Climate Default Swap – Disentangling the Exposure to Transition Risk Through CDS*

Alexander Blasberg[1] Rüdiger Kiesel[1] Luca Taschini[2,3,4]

[1] *University of Duisburg-Essen*

[2] Grantham Research Institute
[3] ESRC Centre for Climate Change Economics and Policy
London School of Economics

[4] *University of Edinburgh Business School*

Abstract

The substantial economic transformation required to mitigate and adapt to climate change will lower the value of certain businesses as well as some firms' assets in the not-too-distant future. Firms will need to transition to a less carbon-intensive business model, but may do so at different times and at different speeds, incurring different costs and risks in the process. We propose and implement a novel market-based measure of exposure to transition risk (transition risk factor) and examine how this risk affects firms' creditworthiness. We discipline the exercise by using Credit Default Swap (CDS) spreads to capture differential exposure to transition risk across economic sectors. We show that the transition risk factor is a relevant determinant of CDS spreads and provide evidence of the relationship between the differential exposure to transition risk and firms' cost of default protection. This effect is particularly pronounced during deteriorating credit market movements. However, effects vary substantially across industries, reflecting the fact that transition risk impacts firms' valuation differently depending on their sector. Our findings also suggest that investors seek greater protection against transition risks in the short– to medium-term, indicating an expectation of a swift transformation of the entire economic structure.

Keywords: Climate Change, Transition Risk, Credit Risk, CDS Spreads.

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

*The authors' email addresses are alexander.blasberg@uni-due.de, ruediger.kiesel@uni-due.de and l.taschini1@lse.ac.uk.

1 Introduction

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

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

In this statement, the chairman and CEO of BlackRock recognises the scope and speed of economic transformation required to mitigate and adapt to climate change. The necessary transformation of the economic structure requires policies to mitigate climate change via reduction of carbon dioxide emissions, considerable technological innovations and changes in consumer and corporate behaviour. These changes can generate sizable costs and have consequential financial impacts for unprepared sectors and companies. Some companies are already well-positioned, harnessing the opportunities presented by the low-carbon transition, and some are actively preparing by reducing their exposure to transition risks. Others, however, will see their businesses and valuations suffer as investors lose confidence in their ability to adapt to the dramatic changes that are coming. This could severely affect their ability to fulfill their financial obligations, ultimately affecting their creditworthiness. As such, it is essential to capture potential risk differentials between industries and firms that are more or less sensitive to the risks associated with the transition to a low-carbon economy.

The transition to a low-carbon economy will be effected through a combination of changes in public regulation, technology, and consumers' preferences, triggering changes in demand-related factors. The risks related to this transition arise from uncertainties regarding the nature of the low-carbon pathway – i.e. the speed and timing of reducing greenhouse gas emissions, which will necessarily restructure the economy.

While there has been a rapid expansion of concepts and evidence concerning transition risks from academia, private industry, and regulators (e.g. Bolton et al., 2020; NGFS, 2019), there is no comprehensive theoretical framework linking the low-carbon structural change to credit dynamics. It is not yet clear what the risk drivers, sectoral origins and transmission channels will be. Most of the current debate on transition-related financial risks focuses on brown industries. For instance, there is a widespread preoccupation with the financial repercussions of asset stranding: the unanticipated or premature write-downs, devaluations, or conversions to liabilities of assets (Caldecott, 2018; van der Ploeg and Rezai, 2020). However, climate change mitigation policy, changing preferences, and ongoing technological change (Syrquin, 2010) will cause some parts of the economy to grow and others to decline in relative importance. Some firms will be more exposed to transition risk, which may manifest themselves through increased default risk or lower asset values, others will be less exposed. At the same time, a number of the world's biggest companies have committed to decarbonising their businesses, either by setting emissions intensity targets or by setting time limits on reaching net-zero emissions. Although not legally binding, non-compliance with self-imposed commitments might become a reputational risk and therefore credit risk. Equally, unambitious emission-reduction strategies might become a transition risk and are therefore credit risk. This is where our analysis makes a contribution: measuring the extent to which firms are exposed to the low-carbon transition and how the market believes this exposure will develop in the future.

To examine whether firms' exposure to transition risk is reflected in their credit risk, we test whether lenders prefer to hold Credit Default Swaps (CDS) of businesses more exposed to transition risk. This is because the CDS is a credit derivative that provides protection against the risk of a credit default. The buyer of the protection makes periodic payments, often referred to as the spread, to the seller of the protection until the occurrence of a credit event or the maturity of the contract. In return, if a credit event occurs, the buyer of the protection receives compensation for the loss incurred by the credit event. We posit that, if lenders demand more of the CDS of more exposed firms, then they are are willing to pay higher spreads. An important data point for calculating risk exposure is the Expected Loss (EL) in case of a default. This is generally defined as the product of three variables: the exposure at default (EAD), the loss given default (LGD), and the probability of default (PD). Whereas historical data are available for EAD, this is not the case for PD and LGD. CDS spreads adequately represent the product PD $\times$ LGD (Jarrow, 2011).[1] As such, changes in lenders' exposures at default are driven by changes in CDS spreads.

The use of CDS offers a multitude of advantages over other commonly used credit risk measures such as corporate bonds (or ratings). First, trading in the CDS market is sufficiently active, whereas bonds have been shown to be inflated by a non-default component due to their illiquidity (Longstaff et al., 2005; Ederington et al., 2015). Second, CDS have been shown to be more reactive to new information arriving in the market than bonds or ratings (Blanco et al., 2005; Zhu, 2006; Norden and Weber, 2009). Third, CDS admit standardized contractual characteristics like prespecified maturity, default event and debt seniority, which make them comparable within the corporate universe. In contrast, corporate bonds may be embellished with additional idiosyncrasies such as embedded options or specific guarantees.

