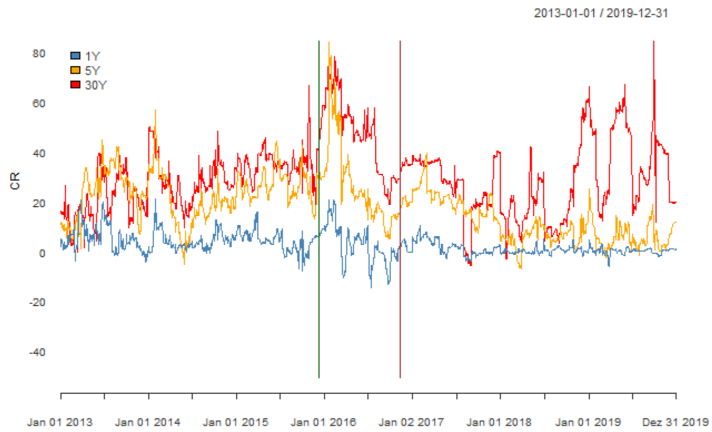
Figure 5.2.: Evolution of the CR over time for maturities 1Y (blue), 5Y (orange) and 30Y (red) for Europe (top) and North America (bottom). The vertical solid lines refer to the Paris Agreement (dark green) and Trump election (brown), respectively.

events, identified in Meinerding et al. (2020), that oppositely affected market perceptions of carbon risk: the Paris Agreement and the election of Donald Trump in the US; these events are represented in Figure 5.2 with vertical solid dark green and brown lines, respectively.

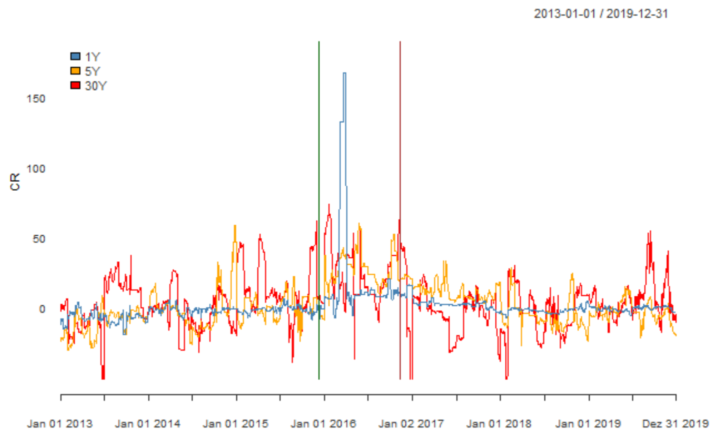
We first examine the European case and observe that all CR time series (CRs) are non-negative. This is in stark contrast with the CRs in North America, where all CRs (except 1Y tenor) continuously swing between positive and negative values, denoting a situation where lenders' perceptions of carbon risk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

The CR replicates a credit insurance portfolio and as such represents an investable risk factor. However, one major drawback in the initially proposed construction is the daily grouping mechanism. This procedure implies a daily rebalancing of the portfolio which may incur significant trading costs. For that reason, we also consider a 'monthly' CR factor where the grouping is conducted only once at the beginning of a month and fixed for the remainder of it. That is, once we fix the median clean and polluting firm, the movement of the CR during the remainder of the month will solely be governed by the CDS spreads of those two firms. Using this construction, however, ensures a portfolio with reasonable rebalancing costs and hence a more realistic setup.

Figure 5.3 depicts the movement of the CR with the adjusted monthly restructuring for both Europe (top) and North America (bottom). Overall, the 'monthly' CR exhibits the same patterns indicating that even under more realistic replication assumptions the directional features of the CR factor persist. There are also differences however. In particular, the CR sometimes rapidly rises and shows irregularities. This is likely due to the dominance of one particular entity governing the CR during that month. Therefore, if a specific firm exhibits an idiosyncratic CDS spread shock (which may not necessarily be related to carbon risk), this immediately translates to the CR factor. The observed effect only vanishes after another rebalancing one month later. The inclusion of more realistic replication features hence comes with the cost of more irregularities in the CR factor. A possible improvement could be the selection of multiple entities and setting up an equally-weighted portfolio with them (that is, computing the mean CDS spread of the selected entities). However, while this procedure smooths out the irregularities, it may further increase rebalancing costs as multiple CDS spreads enter the portfolio. In the following, we will always use the daily construction of the CR described in the beginning of this section.



(a) Europe



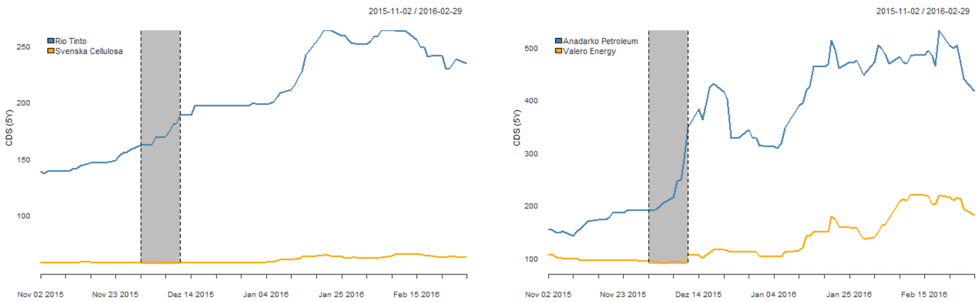
(b) North America

Figure 5.3.: Evolution of the 'monthly' CR over time for maturities 1Y (blue), 5Y (orange) and 30Y (red) for Europe (top) and North America (bottom). The vertical solid lines refer to the Paris Agreement (dark green) and Trump election (brown), respectively.

5.2.2. Sectoral exposures

While the CR is constructed on the entire sample and thus provides an idea about the perception of carbon risk on a broad market level, it disregards the heterogeneity of sectoral exposures. Sectors can face vastly different challenges depending on the emission intensity of their business model, their degree of exposure to regulatory frameworks or varying consumer patterns. For this reason, we also construct sector-specific CR factors based on the Refinitiv Business Classification (RBC) that take the sectoral nuances into account. In particular, we apply the same CR construction from Subsection 5.2.1, but do it separately for each RBC sector which yields a CR for each sector in the end.

Similar to Figure 5.1, we first provide two additional examples of firm pairs who op-



(a) Europe **(b)** North America

Figure 5.4.: Evolution of the 5Y-CDS spreads of Rio Tinto (blue) and Svenska Cellulosa (orange) on the left diagram, and Anadarko Petroleum (blue) and Valero Energy (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).

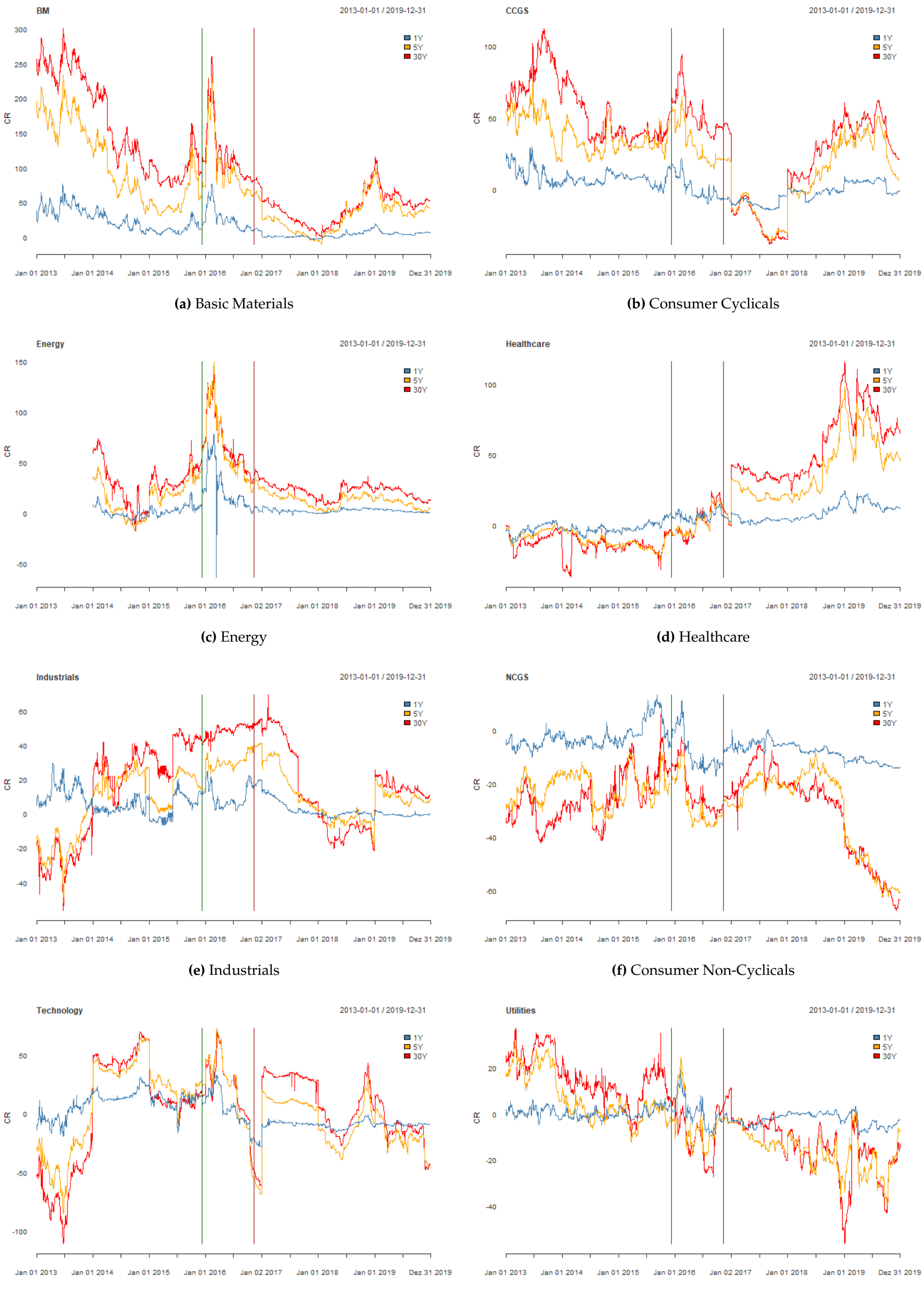
erate in the same industry, but are still exposed to carbon risk differently. Figure 5.4 depicts the evolution of the CDS spreads of two pairs of firms operating in the same industry (with the same credit rating) in North America (left) and Europe (right) before and after COP21. The selected firms in 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 firm engaged in hydrocarbon exploration and was ranked 47th among the World's Top 100 Polluters (CDP, 2017). On the other side, Valero Energy – an international, US-based manufacturer and marketer of transportation fuels – is among the firms with the lowest emission intensity in their industry, albeit a carbon-intensive industry. Rio Tinto is a multinational, UK-based firm 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 firm 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.

Analogously to the examples provided in Figure 5.1, we see that the CDS spreads move on a similar level before COP21 and start to diverge afterwards. Post-COP21 the spreads diverge even further creating a bigger difference in default protection costs for more exposed firms vis-a-vis well prepared firms. So again, this example serves to illustrate that exposure to carbon risk can also be extracted on a sectoral level using CDS data.

Figure 5.5 depicts the evolution of the sectoral CRs over time for tenors of 1, 5 and 30 years in the European sample. Within the construction we excluded the sector Real Estate as well as the first year of the sector Energy due to lack of sufficient data. In general, these subfigures unveil entirely different sectoral carbon risk exposures. The sectors Basis Materials (BM), Consumer Cyclicals (CCGS) and Energy, albeit on different levels, indicate a very similar behavior to the market-wide CR from Subsection 5.2.1. That is, their temporal evolution is comparable to the market-wide perception of carbon risk, although these sectors exhibit different magnitudes of carbon risk. This could be an indication that carbon policy events (e.g. COP21) are relevant in the same way for these sectors. Contrary, the sectors Healthcare and Utilities feature clear upwards, respectively, downwards trends in their CR and do not or only weakly react to events such as COP21. For these sectors, it seems that a clear direction for carbon risk is observable without being significantly affected by policy events. The remaining sectors (Industrials, Consumer Non-Cyclicals (NCGS) and Technology) do not provide a clear picture. In fact, their CRs seem to erratically fluctuate around zero and hence do not give a clear hint on how the market perceives the risk of carbon in these sectors.

In North America (Figure 5.6), the sectoral CRs reveal different patterns. First, we observe that all but the CR for the Energy sector behave markedly dissimilar to the market-wide CR. It seems that these other sectors exhibit very unique exposures to carbon risk compared to the aggregate market. The direction, however, remains unclear as most of the CRs fluctuate erratically around zero. The only exceptions to this are the sectors Healthcare and NCGS which show a clear upward resp. downward movement over time. In terms of reactions to relevant policy events such as the Paris Agreement, we see certain sectors (Energy, Technology, Utilities) that experience an increase in the perception of carbon risk, while others (BM, CCGS) exhibit a significant drop in their respective CR. The remaining sectors (Healthcare, Industrials, NCGS) do not react in any notable fashion.



(a) Basic Materials

(b) Consumer Cyclicals

(c) Energy

(d) Healthcare

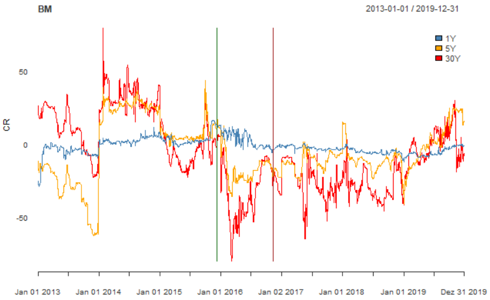
(e) Industrials

(f) Consumer Non-Cyclicals

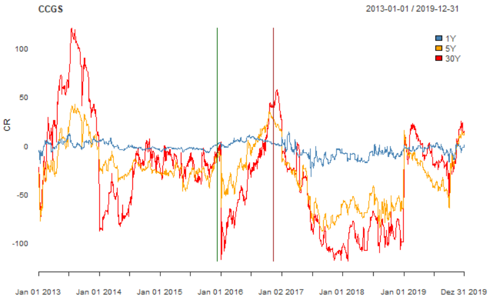
(g) Technology

(h) Utilities

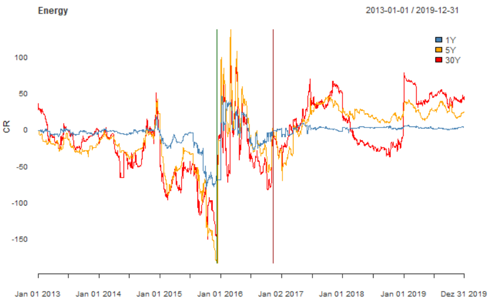
Figure 5.5.: Evolution of the sector-specific CRs over time for maturities 1Y (blue), 5Y (orange) and 30Y (red) for Europe. The first year (2013) in the sector Energy as well as the entire sector Real Estate are excluded due to a lack of enough data for the construction of the CR. The vertical solid lines refer to the Paris Agreement (dark green) and Trump election (brown), respectively.



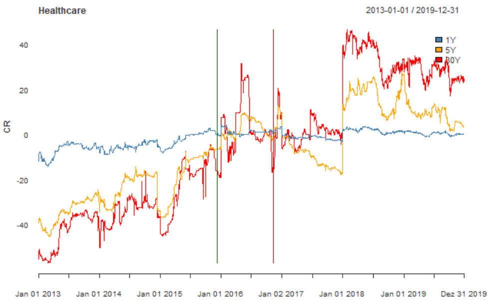
(a) BM



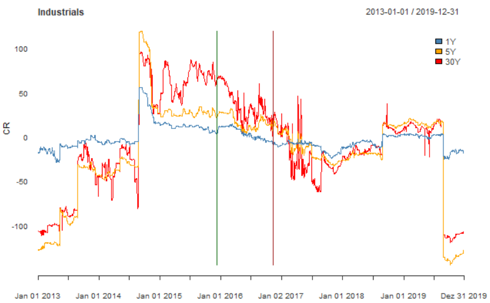
(b) CCGS



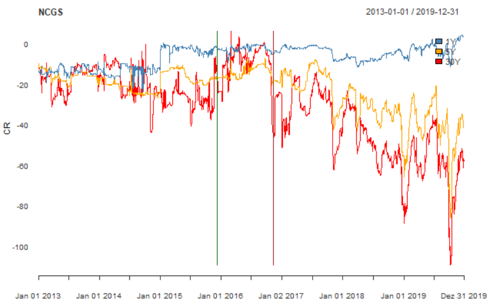
(c) Energy



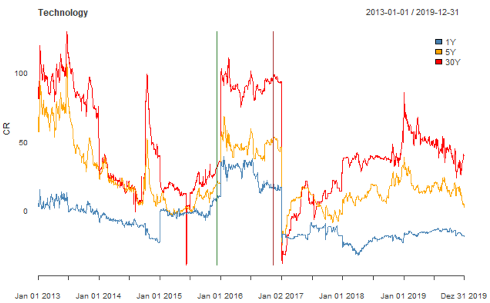
(d) Healthcare



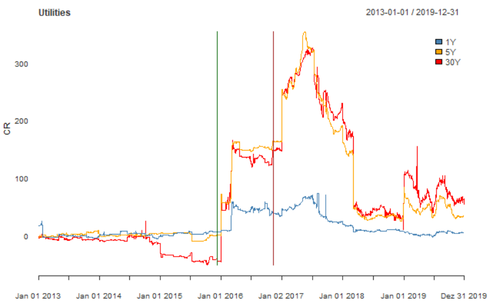
(e) Industrials



(f) NCGS



(g) Technology



(h) Utilities

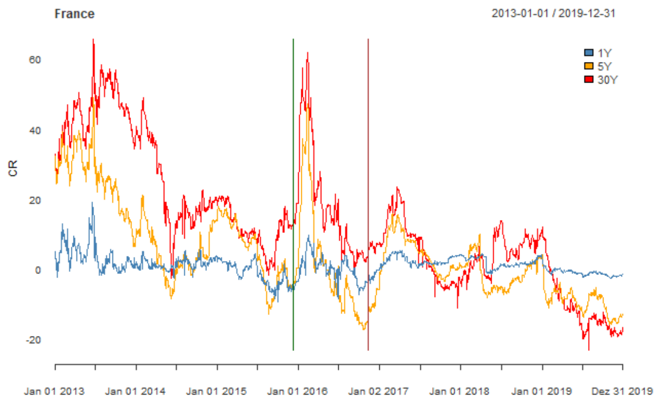
Figure 5.6.: Evolution of the sector-specific CRs over time for maturities 1Y (blue), 5Y (orange) and 30Y (red) for North America. The vertical solid lines refer to the Paris Agreement (dark green) and Trump election (brown), respectively.

5.2.3. Country-specific risk perceptions

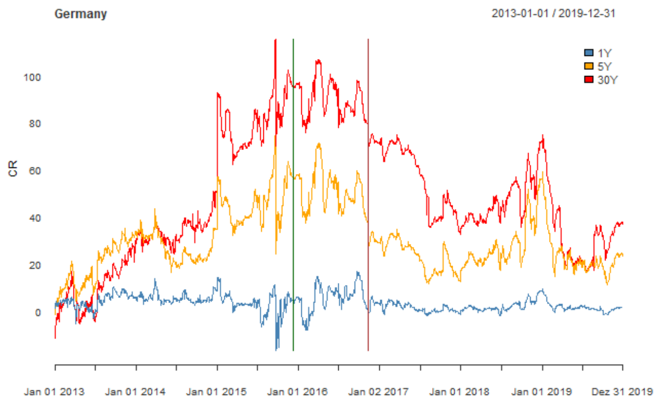
The previous two subsections already illustrated that exposure to carbon risk can vastly differ across sectors and continents (Europe vs. North America). For the latter, we may also want to go a level further and look at the intra-continental (i.e. country-specific) differences in the exposure to carbon risk. Countries may experience very different exposures depending on their implemented national policies or the peoples mindset towards climate change (and with it demand patterns). For that reason, we also construct CRs for specific countries.

We follow the same procedure for constructing the CRs as in the sectoral case, but do it separately for every country under consideration. We omit North America in this analysis, as we only have a few Canadian firms in our sample and hence do not expect to see big differences to the pure North American CR from Subsection 5.2.1. Also, given the small number of available firms, the CRs are likely to exhibit a very erratic behavior or cannot even be constructed due to a lack of sufficient data. In Europe, we focus on the three big countries France, Germany and United Kingdom (UK), as they account for more than 60% of all firms in our sample and we mostly cannot build CRs for the remaining sample countries.