The determinants of CDS spreads have been comprehensively analyzed in the literature (Das et al., 2009; Ericsson et al., 2009; Zhang et al., 2009; Galil et al., 2014; Pereira et al., 2018). Most relevant drivers identified in these works include firm-specific variables like stock return and volatility, but also common variables like the underlying market condition. Despite the consensus on the choice of variables, their sign and magnitude remain unstable yielding ambiguous findings on the effects of these covariates. Other than analyzing the effects on CDS with a fixed maturity, the available grid of different maturities for each CDS additionally allows us to unfold the effects on the term structure of a firm's credit risk. Using the slope of the CDS between different maturities as a term structure measure Han and Zhou (2015) find different market variables (interest rate, slope of the risk-free yield curve, return of market index) as well as the firm-specific variable stock volatility to be among the most influential determinants.

[1] The CDS spread captures a few other risk premia, which in a first approximation can be omitted. We refer to Jarrow (2011) for a more rigorous discussion.

Literature establishing the link between climate change and credit risk is growing. Kleimeier and Viehs (2018) show a significant and negative relationship between CO2 emission levels and the cost of bank loans. Delis et al. (2018) observe that banks appeared to start pricing climate policy risk after the Paris Climate Agreement, while Ginglinger and Moreau (2019) find that greater climate risk leads to lower leverage in the post-2015 period. Capasso et al. (2020) investigate the relationship between exposure to climate change and firms' credit risk and find that the exposure to climate risks affects the creditworthiness of loans and bonds issued by corporates. Jung et al. (2018) provide evidence of the existence of a positive association between the cost of debt and carbon-related risks for firms. Rajhi and Albuquerque (2017) submit that natural disasters are predictive of higher nonperforming loans and higher likelihood of default in developing countries. Battiston et al. (2017) find that while direct exposures to the fossil fuel sector are small, the combined exposures to climate policy-relevant sectors are large, heterogeneous, and amplified by large indirect exposures via financial counterparties. Ilhan et al. (2020) show for a sample of S&P 500 companies that higher emissions increase downside risk – the potential losses that may occur if a particular investment position is taken. Monasterolo and de Angelis (2020) indicate that investors require higher risk premia for carbon-intensive industries' equity. Within the CDS framework Barth et al. (2021) enhance well-established fundamental models with ESG data and show that the market valuation of environmental performance predominantly drives changes in CDS spreads. Kölbel et al. (2020) construct textual, forward-looking measures of climate risk exposure and are able to show that transition risk is priced in CDS, whereas physical risk is not.[2]

We contribute to the existing string of literature on multiple dimensions. First, we propose a novel market-based measure of transition risk (TR) that captures firms' relative differential exposure to the aforementioned risk. Building upon classical factor construction theory and using reliable environmental data, we identify green and brown groups and construct a factor that aptly captures the CDS spread difference between the two groups. As a sensible notion of difference, we use the Wasserstein distance, which, unlike the classical mean spread approach, allows us to extract the entire distributional distance and thus more relevant information. In addition, the reliance on CDS data within our construction ensures that we get a forward-looking measure of the market's perception of transition risk.

Second, we use quantile regression allowing us to provide a more detailed picture of the observed effects. While recent literature (Barth et al., 2021, Kölbel et al., 2020) uncovers sensible effects of transition risk on CDS spreads, their results mostly originate from conditional mean models. Instead, our approach models the entire conditional distribution of CDS spread changes and as such allows for a deeper examination of the exposition by e.g. making statements about the effects on the tails of the distribution. In fact, our results reveal that transition risk impacts are particularly pronounced when CDS spreads are subject to extreme changes. The observed quantile heterogeneous effect is asymmetric and particularly highlighted for positive changes, i.e. when firm-specific creditworthiness deteriorates. From

[2] Physical risk reflects the uncertain economic costs and financial losses from tangible climate-related adverse trends and more severe extreme events. For example, low-lying coastal real estate and public infrastructure face physical risk from higher sea levels and more destructive storms, and hotter temperatures pose chronic risks to human health, worker productivity, and food production.

a risk management perspective, these findings are of particular relevance for institutional investors and regulators.

Third, we set up a detailed sectoral analysis and are able to unfold different effects across industries. In a recent study Kölbel et al. (2020) provide evidence for a positive risk premium in CDS spreads of firms where climate risk is assumed to be a material risk. Following up on their work, we find that certain carbon-intensive sectors (e.g. Energy, Basic Materials) exhibit an increase in default protection cost due to an increased perception of transition risk. More importantly, we also observe a risk mitigation effect for less carbon-intensive industries. This suggests that the market acknowledges those sectors that are well positioned for a transition to a low-carbon economy.

Fourth, we provide a comprehensive analysis of the effect on the temporal dimension of credit risk. Using information from the entire CDS spread curve we show that a shift in the expected temporal materialisation of transition risk directly affects the steepness of the CDS slope. The effect on the CDS term structure is particularly salient for shorter time horizons – this suggests that the market perceives transition risk as a short– to medium-term risk.

The remainder of this paper is organised as follows. Section 2 presents our data basis and discusses the construction of our transition risk factor (TR). In Section 3 we present our panel quantile regression modelling approach. Section 4 reports and discusses the main results. Finally, Section 5 concludes.

2 Data Description and Measuring Transition Risk Exposure

The way firms transition to a low-carbon economy, by adopting new technologies and reducing their emissions, or carrying on their business as usual can have significant financial implications, affecting their credit risk profile and, potentially, impairing their ability to operate. Moreover, transition can occur at different times and at different speeds, resulting in different costs and risks in the process. Thus, transitioning to a low-carbon economy drives a wedge between firms more and less exposed to climate transition risk. Understanding how the market perceives firms' different exposure to transition risk requires measuring firms' environmental profiles. We capture environmental quality/profiles using an assessment of the firms' emission intensity by a third-party ESG rating agency (Refinitiv). Then, we test for the firms' different exposure to transition risk using firms' credit default swap (CDS) spreads, the dependent variable in our empirical analysis.