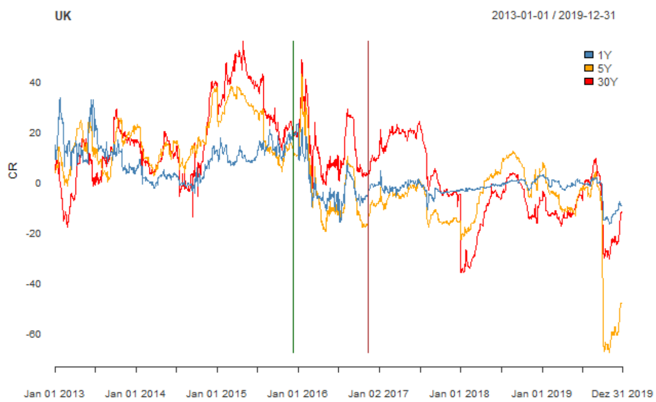
Figure 5.7 depicts the evolution of the French (top), German (center) and British (bottom) CR over time for tenors of 1, 5 and 30 years in the European sample. Starting with the French CRs, we see very high CRs at the beginning of the sample period which drop slowly afterwards. After the Paris Agreement, the CRs spike up to their initial level again which, however, is short-lived. In the end, the mid- and long term CRs move to negative values. Contrary to that, in Germany, the perception of carbon risk evolved continuously over time and peaks around COP21 after which it slowly decreases again. In addition, the CRs are greater than zero for the most part and exhibit an upwards trend over the entire sample period (except 1Y). The CRs for the UK exhibit the least straightforward movements, in that most of their evolution look ambiguous. Only after the referendum to leave the European Union on June 23, 2016 (Brexit), a small effect is observable, in that the CR moves down and ends up in large negative regions.



(a) France



(b) Germany



(c) United Kingdom

Figure 5.7.: Evolution of the country-specific CRs over time for maturities 1Y (blue), 5Y (orange) and 30Y (red) for France (top), Germany (center) and United Kingdom (bottom). The vertical solid lines refer to the Paris Agreement (dark green) and Trump election (brown), respectively.

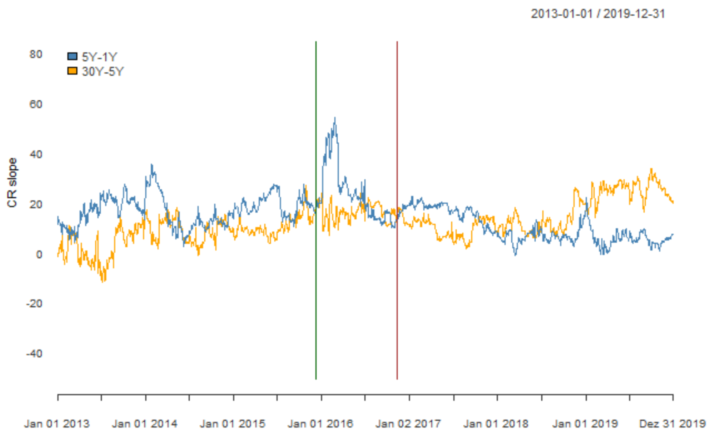
5.2.4. Term structure

So far, we focused on a particular tenor providing information about the carbon risk exposure with respect to a specific future point in time. Additionally, we can extract valuable information about carbon risk over a specific time horizon by considering the difference between two CRs with differing tenors. This difference constitutes the slope of the CR factor, which is constructed as

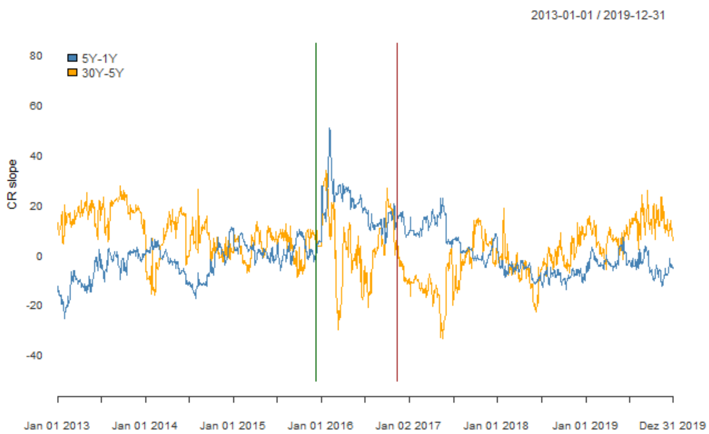
$$\mathrm{CRSlope}_t^{mn} = \mathrm{CR}_t^m - \mathrm{CR}_t^n,$$

where the relationship between tenors is $m > n$. Conceptually, starting from a carbon risk exposure over the next n years, $\mathrm{CRSlope}_t^{mn}$ provides valuable information by describing how the exposure to carbon risk is perceived over the remaining $m - n$ years. $\mathrm{CRSlope}_t^{mn}$ can take positive and negative values, depending on how the market's perception of carbon risk evolves. Compared to the next n years, a positive (negative) CR slope reflects expectations of an increasingly tighter (looser) carbon regulatory framework in the later $m - n$ years.

Figure 5.8 depicts the 5Y-1Y (blue) and 30Y-5Y (orange) CR slopes for Europe and North America. Similar to the CR, the figures again suggest distinct conditions for Europe and North America. Both CR slopes are mostly positive for Europe, indicating a collective perception of continuously, albeit erratic, growing exposure to carbon risk. In other words, the longer the time horizon, the larger the perceived exposure to carbon risk in Europe. Conversely, the perceived future exposure to carbon risk in North America varies continuously and is less clear-cut. For example, contrasting the 5Y-1Y versus 30Y-5Y CR slopes and focusing on the period immediately following COP21, the CR slopes show that the market anticipated a surge in exposure to carbon risk in the four subsequent years, as opposed to the successive 25 years. This indicates that lenders in North America expected most of the risks associated with COP21 to materialize between 2017 and 2021.



(a) Europe



(b) North America

Figure 5.8.: Evolution of the CR slope over time for 5Y-1Y (blue) and 30Y-5Y (orange) for Europe (top) and North America (bottom). The vertical solid lines refer to the Paris Agreement (dark green) and Trump election (brown), respectively.

5.3. Carbon tail risk (CTR) factor

We restricted our focus so far on the measurement of the median risk associated to carbon. In particular, we chose the median polluting (clean) firm in our construction and, with it, depicted the CDS spread movements of firms in the center of each class. Additionally, we may also want to look at the CDS spread behavior of firms in the extremes of each group which – after computing the wedge – would portray the perception of carbon tail risks. The relevance of such a metric is immediate as CDSs are credit insurance products making them of utter importance for risk management purposes.

For the construction of the tail risk factor, we start with the same sets $\mathcal{C}_t^m$ and $\mathcal{P}_t^m$ comprising the CDS spreads of the clean and polluting class introduced in Section 5.2.1. From these sets, we then compute the quantile of default protection costs of clean and polluting firms by calculating the m-year CDS spread level at quantile level τ for each tenor $m \in \{1, 3, 5, 10, 30\}$ at every time t:

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

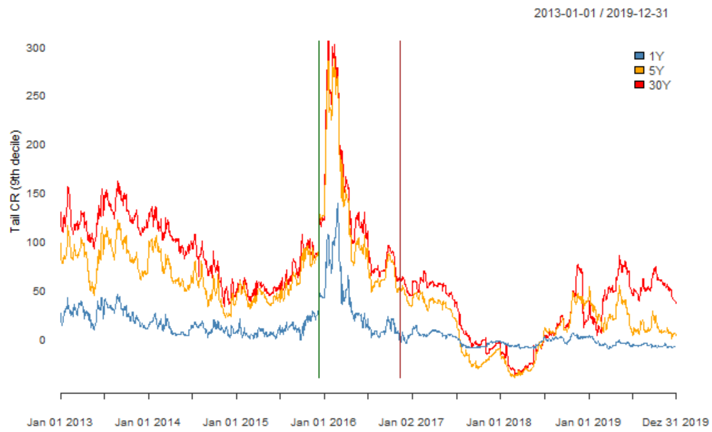
where $\mathrm{Q}_\tau(\cdot)$ denotes the quantile function for some quantile level $\tau \in (0, 1)$. Consequently, the *carbon tail risk* (CTR) factor for some τ is defined as:

$$\mathrm{CTR}_t^m(\tau) = \mathrm{P}_t^m(\tau) - \mathrm{C}_t^m(\tau).$$

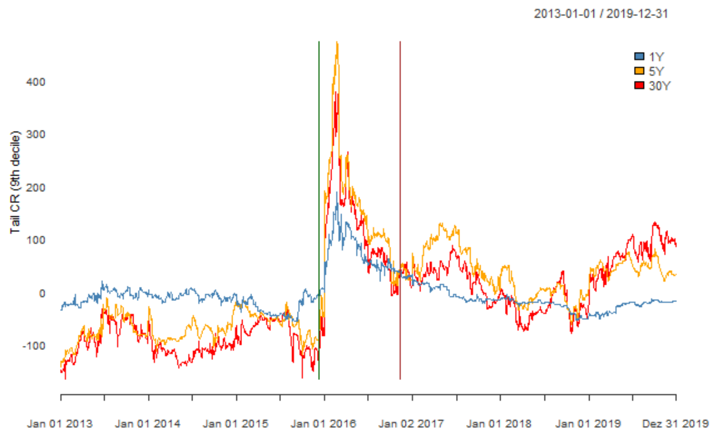
The proposed CTR factor is a generalization of the initial CR factor and can be constructed for every quantile level τ of interest. However, to capture the risk perception of adverse tail events, the CTR factor for $\tau > 0.5$ (upper part) is more useful to look at than the case $\tau < 0.5$ (lower part). This is because the CTRs with $\tau > 0.5$ capture the differential exposure to carbon risk of those firms in both classes with already high CDS spreads. Therefore, contrary to the CR, any CTR in the upper part computes the CDS spread wedge between polluting and clean firms with more adverse credit states. As such, we have a metric that incorporates the tail part of the carbon risk distribution. In what follows, we will first discuss a specific upper CTR factor ($\tau = 0.9$) and afterwards describe the overall (approximate) distributional behavior of carbon risk over time ($\tau = (0.1, \dots, 0.9)'$).

Figure 5.9 shows the evolution of the CTR factor for the ninth decile $\tau = 0.9$ over time for the tenors of 1, 5 and 30 years in both Europe (top) and North America (bottom).[9] In Europe, we observe a similar behavior of the CTR to the CR. Specifically, the CTR factor is mostly positive (except from mid 2017 to mid 2018) and reacts to the events around COP21. However, the spike after the Paris Agreement is markedly larger than the one from the CR (Figure 5.2a). That is, the tail risk of carbon was significantly more relevant for lenders during that period. For North America, we observe the stark reaction to COP21 as well. In fact, compared to the European case, the CTR spikes even further to

[9] We relegate to Figure A.2 in Appendix A.1 that plots all available tenors (including 3Y and 10Y).



(a) Europe

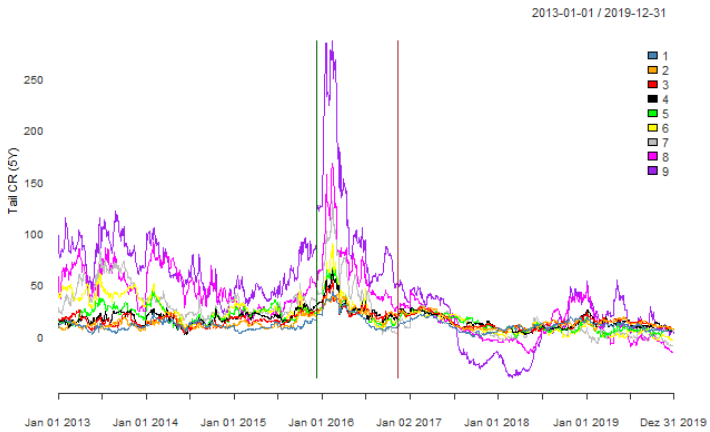


(b) North America

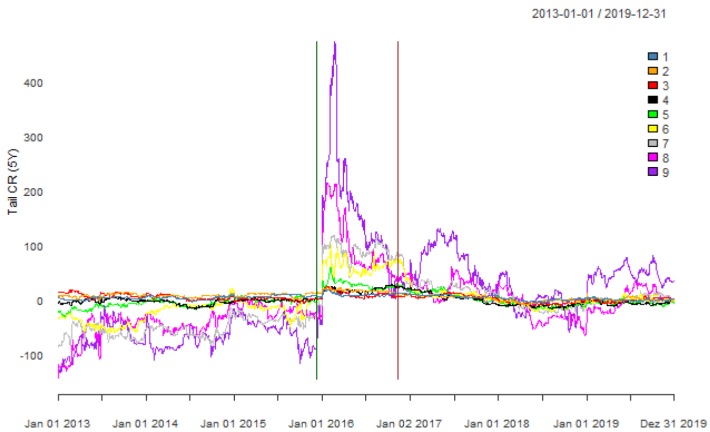
Figure 5.9.: Evolution of the tail CR (9th decile) over time for maturities 1Y (blue), 5Y (orange) and 30Y (red) for Europe (top) and North America (bottom). The vertical solid lines refer to the Paris Agreement (dark green) and Trump election (brown), respectively.

values beyond 400 basis points. This showcases that, although median carbon risk was only mildly perceived after COP21, the tail risk was a much more relevant part of the market's risk perception. From a levels perspective, we observe that the CTR in North America mostly exhibits negative values pre-COP21 and positive values post-COP21. This is also in contrast to the erratic behavior of the CR over the entire sample period.

Figure 5.10 displays the evolution of the 5-years tail CR for all deciles in Europe (top) and North America (bottom). Essentially, these graphs depict the (approximate) distributional behavior of carbon risk over time. The graph for Europe showcases that the distributional distance (i.e., the difference between two CTRs with varying τ) constantly evolves, in particular for CTRs with $\tau > 0.5$. While this difference is particularly large in the beginning of the sample period and during COP21, it decreases for the re-



(a) Europe



(b) North America

Figure 5.10.: Evolution of the 5-years tail CR over time for all deciles in Europe (top) and North America (bottom). The vertical solid lines refer to the Paris Agreement (dark green) and Trump election (brown), respectively.

maining periods. This indicates that the distribution of carbon risk, in particular the right tail, is not constant but varies over time. In North America, the distributional differences for the right tail are also a distinct feature. Additionally, we observe little movements of the CTRs with $\tau < 0.5$ which further substantiates the previous finding of a stark difference in lenders perception of median carbon risk vis-a-vis tail carbon risk in North America.

6. The effects of carbon risk on credit risk

In this chapter, we empirically investigate the impact of carbon risk (proxied by our CR factor) on CDS spreads. We first develop testable hypotheses that are based on theoretical expectations. Afterwards, we run different models to test aforementioned hypotheses. Last, we provide some additional analyses and robustness checks to substantiate our empirical findings.

6.1. Hypothesis development

In the previous section, we argued that CR represents the general perception of carbon risk exposure, such that a higher CR corresponds to a higher perceived carbon risk. We also argued that a firm with high exposure to carbon risk can see a decline in its valuation, a higher probability of default and, therefore, a higher CDS spread. 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 the varying degrees of ambition of environmental regulations and diverse restrictions on carbon emissions (Huij et al., 2021).[1] While Europe has generally been considered a global forerunner in the implementation of stringent carbon policies, North American countries – in particular the US – consistently fall short in their efforts to regulate and reduce carbon emissions. Consequently, the prospect of carbon risks materializing is stronger in Europe than in North America, yielding higher expected CDS spreads for firms located and operating predominantly in Europe vs. North America. This is already reflected in Figures 5.2 and 5.8, which indicate a decidedly larger response to policy-relevant events in Europe vs. North America. It has not been investigated, however, whether the prospect of carbon risks materializing is stronger in Europe than in North America due to the difference approach to carbon pricing. Europe's more aggressive stance on carbon pricing, through mechanisms like the European Union Emissions Trading System, has created a clear and explicit price for carbon emissions. In contrast, the lack of a consistent carbon pricing mechanism in North America may lead to less urgency among firms to reduce emissions. This difference in approach to carbon pricing

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

could partially explain the variations in carbon risk and CDS spreads between the two regions. We thus propose the second hypothesis, as follows:

Hypothesis 2. *The effect of carbon risk on CDS spread returns is stronger in Europe than in North America.*

Emission pricing regulation, particularly in its explicit form, can have profound and immediate implications for businesses. Europe stands out in this regard, having adopted a market-based approach to price carbon, namely the European Union Emission Trading System, EU ETS for short. Such explicit carbon pricing mechanisms can be seen as a direct financial signal to companies, indicating the tangible costs associated with their carbon emissions. When companies are faced with a quantifiable price tag on their emissions, it can lead to more predictable and immediate shifts in their operational strategies and financial planning. Lenders, being astute observers of risk, are likely to pick up on these shifts. Thus, the presence of an explicit carbon price can serve as a clear indicator of a firm's potential financial liabilities related to carbon emissions. This, in turn, can influence lenders' perceptions of a company's creditworthiness. CDS spreads can thus be directly impacted by these perceptions. In essence, when a firm is subject to explicit carbon pricing, the associated costs and risks become more transparent and immediate, leading to more pronounced reactions in the CDS market. On the other hand, nonprice regulations, while important, might not have the same immediate and transparent financial implications. Such regulations might lead to indirect costs, the magnitude and timing of which might be less predictable. Given this backdrop, our third hypothesis emerges:

Hypothesis 3. *The presence of explicit carbon regulation has a discernible influence on how carbon risk impacts CDS spread returns.*

The realm of explicit carbon regulation is multifaceted and its influence on firms extends beyond a mere dichotomy of being regulated or not. While the presence of regulation matters, the depth and breadth of its impact are contingent upon the proportion of a firm's emissions that are actually under the purview of these regulations.
Imagine two firms, both subject to carbon pricing regulations. However, one firm has 90% of its direct emissions regulated, while the other only has 30%. The financial implications for the former are likely to be far more pronounced than for the latter. This is because the firm with a higher percentage of regulated emissions will face more direct costs associated with its carbon footprint, leading to a more substantial impact on its financial health and operational strategies. Furthermore, from a lender's perspective, the extent of a firm's regulated emissions can serve as a barometer for potential financial liabilities. A firm with a larger share of its emissions regulated is more exposed to the financial ramifications of carbon pricing, making it potentially riskier from a credit standpoint. This nuanced understanding goes beyond the simplistic view of just being 'regulated' and delves into the intricacies of how deeply a firm is embedded within the regulatory framework. Given this context, our fourth hypothesis emerges:

Hypothesis 4. *The influence of carbon risk is not solely determined by the presence of regulation: the more a firm's emissions are regulated, the more pronounced the financial implications of carbon risk become.*

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 markedly pronounced in certain sectors, especially those that are inherently carbon-intensive. Their operational nature not only puts them at the forefront of regulatory scrutiny, but also amplifies the financial risks they face due to carbon pricing. As carbon regulations tighten, these sectors could see escalating operational costs, which in turn can impact their financial stability and creditworthiness. Lenders, with their pulse on these evolving dynamics, are likely to perceive heightened risks associated with firms operating in these carbon-intensive sectors. This heightened perception of risk can lead them to seek additional credit protection, manifesting as increased CDS spreads. It is a clear indication of the market's response to the potential financial vulnerabilities of these firms in the face of carbon risk. Hence, we posit our fifth hypothesis as follows:

Hypothesis 5. *The extent to which a sector's emissions are subject to price regulation intensifies the impact of carbon risk on CDS spread returns.*

Climate policies continually evolve within a rapidly changing social and policy environment, as attested to by frequent revisions to national climate policies around the world (Aiello and Angelico, 2021). The inherent uncertainty of climate and carbon regulations may cause a vacillating perception of the associated carbon risk. As new information arrives in the market (e.g. conversations about tighter emissions constraints), lenders update their expectations accordingly. Specifically, when concerns about carbon risks increase during times of heightened attention to climate change in the news, lenders will demand more credit protection, thus increasing CDS spreads. Thus, we state the next hypothesis, as follows:

Hypothesis 6. *The effect of carbon risk on CDS spread returns is stronger during times of heightened attention to climate change.*

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

Hypothesis 7. *There is a positive relationship between the term structure of carbon risk and CDS spread slopes.*

6.2. Empirical results

In this subsection, we present our empirical results to test the hypotheses posited in the previous subsection. First, we focus on the general and regional effects of carbon risk on CDS spreads. Second, we investigate the role of explicit carbon pricing. Third, we examine the effects across different sectors. Fourth, we look at the effect of the CR factor during heightened attention to climate change. Last, we use the CR slope to examine the impact on the CDS term structure.

6.2.1. 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:

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

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 proxy for carbon risk exposure $\Delta\mathrm{CR}_t$, which encapsulates an aggregate of all changes in carbon-related concerns.

The regression is run for every decile $\tau \in \{0.1, \ldots, 0.9\}$ to model the effect of each explanatory variable on the entire conditional distribution of CDS spread returns. In this way, we are able to model the relationship between CDS spread returns and the CR factor for firms that behave according to the median of the conditional distribution, as well as for firms that overperform and underperform relative to the median.[2] Note that (i) an increase in the CDS spread $\{\tau > 0.5\}$ reflects a deterioration in a firm's creditworthiness (credit deterioration), (ii) a decrease in the CDS spread $\{\tau < 0.5\}$ reflects an improvement in a firm's creditworthiness (credit improvement), and (iii) the mid decile $\{\tau = 0.5\}$ corresponds to the unchanged CDS spread case (invariable credit). In essence, the quantile regression allows us to distinctly examine the effect of each explanatory variable along the entire distribution of credit spread returns and, at the same time, to investigate the marginal impact of carbon risk above and beyond these explanatory variables.

Table 6.1 reports the estimated coefficients at different deciles for every tenor under investigation for Europe. First, across all maturities, we observe a positive relationship between CDS spread returns and the CR factor. That is, an increase in market's perception of carbon risk is associated with a rise in CDS spread returns. The coefficients are

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

statistically significant at the 1% level and are also economically significant. For example, considering the 5Y tenor, a one standard deviation increase in the perceived carbon risk exposure (1.6112) is associated with a rise of 0.134 $(= 1.61 \times 0.0834)$ percentage points in the median CDS spread return. This increment accounts for a remarkable 6.1% of the standard deviation of CDS spread returns. To put this number into perspective, we look at the stock return, one of the key determinants of CDS spreads. A one standard deviation increase in the stock return (1.64%), merely decreases the median CDS spread return by 0.071 $(= 1.64 \times (-0.0435))$ percentage points, equivalent to 3.2% of the CDS spread return standard deviation.