2.1 Credit Default Swap Spreads

A single-name CDS is a swap contract that provides protection against adverse credit events (e.g. default) of the reference firm. The protection buyer makes a periodic payment to the protection seller until a credit event occurs, or until the maturity date of the contract, whichever is sooner. This fee, quoted in basis points per USD 1 notional amount, is called the CDS premium, or CDS spread. The higher the perceived risk, the more expensive is protection, thus a higher CDS spread. CDS spreads are therefore market-based indicators of a firms' perceived riskiness and confidence in their future fundamentals. Intuitively, the transition to a low-carbon economy will impact firms' assets, cash flows and ultimately, their creditworthiness. Thus, the larger (smaller) the exposure to transition risk, the higher (lower) the CDS spread.

We obtain CDS spread data from Refinitiv for the period from January 1, 2013 to December 31, 2018. The data set covers single-name CDSs with maturities of 1, 3, 5, 10 and 30 years for North American (US & Canada) entities. Each CDS is denominated in US dollars, refers to senior-unsecured debt and contains the "no restructuring" clause (XR). We exclude all firms with missing values or illiquid CDSs, but retain firms with large CDS spreads.[3] In total, our sample comprises 277,535 available CDS spreads for an unbalanced panel of 212 firms.

Several extant studies explore the time series properties of CDS spreads (Collin-Dufresne et al., 2001; Avramov et al., 2007; Ericsson et al., 2009; Galil et al., 2014; Huang, 2019; Koutmos, 2019). The emerging consensus is that CDS spread levels tend to be non-stationary. Similar to the majority or previous studies, we find that our CDS spread series are not level-stationary and so we analyse first-differences. For each firm, we calculate the CDS spread change as follows:

$$\Delta \mathrm{CDS}_{i,t}^{m} = \mathrm{CDS}_{i,t}^{m} - \mathrm{CDS}_{i,t-1}^{m},$$

[3]Illiquid CDS are identified as CDS where no price movement takes place for at least 250 consecutive trading days. Also, some studies exclude firms with CDS spreads exceeding a certain large threshold. Our robust modeling approach allows us to keep these firms in the sample under investigation.

where $\text{CDS}^m_{i,t}$ is the m-year CDS spread of firm i at day t.

2.2 Control Variables

In the empirical analysis we examine the key determinants of both the CDS spreads and the term structure of the CDS spreads. A number of firm-specific and market-specific measures are commonly used as factors in the finance literature that examines CDS spreads. 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 measures account for both firm-specific and common factors that can affect the probability of default and the expected recovery rate. These have been shown to adequately account for the behaviour of CDS spreads, largely outperforming alternative models (Galil et al., 2014). We use these as control variables to isolate the contribution of transition risk exposure to CDS spread differentials by establishing that the transition factor's significant performance survives controlling for the canonical factors.

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. 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. Empirical results indicate that default probability decreases with the firm's past stock returns. Consequently, we expect a negative relationship between CDS spread and stock return $r_{i,t}$. The stock data are also provided by Refinitiv. 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. Empirical 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 from the market. Specifically, we include a market condition (MRI) variable that captures the perceived general economic climate. Our assumption is that improvements in market-wide conditions decrease the 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 Median Rated Index $\Delta\text{MRI}^m_{i,t}$. 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".[4] It has been documented that MRI has a positive relationship with CDS spread (Galil et al., 2014).

In our analysis, we also empirically examine whether firms are adapting their business models to a low-carbon economy in a timely fashion. We do this by investigating the effect of transition risk on the term structure of CDS spreads. The term structure of CDS spreads reflects the shape of the conditional default probability over different time horizons (Han and Zhou, 2015). The term structure of CDS spreads may be driven by a heterogenous set of firm-specific and market-specific factors. In particular, a variety of macro variables have

[4]Later, when examining term structure effects, we use $\Delta\text{MRISlope}^{m,n}_{i,t}$ to account for term-adjusted changes in the business climate.

been shown to explain the slope of CDS spreads. We follow Collin-Dufresne et al. (2001) and Han and Zhou (2015) and include the risk-free interest rate (IR). As a proxy for $\Delta\mathrm{IR}_t$, we choose the change in the 10-year constant maturity Treasury yield using data collected from the St. Louis Federal Reserve (FRED). Our starting observation is that an increase in the IR reduces risk-adjusted default probabilities, and hence the CDS spread falls. Therefore, we expect a negative relationship between the slope of the CDS spreads and the IR.

Finally, following Han and Zhou (2015), we include the market's view on the future interest rate: the difference between short-term and long-term interest rates. We proxy the change of the slope of the risk-free yield curve $\Delta\mathrm{Term}_t$ computing 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 $\Delta\mathrm{Term}_t$ 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.

While our control variables are widely recognised as natural observable proxies for the unobservable fundamental drivers of credit risk (according to theoretical models), it is important to recognise that these proxies do not contain information about firms' exposure to transition risk. Instead, practitioners often use the carbon intensity of firms as a proxy for transition risk exposure (Oestreich and Tsiakas, 2015; In et al., 2019; Barnett, 2019; Bolton and Kacperczyk, 2020; Cornell, 2021 and Görgen et al., 2020). This literature provides evidence that (i) firms with higher carbon emissions have a higher cost of capital (Chava, 2014), and that carbon emission risk) is reflected in (ii) equity markets (Bolton and Kacperczyk, 2020) and (iii) out-of-the-money put option prices (Ilhan et al., 2020). This literature concludes that there are *differences* in low– and high-carbon intensity firms, respectively "brown" and "green" firms, and that investors tend to demand appropriate remuneration for holding high-carbon intensity firms and/or buy more protection against the possibility of default of high-carbon intensity firms.

This paper analyses spreads from the perspective of structural form models following (Merton, 1974). Central to this approach is that default and, therefore, the value of the default-sensitive security depends on a number of determinants – the key ones have been described earlier. Appendix A shows analytically, starting from the (Merton, 1974) model, how CDS spreads subsume also the determinant linked to the transition exposure that can affect the firm's credit risk. The next empirical challenge is to construct an appropriate criteria to sort firms based on their exposure and build a transition risk factor using the observation that the the difference between spreads highlight the relative impact of transition costs.

2.3 Measuring Transition Risk Exposure

The first step in our analysis is to construct an index that measures differential exposure to the risks and opportunities associated to a transition to a low-carbon economy. A variety of choices must be made when constructing an index that tracks the exposure to the risks arising from the transition to a low-carbon economy. How should we identify the firms' exposure to transition risk that reflects the information investors use in their investment decisions? Once we identify the appropriate data, how do we measure its relative intensity over time? Below we describe how we consider differential exposure using a market-based measure and how we capture environmental profiles using firms' emission intensity.

To date, the finance literature on climate change has approached the pricing of transition risk by focusing on how various financial assets reflect investor concerns about regulatory and carbon pricing risk. In most studies, firms' exposure to transition risk is codified using firms' emission intensity data. This literature argues that high-emitting firms may incur greater costs from emission abatement, policy compliance, and product changes in response to more stringent government policies and changes in consumers' preferences. Substantial financial efforts will be required to adapt business models to the new economic conditions. These could significantly affect the firms' cash flow, their financial wealth, and the value of their collateral, ultimately undermining the firms' capacity to generate enough income to service and repay their debt, and eventually leading to higher probabilities of default.

In this literature, transition risk generally results in repricing where high emitting firms' valuations are bid down and low emitting firms' valuations are bid up in response to changing investor beliefs. Crucially, firms may transition at different times and at different speeds. As such, they are exposed differently to transition risk (Meinerding et al., 2020) and exposure does not solely depend on the sectors in which they operate. In fact, firms in the same industry or sector can have vastly different challenges and transition risks will affect them differently depending on how and where they do business.

We examine firms' different/relative exposure to transition risk investigating how firms' CDS spreads and the term structures of CDS spreads change in response to the costs that firms may face due to changes in public regulation, technology, and consumers' preferences (CDS spreads) and the speed at which these costs could materialise (term structures of CDS spreads). Importantly, CDS spreads respond quicker to changes in market conditions than alternative financial markets, as CDS contracts are traded on standardised terms. Moreover, the CDS market is dominated by professional investors who have the ability to take emission intensity and related environmental information into account.

Examining how the market perceives firms' different exposures to transition risk requires a measurement of firms' environmental profiles and emission intensity as is done in the finance literature on climate change (Bolton and Kacperczyk, 2020). Our primary data are yearly emission intensity (scope 1, 2 & 3 emissions normalized by revenue) from Refinitiv.[5] Estimated emissions were used when no actual emissions were reported. We chose firms' emission profiles 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 environmental classification (Berg et al., 2020; Dimson et al., 2020). Later, when constructing the transition risk exposure measure, we balance the CDS spread data with information on firms' credit rating, as determined by an agency that incorporates

[5] Refinitiv firm-level carbon emissions data follows the Greenhouse Gas Protocol that sets the standards for measuring corporate emissions. The Greenhouse Gas Protocol distinguishes between three different sources of emissions: scope 1 emissions, which cover direct emissions over one year from establishments that are owned or controlled by the company; these include all emissions from fossil fuel used in production. Scope 2 emissions come from the generation of purchased heat, steam, and electricity consumed by the company. Scope 3 emissions are caused by the operations and products of the company but occur from sources not owned or controlled by the company.

environmental and climate change considerations into their rating decision.[6]

Having identified the market information that captures the effects of transition costs on firms and the measure of relative intensity, the next empirical challenge is to track/quantify how the differential exposure evolves over time. Following the standard approach used in empirical asset pricing, we partition the universe of firms based on their emission intensity profile and their credit rating. For emission intensity, we partition firms into terciles: low, intermediate, and high emission-intensity. 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. With regard to the credit dimension we proceed similarly and group firms into poor, medium and good credit rating terciles based on S&P credit ratings.[7] From this two-dimensional split, we obtain nine groups in total. We then classify firms into groups according to how they are likely to be affected by a transition to a low-carbon economy. Conditional on low or high emission intensity, we select the firms in the two best (good/medium) and two worst (poor/medium) groups with respect to credit rating, respectively. We define the former set (good/medium credit rating with low emissions intensity) as "green" firms, and the latter set (poor/medium credit rating with high emissions intensity) as "brown" firms. The set of firms within the former and latter class are denoted green $\mathcal{G}_t^{\text{Green}}$ and brown $\mathcal{G}_t^{\text{Brown}}$ category, respectively.[8] The assignment of firms into both groups is updated on a daily basis.[9] Figure 1 illustrates the group assignment for the first day in our sample. Indicated by brown and green points we can see that all firms with a scaled emission intensity below 24.15 (above 186.78) and an S&P rating above BBB (below BBB+) were classified as green (brown) firms on that day.

Building upon these two classes, we now compute the empirical cumulative distribution functions (ECDF) of the CDS spreads for some fixed maturity $m \in \{1, 3, 5, 10, 30\}$ within each class

$$\widehat{F}_t^m(x) = \frac{1}{|\mathcal{G}_t^{\text{Green}}|} \sum_{i \in \mathcal{G}_t^{\text{Green}}} \mathbf{1}_{\left\{\text{CDS}_{i,t}^m \leq x\right\}},$$

$$\widehat{G}_t^m(x) = \frac{1}{|\mathcal{G}_t^{\text{Brown}}|} \sum_{i \in \mathcal{G}_t^{\text{Brown}}} \mathbf{1}_{\left\{\text{CDS}_{i,t}^m \leq x\right\}}.$$

Equipped with the ECDF of the CDS spreads of green and brown companies, we track their relative evolution in time. Specifically, we measure the first-order Wasserstein distance between these ECDFs and label it the *transition risk factor* (TR). A first hypothesis is that investors would prefer to hold protection for exposed firms. The larger the exposure, the larger the demand for protection, the higher the CDS spreads. Essentially, TR tracks the time evolution of the differential exposure to transition risk measured by the Wasserstein distance between the empirical distribution of the CDS spreads of green and brown companies

[6] We use the credit rating issued by the rating agency Standard & Poor's (S&P).