	1	2	3	4	5	6	7	8	9
				1Y					
StockReturn	−278.16***	−247.33***	−176.63***	−110.96***	−59.85***	−97.00***	−174.14***	−268.26***	−311.87***
	(14.08)	(8.36)	(6.48)	(4.19)	(2.74)	(3.57)	(5.89)	(10.94)	(21.64)
ΔVolatility	−375.35***	−372.85***	−224.13***	−84.19***	20.90*	269.47***	545.53***	825.54***	975.80***
	(41.79)	(41.96)	(34.52)	(19.47)	(10.08)	(18.66)	(24.60)	(22.82)	(32.19)
ΔMRI	1437.23***	1443.18***	1387.76***	1303.93***	1245.62***	1266.45***	1362.81***	1495.83***	1594.38***
	(39.21)	(35.39)	(30.11)	(39.00)	(32.90)	(34.68)	(36.11)	(46.43)	(81.48)
ΔCR	384.46***	326.22***	227.68***	154.43***	107.22***	135.10***	202.51***	315.84***	480.56***
	(21.50)	(15.09)	(11.65)	(8.83)	(8.05)	(9.62)	(14.33)	(23.72)	(39.69)
				3Y					
StockReturn	−217.31***	−201.59***	−162.06***	−106.81***	−62.13***	−92.18***	−159.05***	−213.95***	−276.32***
	(6.84)	(5.95)	(4.84)	(3.73)	(2.62)	(3.11)	(4.79)	(7.82)	(13.64)
ΔVolatility	−395.17***	−287.29***	−193.72***	−73.81***	21.73*	234.92***	471.69***	640.70***	893.79***
	(36.32)	(42.15)	(28.06)	(18.65)	(10.42)	(16.18)	(21.52)	(13.23)	(20.76)
ΔMRI	568.36***	607.75***	608.98***	584.70***	569.69***	577.40***	612.69***	653.08***	690.62***
	(12.43)	(11.91)	(13.99)	(13.13)	(13.65)	(13.55)	(15.41)	(20.71)	(34.12)
ΔCR	256.14***	211.88***	171.98***	119.20***	82.30***	98.46***	149.62***	202.54***	245.41***
	(10.43)	(8.20)	(6.90)	(5.90)	(5.08)	(5.30)	(7.29)	(10.40)	(17.56)
				5Y					
StockReturn	−146.61***	−127.23***	−100.80***	−68.45***	−43.49***	−57.68***	−94.86***	−132.60***	−176.02***
	(4.69)	(3.53)	(2.94)	(2.32)	(1.79)	(1.98)	(2.73)	(4.41)	(8.36)
ΔVolatility	−280.24***	−206.68***	−141.63***	−64.69***	7.67	127.34***	267.89***	418.30***	580.47***
	(28.84)	(27.19)	(18.84)	(13.11)	(6.47)	(11.31)	(12.18)	(3.22)	(7.72)
ΔMRI	304.89***	329.09***	333.79***	332.65***	329.42***	328.44***	341.31***	353.96***	360.95***
	(7.97)	(8.10)	(8.01)	(7.84)	(7.66)	(7.57)	(8.50)	(9.89)	(14.27)
ΔCR	174.66***	161.78***	132.05***	103.33***	83.40***	94.73***	129.70***	168.38***	218.94***
	(7.28)	(5.10)	(5.04)	(4.53)	(4.63)	(4.80)	(5.41)	(6.63)	(11.22)
				10Y					
StockReturn	−115.48***	−91.52***	−72.30***	−49.62***	−31.60***	−42.32***	−68.71***	−95.80***	−135.12***
	(3.31)	(2.42)	(2.04)	(1.61)	(1.22)	(1.41)	(1.90)	(3.04)	(5.46)
ΔVolatility	−208.94***	−159.73***	−102.22***	−42.59***	7.29*	92.50***	201.50***	308.16***	426.82***
	(18.14)	(13.37)	(12.23)	(8.61)	(3.39)	(7.26)	(6.42)	(4.26)	(6.32)
ΔMRI	231.97***	245.74***	246.05***	241.57***	239.52***	239.20***	249.82***	261.89***	270.74***
	(6.29)	(4.30)	(5.46)	(5.22)	(5.24)	(4.86)	(4.90)	(5.93)	(9.77)
ΔCR	63.81***	58.61***	49.43***	39.78***	28.82***	34.57***	49.56***	68.68***	96.56***
	(2.47)	(2.59)	(2.49)	(2.30)	(1.97)	(2.23)	(2.85)	(3.80)	(5.02)
				30Y					
StockReturn	−103.86***	−84.69***	−67.29***	−48.32***	−36.14***	−44.23***	−67.51***	−92.05***	−125.43***
	(3.08)	(2.24)	(1.86)	(1.50)	(1.32)	(1.37)	(1.91)	(3.19)	(6.37)
ΔVolatility	−218.27***	−155.69***	−94.78***	−42.29***	10.88·	95.48***	201.66***	290.80***	398.44***
	(16.70)	(9.52)	(12.94)	(9.20)	(5.71)	(6.85)	(7.68)	(6.98)	(6.66)
ΔMRI	257.21***	251.06***	242.74***	240.79***	240.96***	240.47***	247.23***	263.92***	289.59***
	(4.60)	(4.61)	(4.53)	(5.11)	(5.39)	(5.65)	(5.31)	(6.28)	(10.66)
ΔCR	70.21***	58.65***	50.55***	40.71***	33.21***	36.48***	47.44***	63.48***	79.93***
	(1.84)	(2.20)	(1.85)	(1.82)	(1.80)	(2.12)	(2.76)	(3.81)	(6.53)

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

Table 6.1.: This table reports the coefficient estimates of the base panel quantile regression model for 1-year (top), 3-year (upper center), 5-year (center), 10-year (lower center) and 30-year (bottom) CDS spread returns. The sample includes data of 136 European firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

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

We next examine Hypothesis 2, which posits that the effect of carbon risk on CDS spread returns is stronger in Europe than in North America. We re-estimate our baseline QR separately for each North American tenor. Consistent with the prediction of Hypothesis 2, Table 6.2 shows a substantially weaker relationship between CDS spread returns and the CR factor for the North American sample. For example, considering the 5Y tenor, the coefficient estimate of CR for the median CDS spread return (0.0004) is more than 200 times smaller than its European counterpart (0.0834). Not only are estimates considerably smaller, but they are also only occasionally statistically significant. While the heterogeneity in the magnitudes of the CR effect persists, the symmetry in the effect of CR breaks off in the North American sample. In fact, the long-term tenors (10Y, 30Y) apart, the effect on the ninth decile is at least twice as high as the effect on the first decile, suggesting that in North America, credit risk exposure is particularly relevant when firms' CDS spreads deteriorate.

In delving deeper into the pronounced difference between Europe and North America, it is essential to consider the regulatory landscape of carbon emissions in both regions. 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 their carbon emissions, effectively introducing a direct cost for emitting carbon dioxide and other greenhouse gases. Such explicit carbon pricing can have a more immediate and pronounced effect on firms' financials, which is likely reflected in the CDS spread returns. On the other hand, North America, especially the US, has predominantly relied on non-price emissions regulations. These regulations might not impose a direct cost on emissions, but rather set limits or standards on the amount of emissions a company can produce. While these non-price regulations can still impose costs on firms, such as compliance and operational adjustments, they do not have the same direct and immediate financial implications as an explicit carbon price. This difference in the regulatory approach could be a significant factor behind the observed weaker relationship between CDS spread returns and the CR factor in North America compared to Europe. In essence, the explicit carbon costs borne by European companies might lead to more immediate and discernible changes in their perceived credit risk, as captured by CDS spreads, than the more indirect costs faced by North American firms under non-explicit price regulations. This is what we explore next.

	1	2	3	4	5	6	7	8	9
1Y									
StockReturn	−31.05***	−17.78***	−4.95***	−0.87***	−0.21***	−1.15***	−8.16***	−29.27***	−59.91***
	(4.24)	(1.48)	(0.51)	(0.09)	(0.03)	(0.11)	(0.76)	(3.02)	(5.80)
ΔVolatility	−136.38***	−60.30***	−8.90***	−0.23	0.16***	6.10***	48.36***	167.30***	401.72***
	(19.83)	(6.70)	(1.68)	(0.31)	(0.04)	(0.86)	(4.17)	(16.68)	(18.75)
ΔMRI	149.99***	96.57***	32.39***	10.03***	3.16***	12.21***	51.77***	164.50***	419.40***
	(30.27)	(10.56)	(4.28)	(1.24)	(0.39)	(1.34)	(6.03)	(20.88)	(42.51)
ΔCR	5.60***	5.12***	1.63***	0.34***	0.09***	0.52***	4.24***	18.37***	60.65***
	(1.50)	(0.69)	(0.25)	(0.06)	(0.02)	(0.08)	(0.50)	(2.23)	(6.49)
3Y									
StockReturn	−48.27***	−26.37***	−14.96***	−8.44***	−3.63***	−8.87***	−16.90***	−31.87***	−59.76***
	(4.09)	(1.61)	(0.85)	(0.55)	(0.23)	(0.51)	(0.97)	(2.53)	(5.98)
ΔVolatility	−186.93***	−79.42***	−28.74***	−4.98**	0.56	32.87***	82.77***	175.39***	372.26***
	(17.89)	(8.29)	(3.60)	(1.82)	(0.66)	(2.96)	(4.79)	(11.57)	(23.40)
ΔMRI	99.95***	76.18***	45.56***	28.76***	14.17***	30.05***	53.50***	103.95***	204.25***
	(11.45)	(5.73)	(3.76)	(2.69)	(1.23)	(2.42)	(3.74)	(8.26)	(17.02)
ΔCR	4.85***	3.06***	2.03***	1.28***	0.51***	0.87***	1.63***	3.50***	10.07***
	(0.64)	(0.25)	(0.19)	(0.12)	(0.06)	(0.11)	(0.20)	(0.56)	(1.79)
5Y									
StockReturn	−46.77***	−23.72***	−13.73***	−9.21***	−4.79***	−9.11***	−15.37***	−26.61***	−51.12***
	(3.02)	(1.26)	(0.78)	(0.50)	(0.26)	(0.46)	(0.88)	(1.95)	(4.58)
ΔVolatility	−179.77***	−68.21***	−22.68***	−4.19**	1.02·	33.57***	74.12***	152.18***	328.31***
	(13.14)	(6.14)	(3.96)	(1.46)	(0.54)	(2.55)	(3.47)	(7.67)	(11.78)
ΔMRI	58.12***	42.50***	26.84***	19.75***	11.03***	21.32***	34.80***	63.75***	115.69***
	(5.77)	(3.06)	(2.36)	(1.51)	(0.88)	(1.57)	(2.48)	(4.60)	(6.74)
ΔCR	2.39***	1.81***	1.27***	0.89***	0.35***	0.87***	2.02***	4.53***	11.91***
	(0.39)	(0.18)	(0.14)	(0.11)	(0.05)	(0.13)	(0.25)	(0.52)	(1.32)
10Y									
StockReturn	−40.51***	−20.65***	−11.58***	−7.23***	−3.67***	−6.56***	−11.34***	−20.13***	−41.42***
	(1.87)	(0.93)	(0.55)	(0.34)	(0.18)	(0.30)	(0.59)	(1.53)	(3.61)
ΔVolatility	−145.14***	−60.48***	−20.30***	−4.44**	1.40***	24.92***	56.88***	117.40***	256.77***
	(7.08)	(3.92)	(2.52)	(1.40)	(0.28)	(1.60)	(2.61)	(6.23)	(10.60)
ΔMRI	38.97***	27.58***	17.12***	12.15***	7.03***	11.72***	19.09***	34.37***	63.50***
	(2.68)	(1.60)	(1.15)	(0.70)	(0.42)	(0.69)	(1.19)	(2.75)	(4.76)
ΔCR	2.29***	0.87***	0.48***	0.24***	0.08*	0.19**	0.58***	1.30***	3.44***
	(0.34)	(0.16)	(0.09)	(0.06)	(0.04)	(0.06)	(0.12)	(0.24)	(0.59)
30Y									
StockReturn	−47.31***	−25.44***	−15.37***	−9.78***	−5.36***	−8.41***	−14.31***	−24.48***	−47.92***
	(1.99)	(0.93)	(0.58)	(0.40)	(0.24)	(0.36)	(0.68)	(1.70)	(3.93)
ΔVolatility	−157.03***	−72.20***	−27.27***	−7.75***	2.87**	29.97***	66.49***	131.28***	272.80***
	(6.48)	(5.55)	(3.72)	(1.69)	(0.97)	(1.99)	(3.03)	(6.37)	(10.52)
ΔMRI	37.30***	26.00***	17.65***	12.87***	8.82***	12.45***	18.88***	31.55***	56.22***
	(2.49)	(1.31)	(0.92)	(0.70)	(0.47)	(0.65)	(0.92)	(2.29)	(3.85)
ΔCR	2.98***	1.15***	0.73***	0.38***	0.13**	−0.02	0.01	0.34	2.07**
	(0.32)	(0.16)	(0.10)	(0.07)	(0.05)	(0.06)	(0.10)	(0.26)	(0.69)

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

Table 6.2.: This table reports the coefficient estimates of the base panel quantile regression model for 1-year (top), 3-year (upper center), 5-year (center), 10-year (lower center) and 30-year (bottom) CDS spread returns. The sample comprises of data for 275 North American firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

6.2.2. Explicit carbon pricing matters

The disparity in the regulatory landscape between Europe and North America is further underscored by the data from our sample. According to the responses from the CDP questionnaires, only 20% of the North American firms in our sample are subject to an ETS, whereas in Europe, that figure rises to over 50%, as illustrated in Figure 6.1. 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. Their questionnaire has evolved over time to capture not just whether companies are under mandatory carbon pricing regulations, but also if they are currently regulated by any form of carbon pricing system, be it carbon markets or taxation.

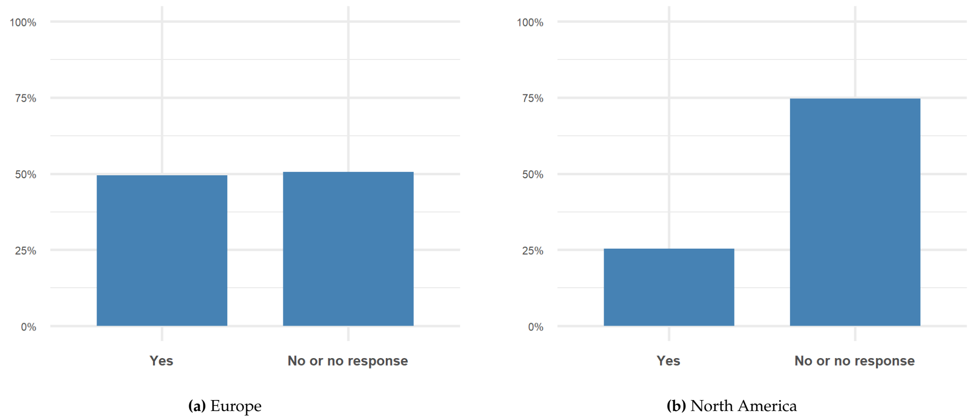


Figure 6.1.: Breakdown of European (left) and North American (right) firms based on whether they are subject to carbon price regulation, compared to those not under carbon price regulation or who did not provide a response to the survey.

This stark difference in the proportion of firms under an explicit carbon pricing regime between the two regions offers a clear insight into the varying degrees of regulatory pressures they face. European firms, with over half of them being subject to an ETS, are more directly impacted by the costs associated with carbon emissions. These costs can have immediate financial implications, affecting everything from operational costs to investment decisions. On the other hand, the majority of North American firms, with 80% of them not being under an explicit price emissions regulation, might not face the same direct financial pressures from carbon pricing. Instead, their primary concerns might revolve around compliance with nonprice emissions regulations, which, while still impactful, do not have the same immediate financial ramifications as an explicit carbon price.

Diving into the details of regulatory exposure, we sought to understand its potential influence on the CDS spread returns in relation to carbon risk. This exploration forms the crux of our Hypothesis 3. To achieve this, we turned to the CDP questionnaire, specifically question C11.1, which inquires: ”Are any of your operations or activities regulated by a carbon pricing system (i.e. ETS, Cap and Trade or Carbon Tax)?”. This question not only captures the current regulatory landscape but also anticipates future shifts, as it has evolved to encompass both present regulatory frameworks and expected future regulations. Companies affirming their regulation under a carbon pricing system are further probed to specify the exact systems they fall under. This data allows us to categorize companies based on their current and anticipated regulatory environments, offering a more detailed perspective on their exposure to explicit carbon pricing. From the responses, we classify companies into four distinct categories. First, there are those that did not provide any feedback, labeled as ”No response”. Next, we have companies that confirmed they are not under any carbon regulation, categorized as "No". Another group consists of companies that are not currently regulated but expect to be in the future, termed "No but anticipation". Lastly, companies that are actively regulated or subject to emission pricing are grouped under "Yes". With this refined classification in hand, we proceeded to re-estimate our baseline QR for each European tenor. By doing so, we aimed to discern patterns or variations in CDS spread returns that might be attributable to the differences in carbon pricing regulations. Our model now reads:

$$Q_{s^m_{i,t}}(\tau|\boldsymbol{x}_{i,t}) = \alpha_{\tau,i} + \beta_{\tau,1} r_{i,t} + \beta_{\tau,2}\Delta\sigma_{i,t} + \beta_{\tau,3}\Delta\mathrm{MRI}^m_{i,t} + \beta_{\tau,4}\Delta\mathrm{CR}^m_t + \sum_{k=5}^{8}\beta_{\tau,k}\mathrm{ETS}_i + \sum_{k=9}^{11}\beta_{\tau,k}\Delta\mathrm{CR}^m_t\mathrm{ETS}_i + \varepsilon_{i,t},$$

where ETS_i denotes firm i's response to question C11.1 from the CDP questionnaire.

	1	2	3	4	5	6	7	8	9
				Europe					
ΔCR $\times$ ETS (No response)	67.86***	56.71***	46.87***	33.21***	19.17***	26.01***	46.50***	61.29***	81.80**
	(13.30)	(6.66)	(9.65)	(7.26)	(5.64)	(6.62)	(9.59)	(14.46)	(27.39)
ΔCR $\times$ ETS (No)	42.30**	47.14***	42.13***	30.95**	27.29**	26.97**	26.88$^{\cdot}$	45.86*	60.78$^{\cdot}$
	(15.27)	(14.01)	(12.77)	(10.54)	(9.12)	(10.24)	(14.12)	(19.15)	(36.55)
ΔCR $\times$ ETS (No but anticipation)	52.23**	21.15	27.10	24.17	34.17$^{\cdot}$	32.40$^{\cdot}$	25.81	43.41*	69.38$^{\cdot}$
	(16.06)	(50.38)	(23.13)	(17.09)	(18.73)	(17.34)	(18.02)	(20.90)	(38.96)
ΔCR $\times$ ETS (Yes)	252.51***	217.93***	184.61***	157.81***	144.74***	147.56***	177.23***	226.78***	286.73***
	(16.28)	(11.11)	(13.84)	(11.79)	(10.17)	(11.25)	(13.75)	(19.63)	(33.39)
				North America					
ΔCR $\times$ ETS (No response)	2.74	3.06***	1.40***	0.75***	0.38***	0.76***	2.48***	8.80***	33.21***
	(2.08)	(0.75)	(0.23)	(0.15)	(0.09)	(0.18)	(0.40)	(1.25)	(3.49)
ΔCR $\times$ ETS (No)	2.70	-0.25	-0.24	-0.11	-0.09	-0.06	-0.57	-2.04	$-8.94^{\cdot}$
	(2.88)	(0.95)	(0.33)	(0.18)	(0.11)	(0.22)	(0.56)	(1.66)	(4.78)
ΔCR $\times$ ETS (No but anticipation)	10.01	4.62*	2.54	0.65	-0.03	0.32	1.95	8.12	17.10
	(9.99)	(1.83)	(2.27)	(0.95)	(0.36)	(0.65)	(2.65)	(9.10)	(21.62)
ΔCR $\times$ ETS (Yes)	5.65*	2.71*	1.11*	0.91**	0.17	0.85*	0.95	0.93	2.47
	(2.29)	(1.22)	(0.48)	(0.33)	(0.19)	(0.38)	(0.76)	(2.32)	(6.58)

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

Table 6.3.: This table presents estimates of the panel quantile regression model (with ETS interaction terms) for 5-year CDS spread returns in Europe (top) and North America (bottom). The sample comprises of data from 136 European firms resp. 275 North American firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

Table 6.3 reports the coefficient estimates of the interaction terms for the 5-year sector model of the European and North American sample. Note that the estimate of ΔCR $\times$ ETS (No response) serves as a reference coefficient. All remaining interaction term estimates should be considered in reference to this coefficient. For example, the coefficient for the first decile ΔCR $\times$ ETS (No but anticipation) interaction term is $67.86 + 52.23 = 120.09$. In line with the expectations set forth by Hypothesis 3, the data presented in Table 6.3 reveals a notably smaller relationship between CDS spread returns and the CR factor for European firms that either are not governed by carbon pricing regulations or chose not to respond to the survey. This observation is particularly insightful when contrasted with the coefficient estimate for companies that, while not currently regulated, anticipate impending carbon pricing regulations. For these firms, the coefficients of most deciles are larger, suggesting that the mere anticipation of future regulations can have a pronounced effect on perceived carbon risk. However, the most significant impact is observed for companies that are already operating under explicit carbon pricing. Their coefficient estimates are approximately double in magnitude compared to firms not subject to explicit price regulation. This stark difference underscores the heightened financial implications these companies face in the present, as they grapple with the tangible costs and complexities of adhering to current carbon pricing mandates. The lenders' market, in its characteristic forward-looking manner, appears to be acutely sensitive to these nuances in regulatory exposure, adjusting its perception of carbon risk accordingly. In North America, however, we mostly do not find significant differences between the baseline estimates of "No response" and the remaining ETS dummies. This suggests that the mere presence of an ETS does not play a role. In fact, the small share of North American firms even subject to a carbon pricing system probably makes it a less influential part of lenders' considerations.