[7] In case of ties, we randomly assign firms to one of the two groups in question.

[8] A more formal description of the construction of $\mathcal{G}_t^{\text{Green}}$ and $\mathcal{G}_t^{\text{Brown}}$ can be found in Appendix B.

[9] Although these quantiles are time-dependent they do not change too frequently (for emission intensity yearly and for credit rating only when there is a change in at least one credit rating at time t).

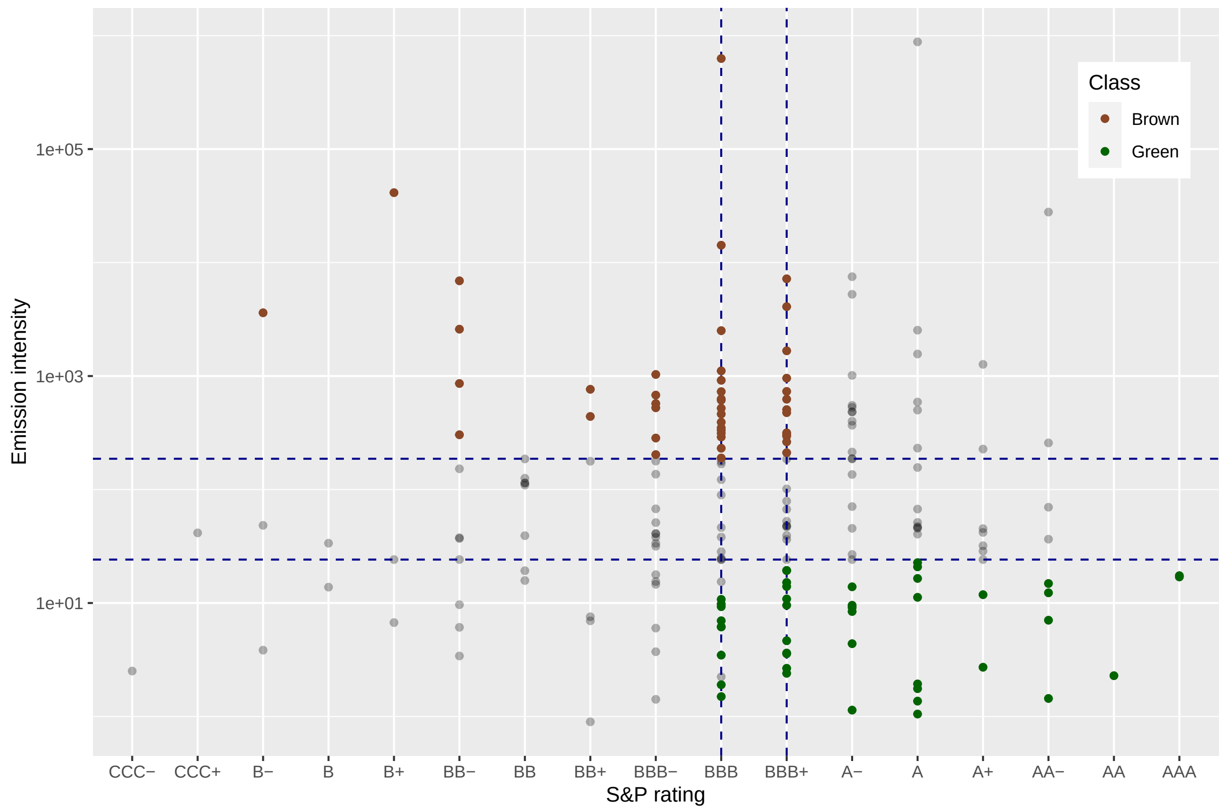

Figure 1: This figure displays each firm's emission intensity vs. its S&P credit rating on 2013/01/02. Blue dashed lines indicate the terciles of the respective (scaled) variable. Green-, brown- and gray-colored dots depict the assignment of a firm to the green class, brown class or no class at all.

$$\mathrm{TR}_t^m = \int_0^1 \left| \left(\widehat{F}_t^m\right)^{-1}(u) - \left(\widehat{G}_t^m\right)^{-1}(u) \right| \mathrm{d}u.$$

The Wasserstein distance captures an intuitive notion of similarity between distributions. The theoretical framework of Wasserstein distance has been applied to the comparison of complex objects in fields of application such as image retrieval (Rubner et al., 2000), computer vision (Ni et al., 2009), pharmaceutical statistics (Munk and Czado, 1998), climate modelling (Vissio et al., 2020) and finance (Rachev et al., 2011), to name but a few.[10] For the purpose of this study, using the Wasserstein distances to measure the transition risk factor helps uncover distributional divergence and provides a more precise representation of the differential exposure to transition risk. This differs from the canonical construction of factors in the empirical asset pricing literature. Traditionally, these are computed as the difference between two aggregate measures (e.g. weighted means) and thus only capture the difference with respect to one point of the distribution.

As discussed earlier, it is crucial to estimate which firms (not just which sectors) are more

[10]In statistics, Wasserstein distances play a prominent role in theory and methodology, and more recently have become an object of inference in themselves.

exposed to transition risk. It might be reasonable to argue that 'brown' industries, like fossil-fuel utilities and mining are the most exposed to transition risk, whereas 'green' industries, like renewable energy and technology, are the least exposed. This, simplification, however, fails to capture intra-industry exposure variation. Some fossil fuel companies have been more progressive in developing alternative energy products. The Wasserstein distance allows us to examine the differential exposure to transition risk of firms otherwise equally credit-worthy. TR aptly tracks in time the evolution of the differential exposure of firms to transition risk. Thus, we argue that the TR contains valuable fundamental information which would be more strongly reflected in the extreme tail of the CDS distribution.