The influence of explicit carbon regulation on firms in Europe is evident, but it is not just a binary matter of whether a firm is regulated or not. The depth of this impact is also determined by the percentage of a firm's direct emissions that fall under these regulations. Essentially, it is not just about being regulated, but how much of a firm's emissions are actually regulated. For instance, two firms might both be subject to carbon regulation, but if one has a higher proportion of its emissions regulated than the other, the financial implications could be vastly different. This brings into focus the perton cost of carbon price regulation, which can provide a more granular understanding of the financial burden on firms. With Hypothesis 4, we delve deeper into this aspect, seeking to understand how the effect of the CR factor evolves based on the percentage of a firm's direct emissions that are regulated. This exploration aims to provide a more nuanced understanding of the financial implications of carbon regulations on firms, beyond just the binary case of being regulated or not.

To that end, we compute the ratio between verified emissions and total global direct emissions. This ratio serves as a measure of the proportion of a firm's emissions that have been officially verified and are therefore subject to regulation. To derive this, we source our data for verified emissions from the CDP questionnaire. The global emissions profile of a firm is sourced from Refinitiv data, which offers insights into total global direct emissions, our scope 1 emissions. These are emissions that come directly from sources owned or controlled by the firm, such as its factories or facilities. By comparing these two data points - the verified emissions from the CDP questionnaire and the total direct emissions from Refinitiv – we can gauge the extent to which a firm's emissions are under regulatory scrutiny and, by extension, the potential explicit cost implications of carbon regulations on the firm. With that, our model now looks as follows:

$$
\begin{aligned}
Q_{s^m_{i,t}}(\tau|\boldsymbol{x}_{i,t}) = {} & \alpha_{\tau,i} + \beta_{\tau,1} r_{i,t} + \beta_{\tau,2}\Delta\sigma_{i,t} + \beta_{\tau,3}\Delta\mathrm{MRI}^m_{i,t} + \beta_{\tau,4}\Delta\mathrm{CR}^m_t + \sum_{k=5}^{8}\beta_{\tau,k}\mathrm{ETS}_i \\
& + \sum_{k=9}^{11}\beta_{\tau,k}\Delta\mathrm{CR}^m_t\mathrm{ETS}_i + \beta_{\tau,12}\Delta\mathrm{CR}^m_t\mathrm{ETS}_i(\mathrm{Yes})\mathrm{ETS\ Share}_i + \varepsilon_{i,t},
\end{aligned}
$$

where $\mathrm{ETS}_i(\mathrm{Yes})$ and ETS Share_i denote firm i's Yes/No reponse to question C11.1 from the CDP questionnaire and ratio of verified emissions to total direct emissions, respectively.

	1	2	3	4	5	6	7	8	9
				Europe					
ΔCR × ETS (No response)	68.48***	56.93***	46.92***	33.21***	19.24***	26.01***	46.60***	61.74***	82.12**
	(13.09)	(6.63)	(9.66)	(7.26)	(5.64)	(6.62)	(9.59)	(14.47)	(27.26)
ΔCR × ETS (Yes) × ETS Share	88.11*	77.88**	107.45***	139.10***	123.43***	132.57***	112.78***	76.27*	47.70
	(34.25)	(25.99)	(28.87)	(33.18)	(33.78)	(35.10)	(29.77)	(36.28)	(56.04)
ΔCR × ETS (No)	41.84**	47.26***	42.42***	31.23**	27.24**	26.97**	26.91$^{\cdot}$	46.13*	60.56$^{\cdot}$
	(15.21)	(13.99)	(12.79)	(10.53)	(9.12)	(10.25)	(14.12)	(19.07)	(36.36)
ΔCR × ETS (No but anticipation)	51.67**	20.99	27.17	23.97	34.26$^{\cdot}$	32.68$^{\cdot}$	26.37	42.95*	68.32$^{\cdot}$
	(15.88)	(50.08)	(23.09)	(17.10)	(18.74)	(17.42)	(17.85)	(21.09)	(38.15)
ΔCR × ETS (Yes)	220.88***	188.67***	149.13***	112.47***	103.30***	105.71***	134.99***	201.13***	268.93***
	(19.45)	(12.12)	(13.79)	(13.14)	(12.27)	(13.19)	(15.85)	(22.75)	(36.93)
				North America					
ΔCR × ETS (No response)	2.75	3.07***	1.40***	0.75***	0.38***	0.76***	2.49***	8.77***	33.20***
	(2.08)	(0.74)	(0.23)	(0.15)	(0.09)	(0.18)	(0.40)	(1.26)	(3.48)
ΔCR × ETS (Yes) × ETS Share	14.38	−2.00	−1.03	−1.20	0.37	−0.52	−3.50	−10.43*	−7.23
	(19.80)	(3.08)	(1.00)	(0.98)	(0.65)	(1.21)	(2.28)	(5.26)	(56.00)
ΔCR × ETS (No)	2.67	−0.26	−0.24	−0.11	−0.09	−0.06	−0.57	−2.03	−8.96$^{\cdot}$
	(2.85)	(0.95)	(0.33)	(0.18)	(0.11)	(0.22)	(0.56)	(1.67)	(4.81)
ΔCR × ETS (No but anticipation)	9.79	4.58*	2.54	0.65	−0.03	0.32	1.95	8.15	17.04
	(9.76)	(1.88)	(2.27)	(0.95)	(0.36)	(0.65)	(2.65)	(9.06)	(21.80)
ΔCR × ETS (Yes)	5.07$^{\cdot}$	2.93*	1.21*	1.08**	0.15	0.91*	1.31	2.32	3.04
	(2.86)	(1.20)	(0.55)	(0.38)	(0.21)	(0.43)	(0.84)	(2.48)	(7.26)

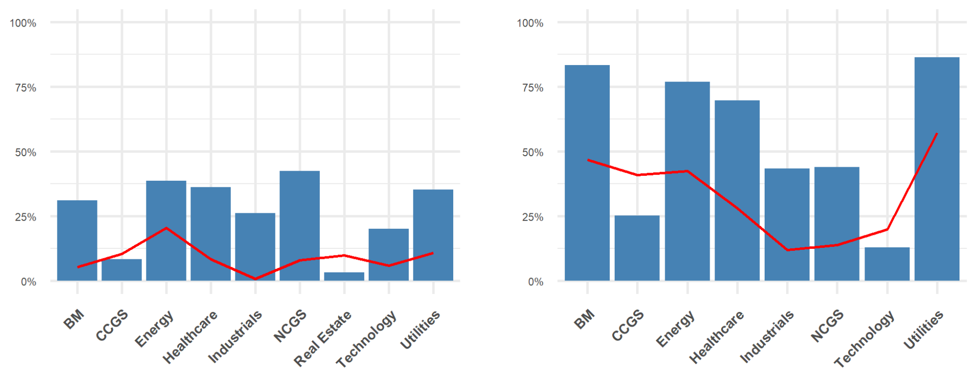
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Table 6.4.: This table presents estimates of the panel quantile regression model (with ETS × ETS share interaction terms) for 5-year CDS spread returns in Europe (top) and North America (bottom). The sample comprises of data from 136 European firms resp. 275 North American firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

In Table 6.4, we present the key coefficient estimates, specifically focusing on the double interaction terms, denoted as ΔCR × ETS (Yes) × ETS Share, for the 5-year sector model within the European and North American sample. Notably, the coefficients for Europe are substantial and exhibit strong positive signs. This suggests a clear relationship: as the proportion of a firm's total scope 1 emissions that are subject to carbon price regulation increases, the impact of CR also intensifies. In other words, firms with a higher percentage of their emissions under carbon pricing regulation are more sensitive to changes in the CR factor. This underscores the importance of understanding the extent of a firm's emissions that fall under regulatory purview, as it has a direct bearing on how the firm's credit profile responds to perceived carbon risks. For North America, we do not find any evidence of the ETS share variable in conjunction with the CR. Given the previously observed weak effect of CR for firms subject to an ETS, this finding however does not surprise. If carbon risk does not even play a significant role for ETS-compliant firms, it is unlikely that the ETS share of those firms matters.

6.2.3. Sectoral effects

Building on the previous observations, we are led to a logical progression in our analysis. It is evident that the typical firm is not immune to carbon risk, especially in Europe. However, this exposure is not uniformly distributed across all sectors. In fact, certain sectors, especially those that are inherently carbon-intensive, rely heavily on processes that emit significant amounts of carbon and can face an increased level of risk.[3] This risk could amplify even further in combination with an explicit price on carbon, as those firms would face higher financial costs for the large amount of their emissions. Figure 6.2 depicts the share of firms subject to an ETS per sector (blue bars) as well as the average ETS share of those compliant firms (red line). Focusing on the three emission-intense sectors BM, Energy and Utilities, it is apparent that most of the firms in these sectors are subject to an ETS, especially in Europe. In conjunction with it, we also see that these sectors exhibit the highest ETS share among all sectors. That is, these sectors are not just regulated but a huge share of their emissions has an actual price tag. Consequently, due to their operational nature, these sectors may experience amplified financial repercussions from carbon risk.



(a) North America **(b)** Europe

Figure 6.2.: Proportions of firms subject to an ETS per sector (bars) and the average share of emissions (verified emissions/scope 1 emissions) for those firms subject to an ETS per sector (red line).

To empirically validate these findings, develop a more nuanced picture of differential sectoral exposure and test Hypothesis 5, we re-estimate our baseline QR, regrouping the firms by the RBC classification. In particular, we include sector dummies and interaction terms with our CR in the baseline regression as follows:

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

[3]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.

where Sector_i indicates firm i's RBC classification.

	1	2	3	4	5	6	7	8	9
Europe									
BM × ΔCR	265.45***	215.77***	168.24***	141.18***	120.40***	129.32***	181.69***	236.53***	317.17***
	(12.25)	(12.54)	(13.35)	(12.61)	(11.85)	(12.51)	(13.94)	(14.24)	(21.18)
CCGS × ΔCR	−155.99***	−87.87***	−64.52***	−66.30***	−65.34***	−62.94***	−82.30***	−102.64***	−155.88***
	(13.31)	(17.19)	(16.98)	(15.90)	(14.89)	(16.49)	(18.80)	(20.19)	(43.16)
Energy × ΔCR	365.55***	406.66***	440.12***	422.91***	417.00***	408.92***	408.97***	470.55***	504.94***
	(16.08)	(25.47)	(27.70)	(38.02)	(36.59)	(41.81)	(38.61)	(37.03)	(42.15)
Healthcare × ΔCR	−68.69·	−59.74**	−72.80**	−84.12***	−84.19***	−86.29***	−106.23***	−92.59***	−96.75*
	(35.13)	(20.54)	(23.40)	(21.92)	(17.38)	(19.38)	(24.44)	(27.42)	(40.14)
Industrials × ΔCR	−159.91***	−141.44***	−104.47***	−98.56***	−95.04***	−97.49***	−129.44***	−156.70***	−191.28***
	(13.24)	(19.43)	(16.87)	(15.44)	(13.70)	(14.75)	(17.37)	(23.10)	(38.80)
NCGS × ΔCR	−113.99***	−79.09***	−69.96***	−74.72***	−72.78***	−74.18***	−87.80***	−84.47***	−90.86*
	(16.72)	(19.65)	(17.20)	(15.85)	(14.45)	(15.35)	(17.39)	(22.03)	(36.02)
Real Estate × ΔCR	−52.16	−78.71***	−72.01*	−80.97**	−76.25***	−77.20***	−110.98***	−117.42***	−129.30***
	(65.28)	(20.93)	(29.56)	(28.56)	(23.00)	(22.79)	(21.29)	(21.16)	(21.89)
Technology × ΔCR	−142.11***	−100.09***	−60.11**	−57.18***	−53.54***	−55.47***	−82.94***	−111.28***	−162.18***
	(19.99)	(20.55)	(20.46)	(16.75)	(15.74)	(15.95)	(19.90)	(22.56)	(40.22)
Utilities × ΔCR	56.81*	92.06***	121.45***	115.99***	105.04***	110.76***	92.80***	82.79*	39.00
	(23.14)	(26.86)	(24.39)	(24.97)	(26.62)	(25.25)	(25.00)	(35.92)	(50.25)
North America									
BM × ΔCR	18.38***	13.55***	5.81***	2.93***	1.50***	3.73***	8.36***	22.92***	78.80***
	(1.60)	(2.31)	(0.92)	(0.57)	(0.33)	(0.62)	(1.47)	(4.84)	(15.76)
CCGS × ΔCR	−16.18***	−9.49**	−3.24**	−0.97	−0.95*	−2.19*	−5.01**	−11.43*	−44.89*
	(3.51)	(3.31)	(1.17)	(0.75)	(0.42)	(0.87)	(1.84)	(5.62)	(18.06)
Energy × ΔCR	16.15·	3.28	0.16	−0.15	−0.20	−0.76	−1.36	0.12	13.08
	(8.50)	(3.25)	(1.31)	(0.73)	(0.44)	(0.79)	(1.92)	(6.05)	(21.57)
Healthcare × ΔCR	−23.09*	−12.68***	−5.65***	−2.36***	−1.21**	−3.23***	−6.29***	−16.56**	−38.64·
	(11.00)	(3.68)	(1.14)	(0.66)	(0.41)	(0.74)	(1.78)	(5.33)	(22.53)
Industrials × ΔCR	−14.28***	−10.26***	−4.46***	−2.26***	−1.20***	−3.19***	−6.63***	−15.48**	−49.43**
	(3.41)	(2.34)	(0.95)	(0.58)	(0.35)	(0.65)	(1.58)	(5.08)	(16.33)
NCGS × ΔCR	−13.09***	−10.99***	−4.66***	−2.28***	−1.34***	−3.45***	−7.45***	−19.24***	−63.57***
	(2.05)	(2.59)	(1.00)	(0.59)	(0.36)	(0.68)	(1.55)	(5.18)	(16.96)
Real Estate × ΔCR	−6.37**	−10.85***	−5.17***	−2.65***	−1.21***	−3.14***	−6.62***	−16.54**	−45.09**
	(2.00)	(2.45)	(0.95)	(0.60)	(0.35)	(0.68)	(1.54)	(5.05)	(16.92)
Technology × ΔCR	−21.38***	−13.92***	−5.70***	−2.75***	−1.40***	−3.45***	−7.47***	−19.76***	−67.85***
	(3.14)	(2.59)	(1.00)	(0.59)	(0.35)	(0.67)	(1.52)	(5.01)	(16.61)
Utilities × ΔCR	−12.09***	−11.55***	−5.10***	−2.49***	−1.36***	−3.08***	−6.92***	−16.70**	−57.52***
	(1.76)	(2.37)	(1.02)	(0.61)	(0.35)	(0.65)	(1.55)	(5.13)	(16.22)

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

Table 6.5.: This table reports the coefficient estimates of the interaction terms of the sector panel quantile regression model for 5-year CDS spread returns in Europe (top) and North America (bottom). The sample comprises of data from 136 European firms resp. 275 North American firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

Table 6.5 reports the coefficient estimates of the interaction terms for the 5-year sector model of the European and North American samples, respectively.[4] Note that the estimate of BM × ΔCR serves as a reference coefficient. All remaining interaction term estimates should be considered in reference to this coefficient. For example, the unscaled coefficient for the CCGS (consumer cyclicals) interaction term in Europe is $0.1164 - 0.0374 = 0.079$. Consistent with Hypothesis 5 that there is a strong relationship between regulated emissions and sectoral carbon risk exposure, Table 6.5 shows that the coefficients on the interaction term between the sector and ΔCR_t is positive and highly significant for Basic Materials (BM), Energy and Utilities. These sectors exhibit the largest effect sizes within their respective regions. For the remaining sectors,

[4] The estimation results for short-term (1Y) and long-term tenors (30Y) do not differ qualitatively, as reported in Table A.1 and A.2, respectively, in Appendix A.2.

the coefficient estimates are significantly smaller and – in the North American sample – can even be negative or insignificant. These findings support the observations in recent literature: carbon risk impacts firms' valuation differently, and it is concentrated in specific sectors. Therefore, a growing difference in carbon risk exposure could translate into higher credit risk for firms in carbon-intensive sectors like construction materials (Basic Materials), fossil fuels (Energy) and Utilities. Conversely, businesses in sectors like industrial and commercial services (Industrials), technology equipment (Technology) and Healthcare are seen as capable of providing the innovation and technologies necessary to facilitate a low-carbon transformation. As such, they are less affected by a growing difference in carbon risk exposure.

	1	2	3	4	5	6	7	8	9
				Europe					
BM × ΔCRS	155.07***	145.90***	137.31***	138.45***	139.49***	139.01***	142.81***	150.05***	164.18***
	(10.33)	(6.80)	(10.14)	(9.63)	(11.04)	(9.92)	(9.37)	(8.85)	(12.82)
CCGS × ΔCRS	−36.49·	−5.04	−18.20	−35.29*	−53.40**	−41.55**	−28.99	−34.28	−44.22*
	(20.52)	(13.16)	(16.06)	(15.90)	(19.27)	(14.68)	(17.78)	(22.10)	(21.15)
Energy × ΔCRS	249.29***	225.23***	223.22***	199.46***	186.84***	181.53***	209.27***	243.09***	239.90***
	(13.99)	(22.48)	(29.29)	(26.37)	(24.38)	(22.63)	(39.33)	(25.57)	(29.61)
Healthcare × ΔCRS	−42.77·	1.20	12.76	−16.32	−22.33	0.23	58.85*	146.22***	240.58***
	(24.95)	(35.33)	(35.01)	(26.11)	(29.93)	(36.36)	(29.00)	(37.70)	(60.64)
Industrials × ΔCRS	−137.13***	−130.84***	−126.19***	−134.68***	−138.61***	−136.47***	−136.00***	−140.73***	−155.21***
	(11.74)	(7.52)	(10.49)	(9.73)	(11.06)	(10.06)	(9.83)	(10.20)	(29.32)
NCGS × ΔCRS	125.54***	61.27*	9.30	−46.41*	−70.02***	−62.68***	−50.23*	−40.15	−32.58
	(31.96)	(24.14)	(24.11)	(20.24)	(17.55)	(16.55)	(22.86)	(26.57)	(29.84)
Technology × ΔCRS	−157.80***	−151.60***	−144.38***	−142.50***	−140.06***	−140.34***	−145.65***	−156.44***	−177.89***
	(10.74)	(8.96)	(12.38)	(10.01)	(11.09)	(9.95)	(9.39)	(8.87)	(13.12)
Utilities × ΔCRS	−126.90***	−161.70***	−158.52***	−159.00***	−149.16***	−156.55***	−178.07***	−212.97***	−235.46***
	(24.45)	(26.20)	(23.01)	(17.84)	(14.24)	(15.50)	(21.22)	(23.14)	(29.82)
				North America					
BM × ΔCRS	4.75***	2.64***	1.22***	0.63·	0.24	0.27	0.69	1.71*	1.41
	(0.41)	(0.39)	(0.26)	(0.34)	(0.19)	(0.32)	(0.58)	(0.79)	(5.83)
CCGS × ΔCRS	−36.91***	−23.27***	−12.26***	−5.97***	−2.01***	−3.90***	−7.31***	−15.60***	−28.12***
	(2.41)	(1.28)	(0.98)	(0.70)	(0.31)	(0.57)	(0.84)	(1.52)	(6.30)
Energy × ΔCRS	7.25***	2.77***	1.01	0.36	0.03	0.25	1.03	5.50*	22.53**
	(0.90)	(0.79)	(0.85)	(0.57)	(0.21)	(0.36)	(1.07)	(2.25)	(7.56)
Healthcare × ΔCRS	23.12***	3.90*	3.20*	1.79	1.15	2.28*	6.78*	14.60*	37.73**
	(1.86)	(1.69)	(1.29)	(1.35)	(0.70)	(1.13)	(2.77)	(6.12)	(14.30)
Industrials × ΔCRS	−3.32***	−1.38***	−0.72*	−0.33	−0.14	−0.18	−0.48	−1.13	0.81
	(0.44)	(0.41)	(0.31)	(0.37)	(0.19)	(0.33)	(0.59)	(0.80)	(5.85)
NCGS × ΔCRS	−17.72***	−10.18***	−6.61***	−4.12***	−2.77***	−4.94***	−9.40***	−20.08***	−47.84***
	(3.81)	(2.31)	(1.35)	(1.00)	(0.68)	(0.96)	(1.82)	(3.32)	(12.47)
Technology × ΔCRS	11.26***	5.81***	2.99***	1.90***	1.32***	2.06***	3.33***	7.77***	26.41*
	(2.35)	(1.11)	(0.76)	(0.55)	(0.34)	(0.48)	(0.96)	(1.86)	(10.82)
Utilities × ΔCRS	−1.54**	−0.66	−0.27	−0.14	−0.08	−0.05	−0.05	−0.39	4.79
	(0.56)	(0.47)	(0.28)	(0.35)	(0.19)	(0.33)	(0.60)	(0.89)	(5.87)

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

Table 6.6.: This table reports the coefficient estimates of the interaction terms of the sector panel quantile regression model for 5-year CDS spread returns in Europe (top) and North America (bottom). The sample comprises of data from 133 European firms resp. 259 North American firms from 2014/01/01 to 2019/12/31 (Europe) resp. 2013/01/01 to 2019/12/31 (North America) in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

So far, we focused our analysis on the sectoral effects of the *market-wide* CR factor. While this investigation is useful to understand how the general market perception of carbon risk acts within each sector, it disregards the unique features of each sector. Sectors such as BM, Energy or Utilities naturally emit more emissions than other low-carbon industries. This, however, does not necessarily imply that these firms are all ill-prepared for a low-carbon transition. There will be firms or even entire sectors that – despite being currently emission-intensive – have a clear pathway to net-zero. The original, market-wide CR factor would not be able to capture this aspect, as it focuses on the entire universe of firms. For that reason, we also examine the effects of the *sector-wide* CR factor (CRS). This risk factor, which we introduced in Subsection 5.2.2, is constructed for each sector and hence incorporates these sectoral peculiarities.

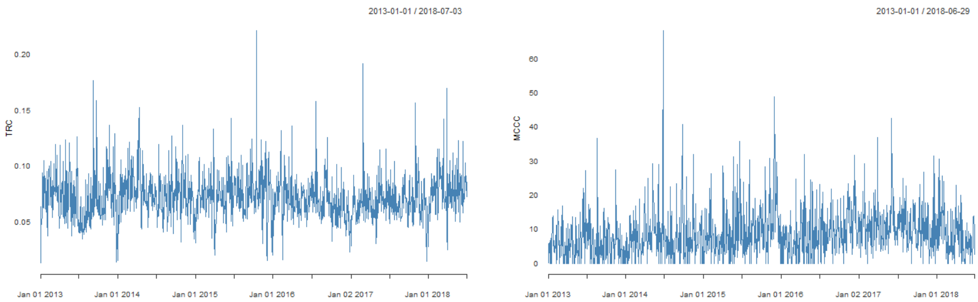
Table 6.6 displays the coefficient estimates of the interaction between the sector dummy and the CRS factor for the 5-year sector model of the European and North American sample, respectively. Similar to the model with the CR factor, we find evidence for a strong positive effect of the CRS for the sectors BM and Energy in Europe. Interestingly, however, the Utilities sector shows converse effects compared to the results we obtained using the market-wide CR. It seems that lenders perceive the impact of carbon risk specific to the Utilities sector very different from the impact of market-wide carbon risk. Given that Utilities is the most affected sector in Europe in terms of explicit carbon regulation (Figure 6.2), this may seem odd at first. However, most of the utility companies in Europe are subject to the EU ETS since its inception and hence needed to adjust their abatement strategies much earlier than others. In fact, many companies in this sector (e.g. Enel, Engie, Iberdrola, etc.) are now considered to be at the forefront of providing solutions for the net-zero transition (Hawcock, 2023). Other sectors such as Technology and Industrials also exhibit similar effects and seem to be considered solution providers as well. In North America, most of the estimates are insignificant and only become significant towards the tails. Exceptions to this are the sectors CCGS and NCGS that exhibit negative coefficients as well as the Technology sector that shows positive effects.

6.2.4. Attention to climate change

Next, we empirically examine Hypothesis 6, which postulates that the perceived exposure to carbon risk surges when attention to climate change is high. For Europe, we adopt the Transition Risk Concern (TRC) index of Bua et al. (2022) as our aggregate attention measure. The TRC scans Reuters News to detect items with a European regional focus that relate to the introduction of new regulations to curb emissions. For North America we use the Media Climate Change Concerns (MCCC) index of Ardia et al. (2022). For each day, the MCCC index generates an aggregate score based on the number of articles related to climate change in major US newspapers and their tone. Because the aggregate MCCC index includes news relating to physical climate risk, we use a variant that only incorporates topics belonging to the superordinate themes "Financial and Regulation", "Agreement and Summit" and "Public Impact".[5] The adjusted MCCC index thereby provides daily information on the coverage and sentiment of North American carbon-related news and excludes any physical climate component.

Figure 6.3 depicts the evolution of the TRC index (left) and MCCC index (right). Both indices exhibit strong volatile behavior and react to significant carbon-related events.

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



(a) Europe

(b) North America

Figure 6.3.: Evolution of the TRC index (left) and MCCC index (right) from 2013/01/01 – 2018/06/29.

However, we can also see that both indices move on different levels. To have comparable indices later on, we thus normalize both indices by subtracting the respective sample mean and dividing by the sample standard deviation for each observation. Also for comparability reasons, we restrict our entire sample period to mid-2018 as the MCCC index is only available until June 29th, 2018.

In our empirical approach, we interact News_t with our CR factor and re-examine the baseline QR by including both the interaction term $\text{News}_t \times \Delta\text{CR}_t$ and News_t:

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

We first discuss the estimation results for Europe, as shown in Table 6.7. Consistent with the prediction in Hypothesis 6, Table 6.7 shows that the coefficient on the interaction term between News and CR is positive and significant, especially for the mid- and long-term tenors (5Y, 10Y and 30Y) indicating a strengthening effect of carbon risk when attention to climate change is high. This observation is largely persistent across all deciles and the effects are more pronounced at the extremes of the conditional distribution. The short-term tenors of 1Y and 3Y, however, do not show any positive effect. In fact, for most coefficients we observe a significant negative estimate showing that, on a short time horizon, carbon risk has a decreasing impact when attention to climate change increases.

Table 6.8 reports the estimation results for North America. These findings are even less clear-cut. While the CR in conjunction with attention seems to have some weak effect on 5Y and 30Y tenors, we mostly find no significant effects for the remaining tenors. Contradicting Hypothesis 6 and similar to the European results, news about adjustments in European carbon policies do not amplify the effect of carbon risk in the very short-term. When market-wide concern about carbon risk is elevated, lenders appear to only be more sensitive to carbon risk for longer tenors (except 10Y).

	1	2	3	4	5	6	7	8	9
					1Y				
ΔCR	354.15***	311.12***	214.16***	150.30***	105.45***	145.91***	214.90***	350.44***	496.21***
	(20.79)	(17.18)	(12.97)	(10.01)	(8.95)	(10.77)	(16.10)	(23.93)	(48.71)
News	−78.53***	−66.81***	−51.35***	−27.37***	−2.96·	12.73***	36.26***	51.90***	32.28*
	(15.31)	(11.22)	(6.41)	(3.06)	(1.72)	(2.44)	(4.65)	(10.18)	(13.96)
ΔCR × News	−150.35***	−98.70***	−54.45***	−27.11***	−15.57*	−25.25**	−38.87**	−65.86***	−85.15*
	(17.00)	(13.43)	(11.52)	(8.05)	(6.84)	(8.89)	(12.88)	(17.22)	(35.00)
					3Y				
ΔCR	296.42***	218.47***	170.20***	123.27***	91.27***	111.55***	168.34***	236.33***	298.13***
	(11.64)	(7.77)	(7.32)	(6.79)	(5.77)	(6.31)	(7.52)	(10.48)	(22.55)
News	−48.49***	−37.70***	−36.93***	−27.83***	−7.79***	7.43**	24.10***	34.77***	35.71***
	(10.09)	(6.83)	(4.52)	(2.40)	(1.46)	(2.28)	(4.15)	(6.12)	(10.25)
ΔCR × News	−36.38***	−20.12**	−2.06	9.30*	5.67	6.43	−7.65·	−24.12***	−57.18***
	(11.05)	(6.77)	(4.85)	(4.55)	(3.66)	(4.10)	(4.29)	(4.55)	(6.78)
					5Y				
ΔCR	159.75***	149.82***	121.43***	93.72***	76.37***	88.48***	124.18***	162.05***	212.61***
	(7.50)	(6.02)	(4.99)	(4.87)	(4.70)	(4.82)	(6.04)	(6.94)	(11.65)
News	−42.26***	−29.89***	−28.73***	−18.07***	−3.15**	6.79***	17.75***	25.11***	29.57***
	(5.35)	(3.98)	(2.92)	(1.80)	(1.11)	(1.59)	(2.94)	(4.73)	(7.48)
ΔCR × News	31.63***	15.91***	11.22***	13.31***	16.19***	14.52***	11.69**	7.66·	−12.94*
	(5.04)	(3.11)	(2.58)	(3.19)	(2.99)	(2.87)	(3.85)	(4.31)	(5.54)
					10Y				
ΔCR	77.28***	59.39***	47.47***	35.62***	26.84***	31.31***	46.29***	64.67***	88.83***
	(2.79)	(2.36)	(1.93)	(1.77)	(1.58)	(2.18)	(2.91)	(4.01)	(6.91)
News	−27.98***	−18.40***	−17.07***	−11.81***	−2.26***	6.11***	18.00***	29.95***	42.86***
	(4.65)	(2.74)	(1.94)	(1.15)	(0.68)	(0.93)	(1.81)	(3.03)	(5.32)
ΔCR × News	26.17***	22.23***	19.18***	15.13***	11.13***	12.27***	18.02***	18.72***	14.42***
	(2.06)	(1.80)	(1.48)	(1.28)	(1.20)	(1.48)	(1.67)	(1.96)	(2.01)
					30Y				
ΔCR	68.52***	54.81***	45.45***	36.26***	31.45***	36.72***	47.34***	64.96***	80.74***
	(2.60)	(2.14)	(1.84)	(1.90)	(2.00)	(2.34)	(3.02)	(4.18)	(7.84)
News	−24.28***	−18.26***	−15.74***	−9.60***	−0.86	7.79***	19.68***	30.85***	39.73***
	(4.69)	(2.81)	(2.16)	(1.29)	(0.83)	(1.08)	(2.18)	(3.70)	(6.24)
ΔCR × News	7.89***	9.59***	9.61***	8.43***	8.29***	8.97***	11.91***	11.79***	5.92**
	(1.95)	(1.57)	(1.52)	(1.46)	(1.51)	(1.52)	(2.09)	(2.45)	(2.21)

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

Table 6.7.: This table reports the coefficient estimates of ΔCR and ΔCR × News of the climate attention panel quantile regression model for 1-year (top), 3-year (upper center), 5-year (center), 10-year (lower center) and 30-year (bottom) CDS spread returns. The sample comprises of data from 136 European firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

6.2.5. Term structure

The previous sections provide evidence of CR being a relevant determinant of CDS spread returns across different tenors, geographies, regulatory regimes and sectors. We now examine lenders' different expectations about how fast the transition to a low-carbon economy needs to occur. A revision of the expected pace of transition could affect companies differently, depending on their location and the nature of their business. To empirically test Hypothesis 7, we examine how a change in the expected temporal materialization of carbon risk affects the term structure of a firm's credit risk. We do this by extracting information about carbon risk over a specific time horizon using the slope of the CR factor, namely the difference between CR over different time horizons (see Section 5.2.4). Following Han and Zhou (2015), we set up a model similarly to the base model from Section 6.2.1, replacing the relevant variables with the appropriate slope measures $\Delta\text{CDSSlope}_{i,t}^{mn}$ and $\Delta\text{CRSlope}_{t}^{mn}$. Regarding the relevant slopes, we select the following slopes: 3Y-1Y, 5Y-1Y, 10Y-5Y and 30Y-5Y. This collection allows us to

	1	2	3	4	5	6	7	8	9
					1Y				
ΔCR	4.28***	2.73***	0.28***	0.02***	0.00*	0.05***	0.73***	10.19***	41.84***
	(1.30)	(0.46)	(0.05)	(0.01)	(0.00)	(0.01)	(0.13)	(1.53)	(7.80)
News	2.15*	−0.67**	−0.07**	−0.00*	−0.00	−0.00	−0.01	0.22	−1.38·
	(0.91)	(0.23)	(0.02)	(0.00)	(0.00)	(0.00)	(0.02)	(0.26)	(0.82)
ΔCR × News	13.30***	3.35***	0.19***	0.01	0.00	0.01	0.03	1.60·	6.59·
	(1.88)	(0.60)	(0.05)	(0.01)	(0.00)	(0.01)	(0.08)	(0.84)	(3.47)
					3Y				
ΔCR	3.76***	1.80***	1.11***	0.55***	0.12***	0.39***	0.92***	2.03***	6.76***
	(0.69)	(0.20)	(0.13)	(0.07)	(0.03)	(0.06)	(0.15)	(0.42)	(1.27)
News	1.89*	−0.25	−0.32*	−0.09	−0.00	0.08	0.78***	1.70***	2.23***
	(0.83)	(0.33)	(0.15)	(0.06)	(0.03)	(0.07)	(0.15)	(0.32)	(0.35)
ΔCR × News	−2.13**	−0.80***	−0.46***	−0.18*	−0.04	0.10	0.49**	0.77*	3.10***
	(0.74)	(0.22)	(0.13)	(0.07)	(0.03)	(0.07)	(0.15)	(0.35)	(0.80)
					5Y				
ΔCR	1.43**	1.50***	0.92***	0.49***	0.14***	0.46***	1.31***	3.28***	11.97***
	(0.49)	(0.19)	(0.10)	(0.06)	(0.03)	(0.07)	(0.19)	(0.42)	(1.56)
News	1.72*	−0.46	−0.36*	−0.20**	−0.04	0.01	0.37*	1.42***	3.55***
	(0.77)	(0.30)	(0.14)	(0.07)	(0.03)	(0.08)	(0.15)	(0.27)	(0.51)
ΔCR × News	3.19***	1.61***	0.69***	0.37***	0.11*	0.40***	0.72***	1.70***	5.85***
	(0.62)	(0.26)	(0.13)	(0.08)	(0.05)	(0.09)	(0.19)	(0.36)	(1.08)
					10Y				
ΔCR	4.40***	1.70***	0.92***	0.48***	0.19***	0.41***	0.84***	1.76***	5.53***
	(0.45)	(0.17)	(0.09)	(0.06)	(0.04)	(0.05)	(0.11)	(0.22)	(0.82)
News	1.51·	−0.73*	−0.57***	−0.23**	−0.00	0.37***	1.08***	2.58***	5.90***
	(0.79)	(0.31)	(0.15)	(0.08)	(0.05)	(0.08)	(0.14)	(0.26)	(0.58)
ΔCR × News	−1.76***	−0.54**	−0.27**	−0.13*	−0.03	−0.10·	−0.06	0.08	0.39
	(0.46)	(0.17)	(0.10)	(0.06)	(0.04)	(0.06)	(0.13)	(0.16)	(0.44)
					30Y				
ΔCR	5.05***	2.08***	1.28***	0.72***	0.31***	0.22***	0.46***	1.23***	4.65***
	(0.51)	(0.16)	(0.10)	(0.07)	(0.05)	(0.06)	(0.12)	(0.30)	(0.79)
News	−0.68	−2.24***	−1.13***	−0.57***	−0.04	0.40**	1.04***	3.23***	8.34***
	(0.99)	(0.50)	(0.27)	(0.16)	(0.11)	(0.14)	(0.21)	(0.38)	(0.89)
ΔCR × News	−0.31	0.35*	0.24*	0.27***	0.14**	0.18**	0.39**	1.06***	3.98***
	(0.46)	(0.18)	(0.12)	(0.08)	(0.05)	(0.07)	(0.12)	(0.27)	(0.67)

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

Table 6.8.: This table reports the coefficient estimates of ΔCR and ΔCR × News of the climate attention panel quantile regression model for 1-year (top), 3-year (upper center), 5-year (center), 10-year (lower center) and 30-year (bottom) CDS spread returns. The sample comprises of data for 275 North American firms from 2013/01/01 to 2018/06/29 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

examine the short-, mid- and long-term effects of carbon risk on the CDS spread curve. We thus estimate the model with the inclusion of the term structure control variables:

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

Table 6.9 reports the estimation results of the term structure model for the four CR slopes (3Y-1Y, 5Y-1Y, 10Y-5Y and 30Y-5Y) in Europe. Before proceeding with the discussion of the results, we recall that a positively sloped term structure indicates higher costs of default protection for the longer tenors. Following this logic, a positive CR slope reveals the incremental (positive) exposure to carbon risk for the longer term vis-a-vis the shorter term.

The results in Table 6.9 show that an increase in the CR slope – a shift in the relative cost-impact of carbon regulation toward future cash flows – steepens the CDS curve. This relationship is especially strong (i) in the extremes of the movements of the credit risk term structure and (ii) for the short-term slopes (3Y-1Y and 5Y-1Y) versus the mid-term slope (10Y-5Y). Compared to the estimated coefficients of the MRI slope, the effects are also economically relevant, in particular for the 5Y-1Y slope. The results for the 30Y-5Y slope do not provide any evidence for an effect of the CR slope on the CDS term structure. These results confirm Hypothesis 7 for all but the long-term slope in Europe. A rapid acceleration of the transformation is likely to have significant and relatively larger financial impacts in the near future and, consequently, a faster decline in credit quality in the shorter versus longer term.

The case of North America (Table 6.10) is less clear-cut: While we find mild effects for the two short-term slopes, coefficients for the mid- and long-term slopes are virtually zero[6] and insignificant. The 5Y-1Y CR slope exhibits the largest effects across all models, although, compared to the MRI slope, the magnitude of the effects is still marginal. The 3Y-1Y CR slope shows ambiguous effects, where some coefficients (e.g. median or right tail) are insignificant but others show some (albeit small) effect. The remaining CR slopes 10Y-5Y and 30Y-5Y show no relevant effect for the central deciles. Merely towards the tails, the CR slopes become a relevant driver of the CDS curve slope. Overall, these results align with the findings from Section 6.2.1 showing no real effect of carbon risk on the CDS term structure in North America.

[6] Overall, the coefficients of all variables in the model of the central deciles move on much a smaller scale. However, they are not exactly zero but lie in the region of 10e-9.