To illustrate the relevance of TR, we examine the behaviour of TR in response to events that affect the transition risk faced by firms without changing either the performance nor the environmental profile of the firms – that is, without affecting firms' fundamentals. Figure 2 plots the evolution of the TR over time for the entire grid of maturities (1, 3, 5, 10 and 30 years). We observe that TR, the wedge between CDS spreads of high and low emission intensity firms, has steadily increased since the middle of 2014. TR aptly captures investors' response to specific climate policy events, such as the speech of the governor of the Bank of England, Mark Carney, on climate change and financial stability and the Paris Agreement. On the one hand, Carney warns that transition risks associated with the revaluation of assets, caused by the adjustment to a lower-carbon economy, could lead to financial crises. On the other hand, the Paris Agreement calls for more ambitious plans to reduce emissions in the near future. It is reasonable to argue that policies associated with these events can increase costs for those firms that are less prepared for a transition to a low-carbon economy. Thus, these firms can be perceived as facing higher transition risks and investors might demand more protection, pushing the corresponding CDS spreads up.
Figure 2 shows dramatic changes around the Paris Agreement, arguably a consequence of a larger demand for default protection for firms largely more exposed to transition risk in the aftermath of the Agreement, followed by a partial reversal due to the uncertainty surrounding which policy would ultimately result from the Agreement.[11] Thus, although the Paris Agreement could have affected investors' expectations of increased exposure to transition risk in the U.S., this change in expectations and demand for CDS of these companies may have been short-lived for the investors.

Being derived from CDS spreads we can also consider a suitable term structure measure of transition risk. In a similar vein to the CDS spread slope, we use the slope of the TR $\text{TRSlope}_t^{mn} = \text{TR}_t^m - \text{TR}_t^n$, defined as the difference between two TRs of differing maturity, to track how the market's perception of transition risk changes with respect to different time horizons. Figure 3 depicts the TR slope for the 5Y-1Y (green) and 30Y-5Y (orange) slopes. Analogously to the TR, we observe distinct behaviors around the turn of the year 2015–2016. In parallel to the movements of the TRs, the slope of the 5Y-1Y TR steadily increases towards the end of 2015 and reaches its peak contemporaneously with the TRs at the beginning of 2016. On the other hand, the 30Y-5Y TR slope decreases. This suggests that the above-

[11] The Agreement was reached in December, with 195 nations committing to reduce greenhouse gas emissions. The uncertainty around the ultimate policy arose because of the 2016 presidential elections in the U.S. As made clear by the US presidential campaign, large differences existed regarding how to approach the Paris Agreement.

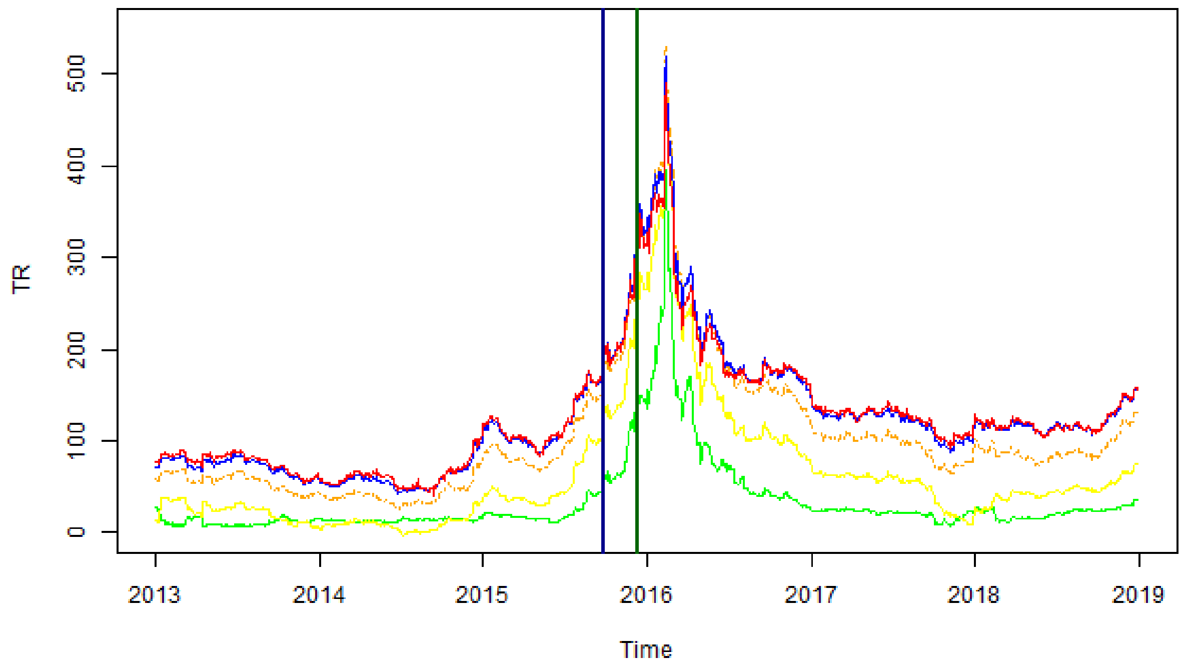

Figure 2: Evolution of the TR over time for maturities 1Y (green), 3Y (yellow), 5Y (orange), 10Y (blue) and 30Y (red). The vertical lines refer to the Carney speech (darkblue) and the Paris agreement (darkgreen), respectively.

mentioned events prompted investors to hedge against transition risk, but also that investors expect transition risk to materialize more in the short– to medium-term. Given that the 5Y-1Y TR slope increased more than the 30-5Y TR slope over the entire sample period, it would seem that over time, the short– to medium-term transition risk became relatively more salient relative to the very long-term risk.