	1	2	3	4	5	6	7	8	9
					3Y-1Y				
ΔVolatility	-5.33^{**}	-1.72^{***}	-0.54^{***}	-0.12^{*}	$0.08^{\cdot}$	0.57^{***}	1.99^{***}	6.87^{***}	15.50^{***}
	(1.69)	(0.21)	(0.12)	(0.05)	(0.04)	(0.03)	(0.17)	(0.39)	(0.62)
ΔMRISlope	13.60^{***}	9.84^{***}	5.03^{***}	2.30^{***}	1.47^{***}	1.72^{***}	3.42^{***}	8.57^{***}	14.59^{***}
	(0.49)	(0.50)	(0.41)	(0.15)	(0.09)	(0.11)	(0.27)	(0.61)	(1.04)
ΔIR	-168.86^{***}	-96.39^{***}	-42.60^{***}	-25.94^{***}	-18.84^{***}	-21.61^{***}	-36.59^{***}	-114.73^{***}	-240.55^{***}
	(13.00)	(6.85)	(2.81)	(1.20)	(0.86)	(0.97)	(2.69)	(9.62)	(25.11)
ΔIR^2	-2676.08^{***}	-1103.76^{***}	-178.75^{***}	20.69^{***}	50.77^{***}	100.08^{***}	389.22^{***}	2850.58^{***}	7494.32^{***}
	(235.65)	(77.87)	(25.07)	(6.13)	(5.03)	(8.23)	(45.99)	(224.73)	(543.41)
ΔTerm	84.13^{***}	52.28^{***}	24.63^{***}	16.20^{***}	11.67^{***}	10.60^{***}	7.35^{***}	-2.81	-27.25^{*}
	(12.19)	(6.50)	(2.58)	(1.15)	(0.81)	(0.87)	(1.83)	(4.38)	(11.31)
ΔCRSlope	2.60^{***}	1.44^{***}	0.56^{***}	0.25^{***}	0.16^{***}	0.15^{***}	0.27^{***}	0.67^{***}	1.37^{***}
	(0.18)	(0.09)	(0.05)	(0.02)	(0.01)	(0.01)	(0.03)	(0.09)	(0.20)
					5Y-1Y				
ΔVolatility	-9.12^{***}	-3.14^{***}	-1.17^{**}	-0.34^{*}	0.08	1.17^{***}	3.50^{***}	9.64^{***}	19.46^{***}
	(1.02)	(0.46)	(0.40)	(0.14)	(0.09)	(0.13)	(0.07)	(0.40)	(0.98)
ΔMRISlope	15.38^{***}	12.32^{***}	7.91^{***}	4.00^{***}	2.51^{***}	2.89^{***}	5.21^{***}	10.50^{***}	16.96^{***}
	(0.66)	(0.54)	(0.56)	(0.30)	(0.19)	(0.19)	(0.36)	(0.35)	(0.79)
ΔIR	-212.94^{***}	-123.41^{***}	-68.10^{***}	-40.19^{***}	-29.41^{***}	-32.22^{***}	-55.16^{***}	-129.52^{***}	-238.05^{***}
	(19.65)	(9.94)	(4.92)	(2.17)	(1.50)	(1.73)	(3.82)	(11.14)	(25.87)
ΔIR^2	-3659.67^{***}	-1473.52^{***}	-436.52^{***}	40.28^{**}	98.31^{***}	152.24^{***}	646.33^{***}	3335.92^{***}	9503.33^{***}
	(419.92)	(97.01)	(56.45)	(12.55)	(8.66)	(11.62)	(64.84)	(258.20)	(678.84)
ΔTerm	102.06^{***}	61.00^{***}	33.97^{***}	19.17^{***}	11.93^{***}	9.44^{***}	5.45^{*}	-17.10^{**}	-75.58^{***}
	(18.99)	(9.51)	(4.43)	(1.95)	(1.35)	(1.52)	(2.55)	(5.66)	(14.41)
ΔCRSlope	4.90^{***}	3.00^{***}	1.52^{***}	0.71^{***}	0.43^{***}	0.52^{***}	1.02^{***}	2.51^{***}	4.63^{***}
	(1.99)	(1.67)	(1.11)	(0.52)	(0.32)	(0.36)	(0.83)	(1.77)	(3.79)
					10Y-5Y				
ΔVolatility	-2.03^{***}	-1.23^{***}	-0.73^{***}	-0.40^{***}	-0.03	-0.03	0.16^{**}	0.60^{***}	1.46^{***}
	(0.15)	(0.09)	(0.08)	(0.06)	(0.03)	(0.05)	(0.06)	(0.06)	(0.19)
ΔMRISlope	0.52^{***}	0.14^{***}	0.09^{***}	0.07^{***}	$0.01^{\cdot}$	0.09^{***}	0.13^{***}	0.27^{***}	0.58^{***}
	(0.04)	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)	(0.06)
ΔIR	18.26^{**}	24.51^{***}	18.17^{***}	18.51^{***}	2.03^{***}	14.14^{***}	14.49^{***}	23.54^{***}	31.79^{***}
	(5.96)	(1.75)	(1.21)	(0.88)	(0.49)	(0.94)	(1.23)	(1.85)	(5.20)
ΔIR^2	-946.47^{***}	-367.10^{***}	-194.42^{***}	-110.18^{***}	-9.22^{*}	26.68^{***}	76.18^{***}	197.01^{***}	801.62^{***}
	(85.63)	(19.51)	(11.37)	(7.81)	(3.75)	(4.53)	(7.46)	(16.79)	(85.80)
ΔTerm	-30.22^{***}	-22.62^{***}	-16.67^{***}	-18.95^{***}	-2.08^{***}	-14.61^{***}	-13.92^{***}	-22.48^{***}	-33.30^{***}
	(5.53)	(1.80)	(1.28)	(0.92)	(0.51)	(0.98)	(1.17)	(1.64)	(4.23)
ΔCRSlope	-0.06	0.03^{***}	0.04^{***}	0.05^{***}	$0.08^{\cdot}$	0.35^{**}	0.71^{**}	$0.70^{\cdot}$	0.32
	(0.07)	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.05)	(0.11)
					30Y-5Y				
ΔVolatility	-4.83^{***}	-2.60^{***}	-1.64^{***}	-0.86^{***}	-0.26	0.05	0.57^{***}	1.43^{***}	3.52^{***}
	(0.74)	(0.23)	(0.16)	(0.12)	(0.10)	(0.13)	(0.13)	(0.17)	(0.34)
ΔMRISlope	5.80^{***}	2.59^{***}	1.68^{***}	1.32^{***}	1.18^{***}	1.31^{***}	1.58^{***}	2.46^{***}	5.73^{***}
	(0.24)	(0.12)	(0.09)	(0.07)	(0.08)	(0.08)	(0.10)	(0.16)	(0.47)
ΔIR	48.61^{***}	46.68^{***}	38.00^{***}	34.21^{***}	28.23^{***}	33.13^{***}	38.41^{***}	42.28^{***}	45.66^{***}
	(10.68)	(3.74)	(2.57)	(1.98)	(1.82)	(1.90)	(2.36)	(3.34)	(10.16)
ΔIR^2	-1604.68^{***}	-624.35^{***}	-333.25^{***}	-160.09^{***}	-30.71^{***}	59.52^{***}	169.26^{***}	439.76^{***}	1559.03^{***}
	(122.74)	(34.92)	(20.35)	(14.00)	(6.69)	(8.11)	(13.36)	(30.07)	(154.85)
ΔTerm	-92.98^{***}	-57.36^{***}	-42.09^{***}	-35.23^{***}	-28.34^{***}	-31.91^{***}	-35.38^{***}	-35.21^{***}	-43.11^{***}
	(11.64)	(3.80)	(2.71)	(1.94)	(1.08)	(2.06)	(2.44)	(3.43)	(8.89)
ΔCRSlope	-0.06	0.01	0.00	0.01	0.02	0.09^{*}	0.17^{**}	$0.17^{\cdot}$	0.08
	(0.08)	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.05)	(0.14)

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

Table 6.9.: This table reports the coefficient estimates of the term structure panel quantile regression model for 5Y-1Y and 30Y-5Y CDS spread slope changes in Europe. The sample comprises data for 136 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 a factor of 1e2.

	1	2	3	4	5	6	7	8	9
					3Y-1Y				
ΔVolatility	-3.17^{***}	-0.84^{***}	-0.25^{***}	-0.01	0.00	0.19^{***}	0.79^{***}	2.71^{***}	7.26^{***}
	(0.25)	(0.12)	(0.05)	(0.01)	(0.00)	(0.03)	(0.06)	(0.17)	(0.50)
ΔMRISlope	1.02^{***}	0.55^{***}	0.24^{***}	0.07^{***}	0.00	0.11^{***}	0.28^{***}	0.86^{***}	2.36^{***}
	(0.11)	(0.03)	(0.02)	(0.01)	(0.00)	(0.01)	(0.02)	(0.08)	(0.27)
ΔIR	-79.69^{***}	-28.34^{***}	-14.03^{***}	-3.25^{***}	-0.07	-6.94^{***}	-15.96^{***}	-46.42^{***}	-124.82^{***}
	(4.33)	(1.20)	(0.69)	(0.25)	(0.04)	(0.39)	(0.68)	(3.23)	(11.52)
ΔIR^2	-837.20^{***}	-136.67^{***}	-23.21^{***}	-6.35^{***}	$0.48^{\cdot}$	48.50^{***}	87.15^{***}	385.06^{***}	1954.06^{***}
	(62.58)	(9.16)	(2.91)	(0.89)	(0.25)	(25.72)	(44.21)	(390.96)	(2423.91)
ΔTerm	32.30^{***}	16.10^{***}	9.06^{***}	2.02^{***}	0.04	2.94^{***}	7.92^{***}	18.29^{***}	31.78^{***}
	(2.59)	(1.04)	(0.60)	(0.21)	(0.02)	(0.26)	(0.46)	(1.13)	(2.25)
ΔCRSlope	0.08^{***}	0.04^{***}	0.02^{***}	0.01^{***}	0.00	0.01^{***}	0.02^{**}	0.00	-0.02
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)
					5Y-1Y				
ΔVolatility	-6.11^{***}	-1.42^{***}	-0.37^{***}	-0.04	0.05^{**}	0.59^{***}	1.91^{***}	6.00^{***}	18.28^{***}
	(0.73)	(0.23)	(0.08)	(0.03)	(0.02)	(0.07)	(0.12)	(0.34)	(1.29)
ΔMRISlope	2.31^{***}	1.27^{***}	0.60^{***}	0.29^{***}	0.16^{***}	0.30^{***}	0.68^{***}	1.97^{***}	5.52^{***}
	(0.27)	(0.09)	(0.04)	(0.02)	(0.01)	(0.02)	(0.04)	(0.24)	(0.63)
ΔIR	-147.16^{***}	-56.13^{***}	-25.38^{***}	-12.76^{***}	-5.80^{***}	-13.26^{***}	-28.77^{***}	-85.37^{***}	-255.57^{***}
	(6.99)	(2.22)	(1.06)	(0.68)	(0.41)	(0.66)	(1.28)	(5.83)	(24.13)
ΔIR^2	-1712.49^{***}	-379.33^{***}	-64.58^{***}	6.90^{*}	32.38^{***}	70.14^{***}	154.40^{***}	887.79^{***}	4753.97^{***}
	(82.93)	(25.09)	(5.38)	(2.83)	(1.97)	(3.30)	(8.34)	(77.17)	(504.42)
ΔTerm	57.47^{***}	28.23^{***}	15.22^{***}	7.81^{***}	2.98^{***}	6.28^{***}	13.97^{***}	29.84^{***}	64.04^{***}
	(4.73)	(1.68)	(0.96)	(0.58)	(0.31)	(0.49)	(0.87)	(2.18)	(6.49)
ΔCRSlope	0.25^{***}	0.11^{***}	0.05^{***}	0.02^{***}	0.01^{***}	0.01^{***}	0.02^{**}	0.04^{*}	0.16^{***}
	(0.06)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)	(0.02)	(0.08)	(0.23)
					10Y-5Y				
ΔVolatility	-2.96^{***}	-1.30^{***}	-0.37^{***}	0.00	0.00	0.00	0.49^{***}	1.93^{***}	5.19^{***}
	(0.41)	(0.15)	(0.05)	(0.00)	(0.00)	(0.00)	(0.04)	(0.19)	(0.65)
ΔMRISlope	0.69^{***}	0.29^{***}	0.07^{***}	0.00	0.00	0.00	0.03^{***}	0.17^{***}	0.45^{***}
	(0.04)	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.06)
ΔIR	-5.08	-1.89	0.26	0.00	0.00	0.00	-0.13	-5.54^{***}	-27.38^{***}
	(4.71)	(1.35)	(0.32)	(0.00)	(0.00)	(0.00)	(1.81)	(10.61)	(49.23)
ΔIR^2	-462.24^{***}	-87.27^{***}	-27.06^{***}	0.00	0.00	0.00	15.75^{***}	75.03^{***}	475.15^{***}
	(75.30)	(11.25)	(3.85)	(0.00)	(0.00)	(0.00)	(29.09)	(133.03)	(841.64)
ΔTerm	3.47	$2.25^{\cdot}$	0.16	0.00	0.00	0.00	0.93	30.40^{***}	138.99^{***}
	(3.95)	(1.33)	(0.29)	(0.00)	(0.00)	(0.00)	(1.61)	(8.85)	(37.00)
ΔCRSlope	0.12^{***}	0.03^{***}	0.02	0.00	0.00	0.00	0.01	0.09^{*}	0.16^{**}
	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.07)	(0.16)
					30Y-5Y				
ΔVolatility	-5.63^{***}	-2.42^{***}	-0.89^{***}	-0.12^{*}	0.00	0.00	1.31^{***}	3.90^{***}	10.23^{***}
	(0.35)	(0.24)	(0.14)	(0.05)	(0.00)	(0.00)	(0.12)	(0.25)	(0.66)
ΔMRISlope	1.18^{***}	0.58^{***}	0.22^{***}	0.05^{***}	0.00	0.00	0.13^{***}	0.40^{***}	1.06^{***}
	(0.06)	(0.03)	(0.02)	(0.01)	(0.00)	(0.00)	(0.01)	(0.04)	(0.12)
ΔIR	-31.94^{***}	-6.67^{*}	-0.67	0.22	0.00	0.00	-0.62	-14.07^{***}	-56.74^{***}
	(7.75)	(3.01)	(1.18)	(0.41)	(0.00)	(0.00)	(0.64)	(2.38)	(10.93)
ΔIR^2	-890.17^{***}	-233.00^{***}	-108.30^{***}	-25.81^{***}	0.00	0.00	65.69^{***}	251.93^{***}	1256.56^{***}
	(90.30)	(23.02)	(9.85)	(34.84)	(0.00)	(0.00)	(82.89)	(293.63)	(1555.57)
ΔTerm	21.94^{**}	6.23^{*}	$1.93^{\cdot}$	0.23	0.00	0.00	0.72	8.35^{***}	30.37^{***}
	(7.79)	(2.95)	(1.15)	(0.38)	(0.00)	(0.00)	(5.53)	(19.45)	(81.97)
ΔCRSlope	0.25^{***}	0.11^{***}	0.04^{***}	0.01^{**}	0.00	0.00	0.03	0.31^{*}	1.27^{**}
	(0.03)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.14)	(0.47)

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

Table 6.10.: This table reports the coefficient estimates of the term structure panel quantile regression model for 5Y-1Y and 30Y-5Y CDS spread slope changes in North America. The sample comprises of data for 275 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 1e02.

6.3. Additional analyses and robustness checks

In this section, we conduct additional analyses and perform a number of robustness checks to substantiate and confirm our baseline findings. First, we present ordinary least squares (OLS) regression results for selected models to illustrate the superiority of the QR methodology. Second, we examine whether the varying degree of liquidity of CDS contracts poses an issue for our analysis. Third, we investigate the dominance of certain sectors within the CR construction which may potentially bias our empirical results. Last, we consider alternative specifications for the construction of our CR factor.

6.3.1. QR versus OLS

In our empirical approach, we use QR to investigate the impact of carbon risk on CDS spread returns. This methodology has the straightforward advantage of providing more information of the effects on the entire conditional distribution. Additionally, it may also yield qualitatively different results regarding the central part (median) than a simple conditional mean regression model would do. For example, previous literature finds ambiguous results on the effect of equity volatility on 5-years CDS spreads. While some find positive effects (Das et al., 2009; Ericsson et al., 2009), others find no or negative effects (Collin-Dufresne et al., 2001; Pereira et al., 2018). In a QR setting, Koutmos (2019) finds no evidence for a relationship between equity volatility and CDS spread changes for the median regression. This is in line with our findings (see Tables 6.1 and 6.2). To investigate whether this phenomenon is present for our CR factor as well, we run the baseline model from Subsection 6.2.1 using OLS. We thus estimate the following model:

$$s_{i,t}^{m} = \alpha_i + \beta_1 r_{i,t} + \beta_2 \Delta\sigma_{i,t} + \beta_3 \Delta \mathrm{MRI}_{i,t} + \beta_4 \Delta \mathrm{CR}_t + \varepsilon_{i,t}.$$

Table 6.11 shows the OLS results of the baseline model for all tenors in Europe and North America. Compared to the median regression results (Column 5 in Tables 6.1 and 6.2), we see significantly smaller estimates for the European sample and slightly larger estimates for the North American sample. However, direction-wise, we still observe positive effects which confirms the initial hypothesis for both regions.

So far, the OLS results for the baseline model indicate different effects in the center of the conditional CDS spread return distribution. However, qualitatively, we still observe the same relationship between the CR and CDS spread returns as posited in Hypothesis 1. That is, although we observe different magnitudes of the effect, we can still confirm the hypothesis. However, things can become even worse. We could for example unravel an effect when, in fact, there is really no indication from the QR. To illustrate this issue, we estimate the term structure model from Subsection 6.2.5 for the North American sample using OLS. Consequently, we estimate the following term structure model:

$$\begin{aligned}\Delta \mathrm{CDSSlope}_{i,t}^{mn} = {}& \alpha_i + \beta_1 \Delta\sigma_{i,t} + \beta_2 \Delta \mathrm{MRISlope}_{i,t}^{mn} + \beta_3 \Delta \mathrm{IR}_t + \beta_4 \Delta \mathrm{IR}_t^2 \\ & + \beta_5 \Delta \mathrm{Term}_t + \beta_6 \Delta \mathrm{CRSlope}_t^{mn} + \varepsilon_{i,t}.\end{aligned}$$

	Europe				
	1 Y	3 Y	5 Y	10 Y	30 Y
StockReturn	-4.44^{***}	-3.47^{***}	-2.26^{***}	-1.76^{***}	-1.43^{***}
	(0.27)	(0.19)	(0.13)	(0.11)	(0.11)
ΔVolatility	4.42^{***}	3.26^{***}	2.45^{***}	1.68^{***}	1.23^{***}
	(0.92)	(0.56)	(0.43)	(0.33)	(0.32)
ΔMRI	17.15^{***}	6.04^{***}	2.71^{***}	1.79^{***}	2.69^{***}
	(1.41)	(0.55)	(0.26)	(0.18)	(0.25)
ΔCR	5.64^{***}	3.44^{***}	2.85^{***}	1.35^{***}	1.05^{***}
	(0.59)	(0.24)	(0.16)	(0.09)	(0.10)
	North America				
	1 Y	3 Y	5 Y	10 Y	30 Y
StockReturn	-3.14^{***}	-2.37^{***}	-2.09^{***}	-1.49^{***}	-1.36^{***}
	(0.22)	(0.16)	(0.13)	(0.10)	(0.10)
ΔVolatility	2.94^{***}	2.06^{***}	2.20^{***}	1.70^{***}	1.64^{***}
	(0.68)	(0.36)	(0.33)	(0.28)	(0.28)
ΔMRI	11.68^{***}	3.65^{***}	1.72^{***}	1.10^{***}	1.04^{***}
	(0.68)	(0.21)	(0.11)	(0.07)	(0.07)
ΔCR	2.90^{***}	0.54^{***}	0.31^{***}	0.24^{***}	0.17^{***}
	(0.30)	(0.06)	(0.04)	(0.04)	(0.05)

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

Table 6.11.: This table presents estimates of the base OLS regression model for CDS spread returns (all tenors) in Europe (top) and North America (bottom). The sample comprises of data from 136 European firms resp. 275 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 clusetered on the firm level (in brackets). All estimates are scaled by factor 1e03.

Table 6.12 displays the estimates of the term structure OLS regression model for all slopes under consideration. Recall that, for the QR regression, we virtually did not observe any effect of the CR slope on the CDS curve (Table 6.10) indicating no relevance of the term structure of carbon risk in North America. In contrast to the results obtained from the QR regression, we now see significant positive coefficients for all but the 3Y-1Y slope model. That is, the use of OLS now hints towards a relevant relationship between the CR slope and the CDS curve, although the QR results clearly rejects this. Therefore, this example illustrates the problems that can arise by using OLS regression.

6.3.2. Liquidity of CDS spreads

In the baseline analysis, we exclude CDS contracts from our sample when “no spread movement for 245 days” is detected. We acknowledge this restriction is rather lax. Yet, it ensures a sufficient number of contracts in our sample – 136 European firms and 275 North American firms. We now examine the effect of a significantly more stringent

	3Y-1Y	5Y-1Y	10Y-5Y	30Y-5Y
ΔVolatility	2.06	24.11^{***}	13.87^{*}	19.44^{*}
	(5.39)	(7.31)	(5.44)	(7.94)
ΔMRISlope	10.66^{***}	16.69^{***}	4.26^{***}	6.25^{***}
	(1.26)	(1.40)	(0.84)	(1.04)
ΔIR	-320.88^{***}	-690.46^{***}	-74.47^{*}	$-98.20^{\cdot}$
	(38.97)	(67.68)	(30.80)	(51.89)
ΔIR^2	709.90^{***}	1377.54^{***}	-185.36	-23.05
	(176.18)	(267.65)	(179.28)	(277.01)
ΔTerm	162.92^{***}	383.09^{***}	80.95^{*}	$94.46^{\cdot}$
	(38.49)	(58.66)	(35.86)	(55.24)
ΔCRSlope	0.02	1.81^{***}	1.84^{***}	1.68^{*}
	(0.67)	(0.55)	(0.47)	(0.80)

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

Table 6.12.: This table presents estimates of the term structure OLS regression model for CDS spread slope changes (all tenors). The sample comprises of data from 275 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 clustered on the firm level (in brackets). All estimates are scaled by factor 1e02.

condition: "no spread movement for 25 days".[7] After applying this more stringent condition, the number of firms in our sample decreases to 166 in North America and 120 in Europe. Especially in North America this more stringent filtering has a significant impact on the sample size (42% decrease) which indicates that liquidity seems to be particularly problematic for this region.

To examine whether liquidity causes problems in our empirical approach, we reconstruct our CR factor using the smaller sample and rerun the baseline regression from Subsection 6.2.1. Table 6.13 shows the ΔCR estimates for all tenors in both Europe and North America. In both regions, we observe an increase in the magnitude of the estimates due to the removal of less traded CDS contracts. In North America, the relative increase is larger which seems plausible given the larger relevance of illiquidity in the original sample. In total, we observe that the main findings remain unchanged with respect to the baseline findings reported in Section 6.2.1.