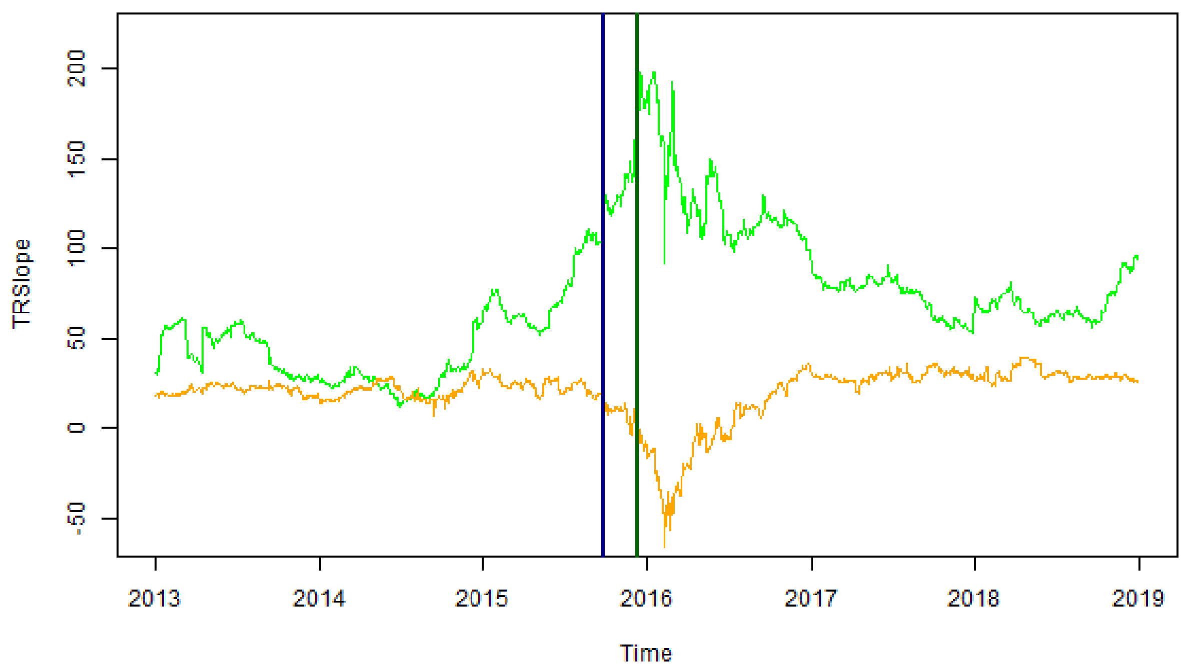

Figure 3: Evolution of the TR slope over time for 5Y-1Y (green) and 30Y-5Y (orange) slopes. The vertical lines refer to the Carney speech (darkblue) and the Paris agreement (darkgreen), respectively.

2.4 Descriptive Statistics

Table 1 presents descriptive statistics for all – dependent and independent – variables under consideration.[12] Average CDS spread changes fluctuate around zero and slightly decrease towards longer maturities. The corresponding standard deviations indicate a large dispersion with numbers varying around 12 to 18. All maturities admit maximum spread changes around 4,000 basis points, with the shortest maturity of 1 year being an exception by reaching a maximum change of over 7,500 basis points. The CDS spread change distributions are heavily right-skewed and characterised by fat tails, especially for the shorter maturities. These CDS spread statistics are in line with the one reported in previous literature and illustrate the typical the unconventional characteristics of CDS data.[13] In contrast, all dependent variables (including CDS-dependent data such as the MRI and TR) exhibit considerably less extreme statistics.

Table 2 shows descriptive statistics for 5-year CDS spread changes differentiated by (i) sector, (ii) year, and (iii) rating category. Within our sample we use the 10-sector classification provided by ThomsonReuters (TRBC 2012) to identify a firm's sectoral affiliation.[14] Panel

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

[13]Compared to previous literature, these descriptive measures are even significantly smaller in magnitude. E.g. also due to the financial crisis, the data of Han and Zhou (2015) are interspersed with many more outliers and move on a larger scale in general.

[14]The ThomsonReuters Business Classification (TRBC) is a global industry classification system owned

Variable	Mean	Median	Q25	Q75	Min	Max	SD	Skew	Kurt
Dependent variables									
$\Delta\text{CDS}^1_{i,t}$	-0.0082	0.0000	-0.0100	0.0100	-2204.5080	7549.7430	17.7551	263.7060	119286.7062
$\Delta\text{CDS}^3_{i,t}$	-0.0123	0.0000	-0.0300	0.0200	-1424.4690	4652.3510	12.5897	168.8718	68658.1391
$\Delta\text{CDS}^5_{i,t}$	-0.0046	0.0000	-0.0400	0.0300	-1506.4420	4668.3000	12.7267	165.8394	66584.6442
$\Delta\text{CDS}^{10}_{i,t}$	-0.0008	0.0000	-0.0800	0.0400	-1434.8210	4391.3870	12.9242	130.9449	49518.0900
$\Delta\text{CDS}^{30}_{i,t}$	-0.0001	0.0000	-0.1340	0.0700	-1618.8710	3940.7600	13.2365	87.6400	30018.5712
Independent variables									
$r_{i,t}$	0.0002	0.0002	-0.0074	0.0082	-0.5174	0.4206	0.0183	-0.5715	31.8825
$\Delta\sigma_{i,t}$	0.0000	0.0000	-0.0002	0.0002	-0.2653	0.3127	0.0032	3.2333	1863.1696
$\Delta\text{MRI}^1_{i,t}$	-0.0019	0.0000	-0.1400	0.0900	-79.1700	83.5450	1.2709	1.8226	397.5380
$\Delta\text{MRI}^3_{i,t}$	-0.0069	0.0000	-0.2400	0.1010	-183.9600	181.8300	2.7068	1.1695	1085.8993
$\Delta\text{MRI}^5_{i,t}$	0.0002	0.0000	-0.2900	0.1950	-265.2549	255.5099	4.3349	2.0155	1271.2578
$\Delta\text{MRI}^{10}_{i,t}$	-0.0018	0.0000	-0.3700	0.2400	-318.6550	317.1349	5.1811	2.2768	1178.0998
$\Delta\text{MRI}^{30}_{i,t}$	-0.0035	0.0000	-0.4500	0.2700	-359.5399	352.2948	5.5990	1.5136	1013.6336
ΔTR^1_t	0.0021	0.0007	-0.3176	0.3228	-48.8961	172.6987	5.5181	19.2311	637.3361
ΔTR^3_t	0.0188	0.0000	-0.5393	0.5537	-34.4526	105.6897	4.3793	8.0344	235.5177
ΔTR^5_t	0.0417	-0.0322	-0.7073	0.6993	-37.3378	105.6400	4.6587	6.6439	186.3657
ΔTR^{10}_t	0.0497	-0.0036	-0.8030	0.8396	-36.8462	99.1012	4.6578	5.3644	147.7664
ΔTR^{30}_t	0.0477	0.0000	-0.9284	0.9652	-37.7713	88.7951	4.5756	4.0249	106.3806