6.3.3. Sector concentration

The list of CR constituents (Table 5.1) reveals the dominance of emission-intense sectors like BM, Energy and Utilities in the polluting class. Although this composition is plausibly explained by the high emission intensities of these sectors, it raises the question whether the results are solely driven by stereotypical high emitters. Additionally, each sector-wide CDS spread level is heavily influenced by external factors (e.g. commodity

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

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

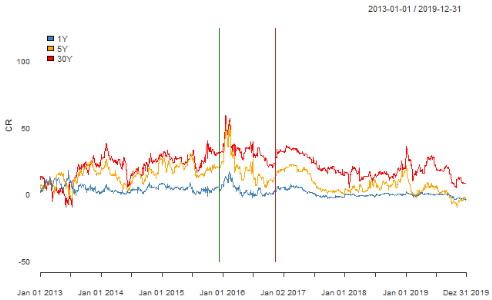
*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; · $p < 0.1$

Table 6.13.: This table reports the ΔCR coefficient estimates of the base panel quantile regression model for CDS spread returns of all tenors in both regions. The sample now includes data for 166 European and 120 North American firms, respectively, from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

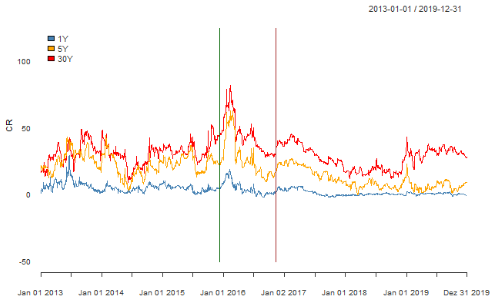
price shocks) which possibly causes problems to attribute changes in the CR to a changing market perception of carbon risk. To investigate this issue, we rerun the base model for the 5-year CDS spread returns without the aforementioned sectors. In particular, we exclude all sectors individually and jointly from our sample, build a new CR and conduct the same analysis from Subsection 6.2.1.

Figure 6.4 depicts the evolution of the CR for the tenors 1Y, 5Y and 30Y in Europe without the sectors individually as well as jointly. The features observed for the original CR (Figure 5.2) such as the non-negativity or the clear reaction to the Paris agreement mostly remain observable for the new CRs as well. Depending on the excluded sectors, however, the level of the CR significantly changes. But overall, the exclusion of certain industries does not alter the CR qualitatively.

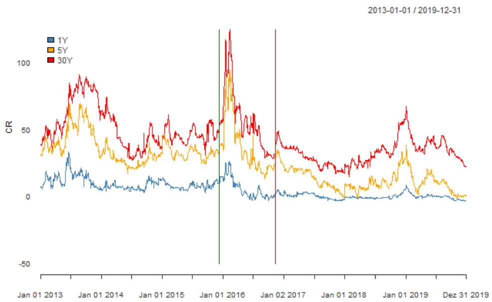
The analysis so far has been based on non-quantified visual analysis. To rigorously investigate whether the effects of carbon risks persist, we rerun the baseline model with the newly adjusted CRs. Table 6.14 displays the corresponding results for 5-years CDS



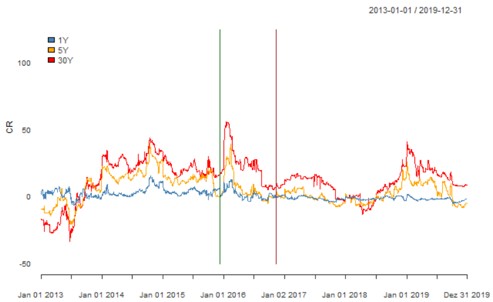
(a) Without BM



(b) Without Energy



(c) Without Utilities



(d) Without BM, Energy and Utilities

Figure 6.4.: Evolution of the CR over time for maturities 1Y (blue), 5Y (orange) and 30Y (red) for Europe without the sectors BM (top left), Energy (top right), Utilities (bottom left) and all of them jointly (bottom right). The vertical solid lines refer to the Paris Agreement (dark green) and Trump election (brown), respectively.

spreads in the European sample. In terms of the general direction and significance of the CR, no qualitative changes can be observed. Excluding utility firms slightly increases the CR estimates for most deciles, while their size decreases when the remaining two sectors or all three sectors together are excluded.

We now turn to the North American case. Figure 6.5 depicts the evolution of the adjusted CR for the tenors 1Y, 5Y and 30Y in North America. Contrary to the European case, the exclusion of certain industries now matters for the general behavior of the CR, especially around the Paris Agreement. While the exclusion of BM and Utilities still causes a significant spike around COP21, the effect completely disappears when removing the Energy sector or all three emission-intense sectors jointly. In fact, with these exclusions the CRs look entirely flat with no significant movements or visible pattern.

Again, we empirically investigate the robustness of the findings by rerunning the baseline model with the new CRs. Table 6.15 shows the results for 5-years CDS spreads in the North American sample. Similar to the European results, we observe consistent estimates which become larger for the exclusion of Utilities and slightly smaller for the exclusion of the BM sector. Surprisingly, the CR estimates without the Energy sector remain positive and significant as well – despite showing weak movements in Figure

	1	2	3	4	5	6	7	8	9
Without BM									
StockReturn	-135.79^{***}	-117.56^{***}	-96.39^{***}	-63.95^{***}	-37.95^{***}	-53.90^{***}	-91.07^{***}	-126.61^{***}	-163.94^{***}
	(4.94)	(3.79)	(3.27)	(2.53)	(1.75)	(2.14)	(3.07)	(5.29)	(8.64)
ΔVolatility	-273.17^{***}	-205.25^{***}	-139.27^{***}	-64.03^{***}	7.37	113.34^{***}	242.24^{***}	379.69^{***}	544.44^{***}
	(16.51)	(20.29)	(21.23)	(11.54)	(7.34)	(12.60)	(13.45)	(4.66)	(9.88)
ΔMRI	343.59^{***}	374.46^{***}	371.25^{***}	361.62^{***}	352.83^{***}	348.79^{***}	371.61^{***}	394.86^{***}	410.26^{***}
	(8.69)	(9.54)	(9.77)	(10.16)	(10.39)	(10.56)	(11.18)	(12.42)	(22.07)
ΔCR	175.21^{***}	159.91^{***}	130.77^{***}	102.08^{***}	77.50^{***}	88.99^{***}	115.52^{***}	146.23^{***}	166.51^{***}
	(6.76)	(6.30)	(5.39)	(4.95)	(4.55)	(4.74)	(5.36)	(7.11)	(10.72)
Without Energy									
StockReturn	-145.14^{***}	-122.99^{***}	-97.99^{***}	-64.34^{***}	-36.99^{***}	-52.94^{***}	-91.19^{***}	-131.93^{***}	-174.54^{***}
	(5.49)	(3.80)	(3.09)	(2.38)	(1.63)	(1.90)	(2.77)	(5.02)	(7.77)
ΔVolatility	-289.67^{***}	-205.60^{***}	-134.32^{***}	-72.22^{***}	5.46	120.72^{***}	262.36^{***}	404.76^{***}	579.40^{***}
	(23.99)	(25.09)	(19.20)	(12.36)	(6.00)	(10.74)	(10.54)	(3.76)	(13.21)
ΔMRI	313.78^{***}	330.85^{***}	332.43^{***}	326.60^{***}	324.23^{***}	325.37^{***}	338.58^{***}	356.98^{***}	367.18^{***}
	(7.59)	(6.76)	(8.06)	(8.10)	(8.12)	(7.56)	(9.32)	(10.18)	(12.38)
ΔCR	120.63^{***}	103.44^{***}	83.11^{***}	61.69^{***}	45.09^{***}	54.12^{***}	83.16^{***}	113.45^{***}	144.68^{***}
	(4.00)	(5.28)	(4.19)	(4.05)	(3.40)	(3.66)	(4.44)	(5.50)	(9.28)
Without Utilities									
StockReturn	-147.88^{***}	-127.33^{***}	-104.36^{***}	-70.70^{***}	-45.25^{***}	-57.75^{***}	-93.91^{***}	-134.02^{***}	-174.64^{***}
	(5.28)	(3.80)	(3.13)	(2.53)	(1.90)	(2.06)	(2.85)	(4.66)	(8.58)
ΔVolatility	-296.35^{***}	-224.27^{***}	-142.82^{***}	-67.85^{***}	11.19	132.53^{***}	278.36^{***}	409.30^{***}	561.77^{***}
	(12.61)	(27.19)	(19.76)	(14.02)	(7.48)	(12.44)	(12.65)	(8.86)	(14.45)
ΔMRI	278.67^{***}	304.25^{***}	309.84^{***}	307.82^{***}	305.22^{***}	303.23^{***}	312.63^{***}	323.66^{***}	328.41^{***}
	(10.10)	(6.75)	(6.71)	(7.37)	(7.58)	(8.09)	(7.25)	(8.53)	(14.12)
ΔCR	155.26^{***}	138.51^{***}	125.60^{***}	111.33^{***}	99.69^{***}	110.44^{***}	135.75^{***}	165.74^{***}	198.42^{***}
	(4.60)	(4.86)	(4.42)	(4.98)	(4.53)	(4.73)	(4.44)	(6.17)	(8.71)
Without BM, Energy and Utilities									
StockReturn	-124.32^{***}	-110.03^{***}	-90.13^{***}	-58.30^{***}	-31.80^{***}	-46.95^{***}	-82.87^{***}	-123.80^{***}	-157.97^{***}
	(5.97)	(4.39)	(3.51)	(2.65)	(1.72)	(2.09)	(3.31)	(5.67)	(11.60)
ΔVolatility	-245.19^{***}	-165.39^{***}	-120.15^{***}	-50.01^{***}	10.25	124.09^{***}	246.17^{***}	372.82^{***}	521.09^{***}
	(34.46)	(19.32)	(13.42)	(12.27)	(8.26)	(15.42)	(13.55)	(11.81)	(14.10)
ΔMRI	324.58^{***}	347.66^{***}	346.17^{***}	331.04^{***}	316.30^{***}	320.66^{***}	345.50^{***}	371.48^{***}	384.95^{***}
	(11.51)	(12.16)	(12.34)	(12.90)	(12.77)	(12.21)	(11.28)	(11.46)	(17.74)
ΔCR	103.65^{***}	80.03^{***}	63.74^{***}	48.88^{***}	34.83^{***}	44.18^{***}	70.73^{***}	96.42^{***}	132.00^{***}
	(3.18)	(3.73)	(4.63)	(4.50)	(3.96)	(4.51)	(5.41)	(7.70)	(8.81)

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

Table 6.14.: This table presents estimates of the base panel quantile regression model for 5-year CDS spread returns without the sectors BM (top), Energy (top center), Utilities (bottom center) and all of them jointly (bottom). The sample comprises of data from 115 (BM), 129 (Energy), 120 (Utilities) and 92 (all) European firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

6.5. Only removing all three sectors jointly causes the estimates to switch directions. In that case, the results are not robust and we cannot confirm Hypothesis 1.

(a) Without BM

(b) Without Energy

(c) Without Utilities

(d) Without BM, Energy and Utilities

Figure 6.5.: Evolution of the CR over time for maturities 1Y (blue), 5Y (orange) and 30Y (red) for North America without the sectors BM (top left), Energy (top right), Utilities (bottom left) and all of them jointly (bottom right). 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
					Without BM				
StockReturn	-38.09^{***}	-18.92^{***}	-10.71^{***}	-6.84^{***}	-3.65^{***}	-6.83^{***}	-12.07^{***}	-22.41^{***}	-45.53^{***}
	(2.14)	(1.01)	(0.58)	(0.42)	(0.22)	(0.36)	(0.73)	(1.79)	(4.21)
ΔVolatility	-154.95^{***}	-57.67^{***}	-18.54^{***}	-2.77^{**}	$0.72^{\cdot}$	25.67^{***}	59.35^{***}	133.32^{***}	297.03^{***}
	(10.97)	(5.16)	(2.85)	(0.86)	(0.37)	(2.10)	(3.83)	(9.81)	(12.75)
ΔMRI	44.09^{***}	33.30^{***}	20.10^{***}	14.18^{***}	7.94^{***}	12.88^{***}	20.90^{***}	41.18^{***}	74.01^{***}
	(3.69)	(2.30)	(1.77)	(1.33)	(0.71)	(1.09)	(1.73)	(3.66)	(4.61)
ΔCR	3.14^{***}	1.57^{***}	0.89^{***}	0.45^{***}	0.12^{**}	0.04	$0.17^{\cdot}$	$0.43^{\cdot}$	1.07^{*}
	(0.40)	(0.20)	(0.10)	(0.07)	(0.04)	(0.03)	(0.09)	(0.25)	(0.47)
					Without Energy				
StockReturn	-41.73^{***}	-22.55^{***}	-13.80^{***}	-9.39^{***}	-4.79^{***}	-9.17^{***}	-14.97^{***}	-24.84^{***}	-45.21^{***}
	(2.77)	(1.29)	(0.78)	(0.56)	(0.28)	(0.48)	(0.92)	(1.73)	(4.45)
ΔVolatility	-167.72^{***}	-67.11^{***}	-22.69^{***}	-5.72^{***}	$1.07^{\cdot}$	31.89^{***}	70.38^{***}	143.00^{***}	296.83^{***}
	(16.30)	(6.93)	(3.62)	(1.48)	(0.60)	(2.39)	(4.51)	(8.04)	(9.73)
ΔMRI	59.35^{***}	47.58^{***}	31.02^{***}	22.80^{***}	12.28^{***}	23.47^{***}	37.36^{***}	66.78^{***}	112.39^{***}
	(5.33)	(3.26)	(2.63)	(2.05)	(1.10)	(1.78)	(2.48)	(3.68)	(9.86)
ΔCR	2.18^{***}	1.98^{***}	1.20^{***}	0.70^{***}	0.26^{**}	0.83^{***}	1.65^{***}	3.32^{***}	6.61^{***}
	(0.51)	(0.28)	(0.19)	(0.13)	(0.08)	(0.14)	(0.24)	(0.50)	(1.39)
					Without Utilities				
StockReturn	-51.46^{***}	-26.99^{***}	-16.15^{***}	-11.30^{***}	-6.12^{***}	-10.77^{***}	-17.61^{***}	-29.43^{***}	-53.70^{***}
	(3.50)	(1.55)	(0.93)	(0.71)	(0.35)	(0.58)	(1.05)	(2.26)	(4.74)
ΔVolatility	-191.32^{***}	-78.25^{***}	-28.11^{***}	-7.00^{***}	0.90	37.71^{***}	83.11^{***}	162.70^{***}	339.16^{***}
	(14.50)	(7.35)	(4.43)	(1.85)	(0.79)	(2.78)	(4.20)	(8.81)	(11.70)
ΔMRI	60.89^{***}	47.64^{***}	31.08^{***}	23.22^{***}	13.26^{***}	23.48^{***}	37.05^{***}	62.98^{***}	110.29^{***}
	(6.05)	(3.26)	(2.64)	(2.24)	(1.23)	(1.90)	(2.51)	(4.17)	(8.08)
ΔCR	13.69^{***}	7.34^{***}	4.57^{***}	3.31^{***}	1.83^{***}	3.31^{***}	5.98^{***}	10.53^{***}	22.03^{***}
	(1.12)	(0.51)	(0.30)	(0.25)	(0.15)	(0.23)	(0.43)	(0.95)	(2.24)
					Without BM, Energy and Utilities				
StockReturn	-37.42^{***}	-19.44^{***}	-11.75^{***}	-8.17^{***}	-4.49^{***}	-8.06^{***}	-12.72^{***}	-21.97^{***}	-41.09^{***}
	(2.66)	(1.15)	(0.69)	(0.52)	(0.29)	(0.49)	(0.85)	(2.02)	(5.35)
ΔVolatility	-150.15^{***}	-56.30^{***}	-18.71^{***}	-3.60^{*}	0.97	28.26^{***}	59.37^{***}	125.86^{***}	272.75^{***}
	(19.95)	(5.39)	(3.58)	(1.59)	(0.61)	(2.74)	(4.36)	(9.49)	(19.09)
ΔMRI	40.55^{***}	30.16^{***}	17.32^{***}	12.99^{***}	7.26^{***}	11.94^{***}	19.05^{***}	35.48^{***}	59.00^{***}
	(4.93)	(2.46)	(1.72)	(1.40)	(0.83)	(1.26)	(1.85)	(4.22)	(9.48)
ΔCR	-2.79^{***}	-1.60^{***}	-0.93^{***}	-0.57^{***}	-0.29^{**}	-0.18	0.06	$0.67^{\cdot}$	1.01
	(0.46)	(0.32)	(0.19)	(0.14)	(0.09)	(0.12)	(0.20)	(0.41)	(0.96)

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

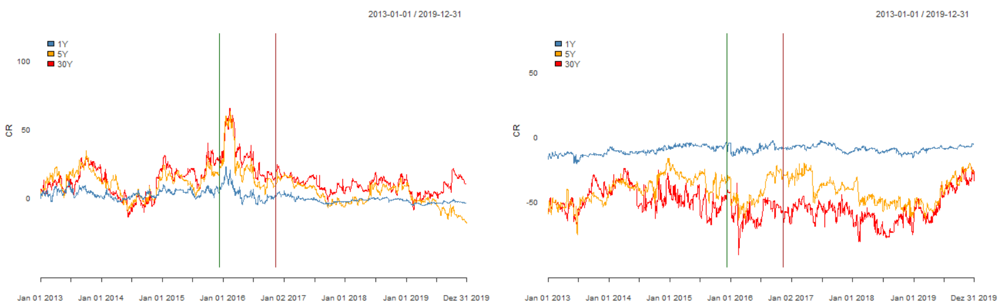
Table 6.15.: This table presents estimates of the base panel quantile regression model for 5-year CDS spread returns without the sectors BM (top), Energy (top center), Utilities (bottom center) and all of them jointly (bottom). The sample comprises of data from 245 (BM), 250 (Energy), 253 (Utilities) and 200 (all) North American firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

6.3.4. Alternative specifications for factor construction

The baseline CR factor is constructed by a univariate sorting of firms with respect to their emission profiles. That is, our CDS universe is sorted by emission intensity from low to high. The use of firms' emission intensity allows for a straightforward interpretation of the CR factor. Such a construction, however, might have shortcomings. Alternative emission classifications may be more suitable (absolute emissions vs. emission intensity). Also, univariate sorting might have its own limitations. Double sorting helps control for the possibility that other firm-specific characteristics (size, leverage, etc.) may consistently coincide with the firm's emission profile. To investigate whether the identification of carbon risk exposure via firms' emission profiles is possibly misspecified, we examine alternative specifications for the construction of the CR factor and rerun our base model.

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. The rationale is that the total amount of emissions is the only relevant metric for a net-zero transition to be successful. We now also investigate this topic by dividing firms into groups based on their absolute level of emissions within our CR construction and rerunning the baseline regression.



(a) Europe **(b)** North America

Figure 6.6.: Evolution of the CR (based on total absolute emissions) over time for maturities 1Y (blue), 5Y (orange) and 30Y (red) for Europe (left) and North America (right). The vertical solid lines refer to the Paris Agreement (dark green) and Trump election (brown), respectively.

Figure 6.6 displays the evolution of the CR over time for the three tenors 1Y, 5Y and 30Y in Europe (left) and North America (right). While in Europe the CRs mostly maintain their features and only the levels decrease slightly compared to the original CR, the North American CRs move entirely on a negative range. That is, using absolute emissions instead of intensities paints a whole different picture in terms of carbon risk perception in North America. Polluting firms with a high amount of emissions are considered less risky to default than clean firms who emit significantly less.

	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)

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

Table 6.16.: 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 136 European resp. 275 North American firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

Table 6.16 reports the results of the baseline model for the CR sorted by absolute emissions in both Europe and North America. The results for Europe do not indicate relevant qualitative differences to the original results. All effects stay highly significant and, except the long-term of 30 years, also exhibit an increase in the size of the estimates. In North America, however, the estimates either become insignificant or the sign reverses to negative values. That is, again, we observe that the results for North America are not robust and the selected emission metric within the CR construction seems to matter.

Possible confounding variables

We begin by noting the strong relationship documented in the literature between firms' emissions and some key firm characteristics. High absolute emissions are related to (log)size, high book-to-market ratios, and highly leveraged firms. Conversely, emission intensities are weakly negatively related to size (Bolton and Kacperczyk, 2021; Huij et al., 2021). Thus, sorting firms solely by emission intensities 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 divide the CDS sample into two groups $\mathcal{X}_t^m$ and $\mathcal{Y}_t^m$ based on the median of the (one-year lagged) candidate variable (size, book-to-market ratio, leverage, etc.). Then, we divide firms within each group into five additional groups based on the quintiles of the one-year lagged emission intensities. Firms below the first quintile are the clean subgroup ($\mathcal{XC}_t^m$ or $\mathcal{YC}_t^m$), whereas firms above the fifth quintile are the polluting subgroup ($\mathcal{XP}_t^m$ or $\mathcal{YP}_t^m$). Then, we compute the median CDS spread in each subgroup resulting in four different medians (XP_t^m, XC_t^m, YP_t^m, YC_t^m) in total. Finally, we compute the conditional, double-sort CR as follows

$$\mathrm{CR}_t^m = \frac{1}{2}\left(\mathrm{XP}_t^m + \mathrm{YP}_t^m\right) - \frac{1}{2}\left(\mathrm{XC}_t^m + \mathrm{YC}_t^m\right), \tag{6.1}$$

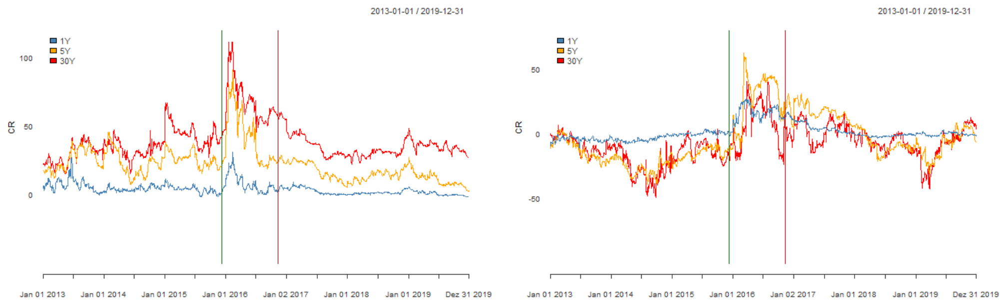
and replace the original CR with the new CR in the base model from Section 6.2.1 to check the robustness of our baseline CR.

First, we consider firms' market capitalization – the size variable. We divide the CDS sample into two groups based on the median market capitalization (lagged by one year) to distinguish between small (S) and big firms (B). Dividing by emission intensities afterwards, and computing the median CDS spread, leaves us with four medians for each subgroup: small and polluting SP_t^m, small and clean SC_t^m, big and polluting BP_t^m, and big and clean BC_t^m. We can then straightforwardly obtain the size-adjusted CR by using Equation (6.1) and replace X with small (S) and Y with big (B)

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

Figure 6.7 depicts the evolution of the double-sorted CR over time for the three tenors 1Y, 5Y and 30Y in Europe and North America. Similarly to the case of absolute emissions, we observe no significant changes in the movement of the European CRs while the North American CRs display an erratic evolution with a mild reaction around COP21. Table 6.17 reports the new estimates and shows that using the size-adjusted CR leaves results virtually unchanged with respect to the baseline model for the European sample. For North America, however, the results are not robust as most estimates become insignificant or switch signs.

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). Pástor et al. (2022) documented that polluting firms tend to be disproportionately more represented by value firms, whereas clean firms tend to be disproportionately more represented by growth



(a) Europe **(b)** North America

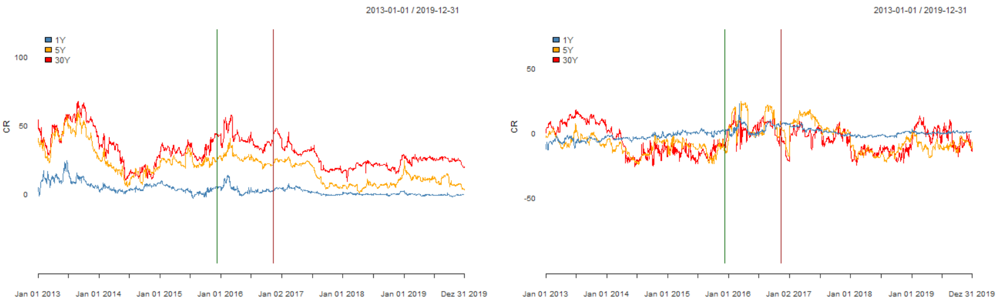
Figure 6.7.: Evolution of the CR (double-sorted on size) over time for maturities 1Y (blue), 5Y (orange) and 30Y (red) for Europe (left) and North America (right). The vertical solid lines refer to the Paris Agreement (dark green) and Trump election (brown), respectively.

	1	2	3	4	5	6	7	8	9
					Europe				
					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·	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·	−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)

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

Table 6.17.: 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 136 (275) European (North American) firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

firms. Similarly 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 (6.1).



(a) Europe **(b)** North America

Figure 6.8.: Evolution of the CR (double-sorted on book-to-market ratio) over time for maturities 1Y (blue), 5Y (orange) and 30Y (red) for Europe (left) and North America (right). The vertical solid lines refer to the Paris Agreement (dark green) and Trump election (brown), respectively.

In Figure 6.8, we plot the evolution of the B/M-adjusted CR for both Europe and North America. Contrary to the previous graphs, the CRs in Europe now slightly change in that the reaction around COP21 is less pronounced. In North America, the CRs now exhibit a completely flat pattern that fluctuates randomly around zero. Table 6.18 reports the estimates with the B/M-adjusted CR. Despite the change in the CR, the results for Europe are still in line with Hypothesis 1. The results for North America, again, hint towards non-robustness as most estimates change signs.

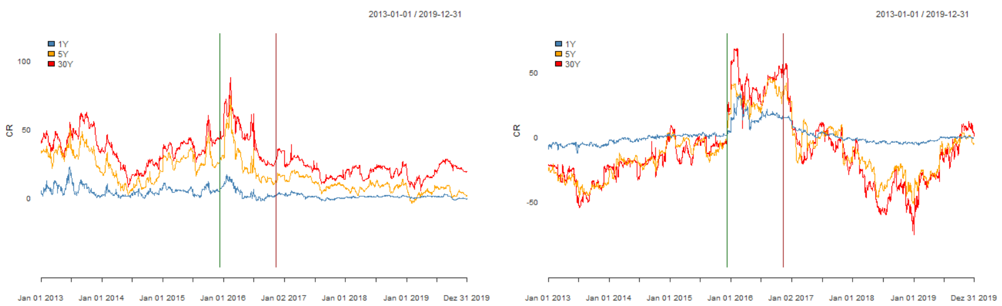
Third, we consider the leverage ratio, defined as the book value of debt divided by the book value of assets, for the first sorting. Polluting firms tend to have disproportionately more tangible assets compared to clean firms (Iovino et al., 2021), hence we control for the possibility that higher leverage 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 (6.1).

Figure 6.9 displays the evolution of the leverage-adjusted CR in Europe (left) and North America (right). The CRs in Europe display a qualitatively similar behavior to the original CRs. For North America, the evolution looks similar to the size-adjusted CRs, as we also observe some reaction towards the time period of COP21. Table 6.19 displays the results of the base model using the leverage-adjusted CR for Europe and North America, respectively. Again, using the leverage-adjusted CR, results remain unchanged with respect to the baseline model in Europe while in North America estimates turn to negative values and are not robust.

	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 6.18.: 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 136 (275) European (North American) firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.



(a) Europe **(b)** North America

Figure 6.9.: Evolution of the CR (double-sorted on leverage) over time for maturities 1Y (blue), 5Y (orange) and 30Y (red) for Europe (left) and North America (right). The vertical solid lines refer to the Paris Agreement (dark green) and Trump election (brown), respectively.

	1	2	3	4	5	6	7	8	9
					Europe				
					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 6.19.: 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 136 (275) European (North American) firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

7. Conclusions and outlook

Climate change significantly shaped the globe for the past two centuries and the economic consequences associated with this development already unraveled and will continue to do so. Hence, it is important to comprehensively apprehend the financial consequences that follow, particularly for vulnerable and exposed corporations. In this thesis, we make several contributions to the understanding of the interplay between climate risk and firm-specific credit risk – both theoretically and empirically.

First, we build a theoretical credit model that incorporates climate risk by adjusting the firm value process through a random growth component. The model produces higher default probabilities and credit spreads for more exposed firms. Additionally, we provide an overview of further structural credit models and their adaption for climate risks. The model by Bouchet and Guenedal (2020) uses the seminal Merton model as a starting point and integrates adjustments in the firm value process through carbon price shocks. Building upon this, another model with jump risks by Kölbel et al. (2022) to account for the possibility of sudden adjustments is introduced. Last, using the more elaborated model of Leland and Toft (1996), Le Guenedal and Tankov (2022) take a Bayesian point of view to integrate scenario uncertainty.

Second, we propose a method for constructing a forward-looking metric of carbon risk exposure. In particular, we utilize the information contained in CDS spreads to construct the CR factor – a market-based measure of carbon risk. The constructed CRs aptly react to policy-relevant events such as COP21 and, at least for Europe, are robust to different alternative specifications. We also adopt different variants of the CR, that measure the exposure to carbon risk within sectors, countries and across the term structure. Finally, we also introduce a generalization of the CR, the CTR, which is able to capture the entire distribution of carbon risk, in particular the parts in the tail ends.

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

Overall, our results add to the growing evidence on the effect of carbon risk on CDS spreads and provide some quantitative assessment of its economic impact. Our findings also have important policy implications. They suggest that an improvement in the quality and comparability of current carbon emissions disclosures and emissions reduction strategies would facilitate better assessment of firm-level carbon and credit risk. Additionally, our results highlight the importance of large-scale carbon pricing mechanisms as financial markets seem to better incorporate the risks associated to carbon when an observable and explicit price tag for emissions exists. As such, our findings are relevant for the regulatory framework. In particular, they highlight the relevance of a periodic and transparent disclosure practice in the market as well as the need for explicit carbon pricing mechanisms to better reflect firm-level carbon and transition risk.

Nonetheless, our research still leaves open questions for future research. The incorporation of climate aspects in structural credit models is still an ongoing field of research. Most of the approaches presented here impose a simplified Merton-type model structure with default only possible at maturity. As such, those models are mainly useful to gain qualitative insights on the effect of climate risks on credit, but should not be used in practical pricing applications. An exception to this represents the model by Le Guenedal and Tankov (2022) which assumes the more realistic setup of Leland and Toft (1996) and integrates scenario uncertainty inherent to any climate analysis. Still, more research is needed to address some shortcomings that remain unsolved. For instance, even the model by Le Guenedal and Tankov (2022) seems not perfectly suitable for the physical risk channel as the assumption of equal jump size distributions in each scenario is too strict. Also, none of the approaches presented here attempts to address both types of climate risk and couple them in one credit model.

Also, for the CR factor, there are several directions in which our research can be extended. Note that the CR we propose can be constructed for any subsample provided the sample size is sufficiently large. However, we cannot construct a firm-specific CR within our approach. Future research may build on that, e.g. by combining the CR with the approaches of Faccini et al. (2021) or Huij et al. (2021). Furthermore, risk factors that capture more than just carbon risk could be of interest. By choosing appropriate variables to divide firms into distinctive groups, a factor for transition risk or the multiple facets of physical risk could be built. In this case, a procedure to decompose the more aggregated risk factors into multiple single risk factors would be useful as well.

With regards to the empirical analysis, we sketch additional ideas for future research. First, we emphasize that we focused on the median CR factor when examining the impact on CDS spreads. However, we omitted the CTR factor which could provide more information on the effect of very adverse carbon events. Additionally, it would be interesting to investigate the impact of the CR in different markets, e.g. the equity market. Although factors derived from the equity space can be forward-looking as well, they lack the ability of exactly pinpointing the risk with respect to a certain time horizon. For that case, our CR has a competitive edge and could provide further insights on the persistence of a carbon risk premium in the equity market.

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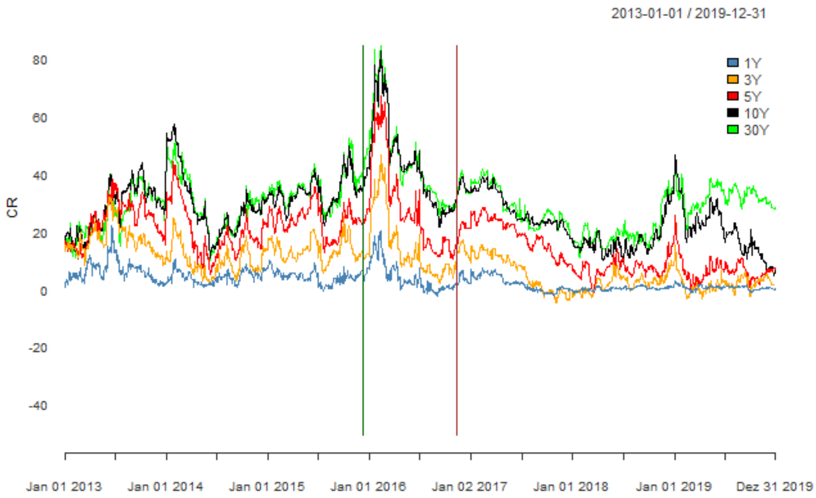
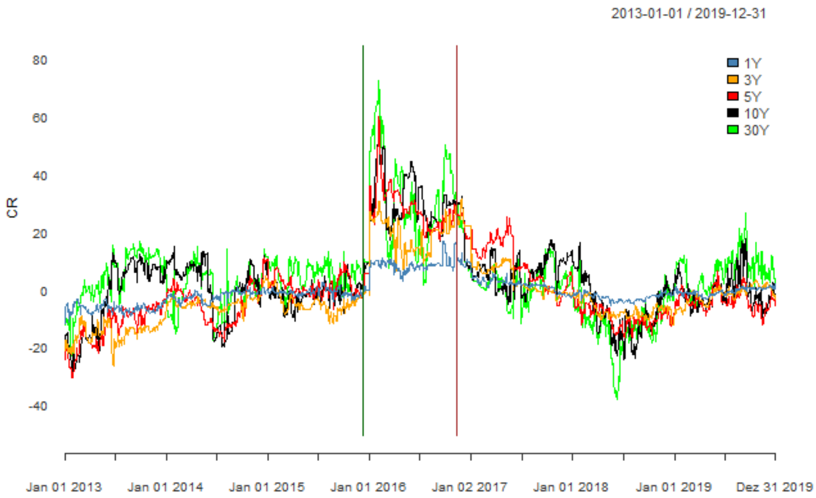
A. Appendix

A.1. Additional figures

This section provides supplementary material in the form of additional figures. Figure A.1 depicts the evolution of the CR for all tenors (1Y, 3Y, 5Y, 10Y, 30Y) in Europe (top) and North America (bottom). Figure A.2 depicts the evolution of the CTR for all tenors (1Y, 3Y, 5Y, 10Y, 30Y) in Europe (top) and North America (bottom).

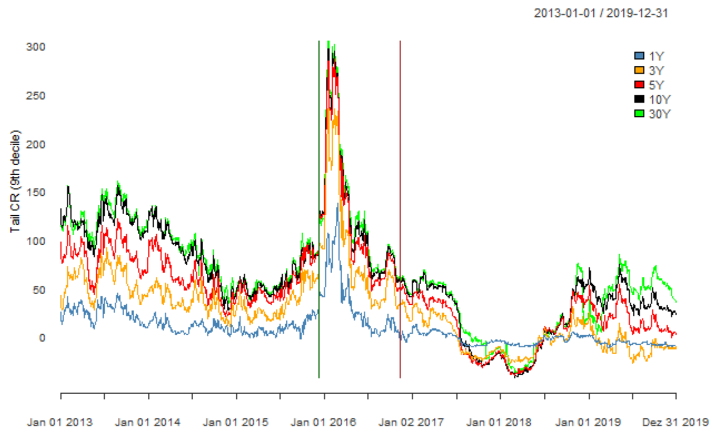


(a) Europe

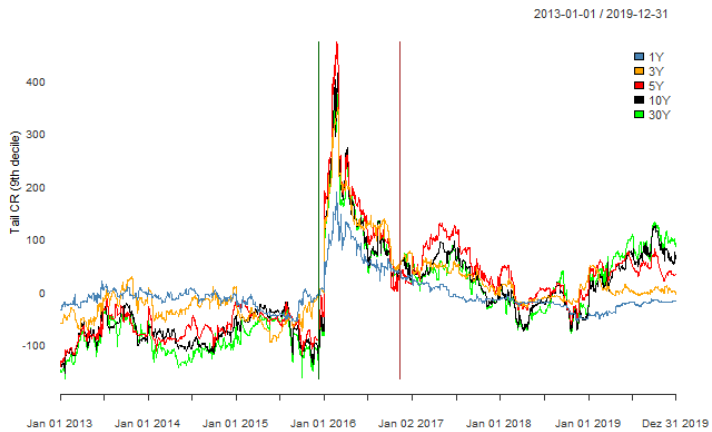


(b) North America

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



(a) Europe



(b) North America

Figure A.2.: Evolution of the tail CR (9th decile) 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.2. Additional tables

This section provides supplementary material in the form of additional tables. Table A.1 and Table A.2 report the coefficient estimates of the interaction terms of the sector model from Section 6.2.1 for the 1Y and 30Y tenors, respectively.

	1	2	3	4	5	6	7	8	9
					Europe				
BM × ΔCR	528.94***	365.15***	247.62***	202.90***	136.77***	154.93***	223.53***	318.46***	497.52***
	(58.07)	(38.42)	(27.76)	(27.87)	(23.21)	(27.36)	(35.05)	(63.14)	(125.63)
CCGS × ΔCR	−226.41·	−132.15*	−77.46	−98.75*	−62.09·	−62.78	−70.05	−70.88	−123.99
	(126.98)	(67.13)	(51.01)	(42.99)	(35.87)	(40.69)	(58.81)	(86.63)	(181.31)
Energy × ΔCR	987.47***	839.52***	776.47***	580.93***	547.64***	574.49***	635.36***	783.19***	921.54***
	(102.03)	(70.01)	(76.20)	(94.23)	(84.83)	(102.29)	(75.73)	(72.59)	(266.73)
Healthcare × ΔCR	−124.66*	−129.14·	−171.39***	−170.37***	−123.05***	−133.32***	−172.64***	−121.70	24.43
	(61.56)	(78.13)	(51.56)	(35.88)	(27.71)	(33.61)	(52.29)	(142.29)	(173.92)
Industrials × ΔCR	−230.98**	−174.43***	−131.81**	−132.90***	−77.00**	−80.60*	−83.40·	−84.90	−107.92
	(74.00)	(52.96)	(40.69)	(32.48)	(28.88)	(33.93)	(48.78)	(84.66)	(170.87)
NCGS × ΔCR	40.99	34.11	14.18	−45.25	−26.75	−16.26	33.34	121.34	157.84
	(131.01)	(62.57)	(48.17)	(38.74)	(33.49)	(37.22)	(48.38)	(90.58)	(148.50)
Real Estate × ΔCR	274.95*	106.30	24.01	11.33	14.28	34.77	64.96	185.23	303.74
	(117.50)	(145.35)	(102.34)	(94.71)	(95.55)	(114.95)	(100.22)	(149.55)	(253.25)
Technology × ΔCR	−217.61**	−81.18	−35.36	−47.05	−34.54	−24.82	−33.97	−92.62	−218.47
	(73.67)	(65.20)	(58.67)	(47.73)	(38.10)	(43.31)	(54.66)	(93.63)	(159.85)
Utilities × ΔCR	495.94***	374.85***	353.01***	240.77***	231.30***	248.95***	322.94***	428.22***	460.96*
	(64.91)	(77.71)	(73.71)	(68.29)	(54.18)	(59.44)	(73.80)	(112.78)	(208.96)
					North America				
BM × ΔCR	93.36·	16.84***	4.33*	0.44·	0.18·	1.31**	11.77***	50.45***	214.81***
	(48.17)	(4.94)	(1.68)	(0.24)	(0.11)	(0.49)	(2.46)	(11.83)	(55.23)
CCGS × ΔCR	−228.28***	−40.73***	−7.58***	−0.46	−0.14	−1.08·	−9.21**	−31.90*	−112.57·
	(52.62)	(6.77)	(2.17)	(0.32)	(0.15)	(0.60)	(2.95)	(13.40)	(65.41)
Energy × ΔCR	16.25	14.95	5.16*	0.27	−0.02	0.05	0.52	3.07	−23.24
	(51.98)	(9.10)	(2.46)	(0.32)	(0.13)	(0.58)	(3.28)	(14.09)	(64.49)
Healthcare × ΔCR	−241.07***	−26.50***	−4.50*	−0.43	−0.15	−1.12·	−10.39***	−30.12*	−90.44
	(54.87)	(5.99)	(1.93)	(0.35)	(0.18)	(0.59)	(2.87)	(13.44)	(71.06)
Industrials × ΔCR	−92.66·	−12.98*	−2.32	−0.21	−0.11	−0.80	−6.68*	−25.10*	−112.59·
	(48.92)	(5.59)	(1.83)	(0.26)	(0.11)	(0.51)	(2.65)	(12.58)	(62.86)
NCGS × ΔCR	−97.79*	−15.13**	−2.41	−0.27	−0.13	−0.80	−6.35*	−29.13*	−118.63·
	(48.91)	(5.47)	(1.83)	(0.27)	(0.12)	(0.53)	(2.85)	(12.81)	(65.40)
Real Estate × ΔCR	−82.23	−17.05**	−3.03·	−0.16	−0.11	−0.94·	−9.22**	−35.20**	−128.60*
	(50.12)	(5.46)	(1.84)	(0.27)	(0.12)	(0.52)	(2.86)	(13.44)	(58.36)
Technology × ΔCR	−112.40*	−20.14***	−4.29*	−0.33	−0.13	−0.75	−8.21***	−32.55**	−149.53*
	(48.46)	(5.25)	(1.75)	(0.25)	(0.11)	(0.50)	(2.48)	(11.93)	(59.78)
Utilities × ΔCR	−44.78	−1.85	−0.24	0.02	−0.07	−0.56	−5.46*	−24.95*	−105.61·
	(48.38)	(5.28)	(1.75)	(0.25)	(0.11)	(0.50)	(2.54)	(11.93)	(55.02)

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

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

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

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

Table A.2.: This table reports the coefficient estimates of the interaction terms of the sector panel quantile regression model for 30-year CDS spread returns in Europe (top) and North America (bottom). The sample comprises of data from 137 European firms resp. 281 North American firms from 2013/01/01 to 2019/12/31 in daily frequency. All variables in the model are in first-differences due to present nonstationarity. Estimates and standard errors (in brackets) are reported for all nine deciles. All estimates are scaled by factor 1e03.

Eidesstattliche Erklärung

Ich versichere an Eides statt durch meine Unterschrift, dass ich die vorstehende Arbeit selbständig und ohne fremde Hilfe angefertigt und alle Stellen, die ich wörtlich oder annähernd wörtlich aus Veröffentlichungen entnommen habe, als solche kenntlich gemacht habe, mich auch keiner anderen als der angegebenen Literatur oder sonstiger Hilfsmittel bedient habe. Die Arbeit hat in dieser oder ähnlicher Form noch keiner anderen Prüfungsbehörde vorgelegen.

Essen, 26.10.2023