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

A shows that within our sample, Financials constitute the lion's share with 21%, followed by Cyclical Consumer Goods & Services (CCGS) and Industrials with 14% and 13%, respectively. At the lower end we have the Healthcare, Utilities and Telecommunication Services sectors with a share of 7%, 5% and 4%, respectively. In terms of CDS characteristics, it is apparent that the Energy sector exhibits by far the most extreme statistics. Itemized by years, Panel B reveals the most extreme CDS spread movements occurred in the year 2016, in the aftermath of the Paris Agreement and when the oil price crisis induced by the 2010s oil glut took place.

For our subsequent modeling it is crucial to understand how changes in perceived transition risk act on changes in the CDS spread. As a starting point, Figure 4 shows a boxplot of 5-year CDS spread changes as a function of 5-year TR changes. It is evident that the distribution of CDS spread changes depends on the level of TR changes. But more importantly, there is a clear tendency for the CDS spread change distribution to widen for more extreme TR changes, constituting a U-shaped pattern.

and operated by Refinitiv. We consider the following sectors: Basic Materials (BM), Cyclical Consumer Goods & Services (CCGS), Energy, Financials, Healthcare, Industrials, Non-Cyclical Consumer Goods & Services (NCGS), Technology, Telecommunication Services, and Utilities. We refer to this document for an overview of the classification.

	Mean	Median	Q25	Q75	Min	Max	SD	Skew	Kurt	Share
Panel A					Sector					
BM	-0.0124	0	-0.1300	0.0400	-366.0300	400.2500	10.9234	3.0561	293.7067	0.0836
CCGS	-0.0135	0	-0.4000	0.0790	-136.5859	280.5000	5.0232	4.7846	375.3873	0.1357
Energy	0.0676	0	-0.1399	0.0630	-1506.4420	4668.3000	35.8255	75.8098	10800.0300	0.0981
Financials	-0.0540	0	-0.0300	0.0200	-576.0301	245.6799	6.0063	-17.0600	1779.0740	0.2054
Healthcare	0.0013	0	-0.0300	0.0200	-79.8898	93.4099	3.7099	2.6528	156.3194	0.0706
Industrials	-0.0216	0	-0.0300	0.0200	-213.1800	216.8000	5.0961	0.0279	604.2530	0.1256
NCGS	0.0284	0	-0.0300	0.0268	-216.2098	141.8602	5.9587	-1.0522	219.3201	0.1091
Technology	-0.0489	0	-0.0700	0.0300	-230.8802	318.5098	6.9383	5.0186	414.6709	0.0808
Tel. Services	0.1787	0	-0.0200	0.0200	-200.7900	184.5400	8.1150	1.8683	207.0310	0.0413
Utilities	-0.0227	0	-0.0101	0.0200	-193.4599	80.7359	3.1807	-15.5252	1108.3880	0.0498
Panel B					Year					
2013	-0.2026	0	-0.0200	0.0280	-576.0301	117.6489	5.0123	-34.4432	3752.6150	0.1767
2014	0.0278	0	-0.0200	0.0100	-102.8600	196.1699	3.6499	4.6940	291.6455	0.1716
2015	0.3362	0	-0.0300	0.0300	-366.0300	683.2770	10.5325	14.2909	847.7378	0.1622
2016	-0.2826	0	-0.0300	0.0200	-1506.4420	4668.3000	27.5530	97.0757	18089.1600	0.1674
2017	-0.0413	0	-0.1000	0.0200	-213.3400	280.5000	5.3127	5.4916	543.1269	0.1626
2018	0.1624	0	-0.1600	0.1800	-200.7900	184.5400	5.8984	-1.0975	287.5394	0.1596
Panel C					S&P rating category					
BB+ or lower	-0.0115	0	-0.3501	0.1300	-1506.4420	4668.3000	26.0599	87.2116	17102.6600	0.2214
BBB	0.0123	0	-0.0300	0.0200	-245.1202	245.6799	4.3833	3.1368	498.4099	0.4596
A	-0.0214	0	-0.0200	0.0200	-157.2200	153.9600	2.8488	-9.0142	862.3179	0.2647
AAA/AA	-0.0370	0	-0.0200	0.0200	-83.2500	79.9400	3.3343	0.1622	178.7875	0.0542

Table 2: This table presents descriptive statistics (mean, median, 1st & 3rd quartile, minimum, maximum, standard deviation, skewness, kurtosis, share) of 5-year CDS spread changes $\Delta \mathrm{CDS}_{i,t}^{m}$ differentiated by industry (Panel A), year (Panel B) and rating category (Panel C).

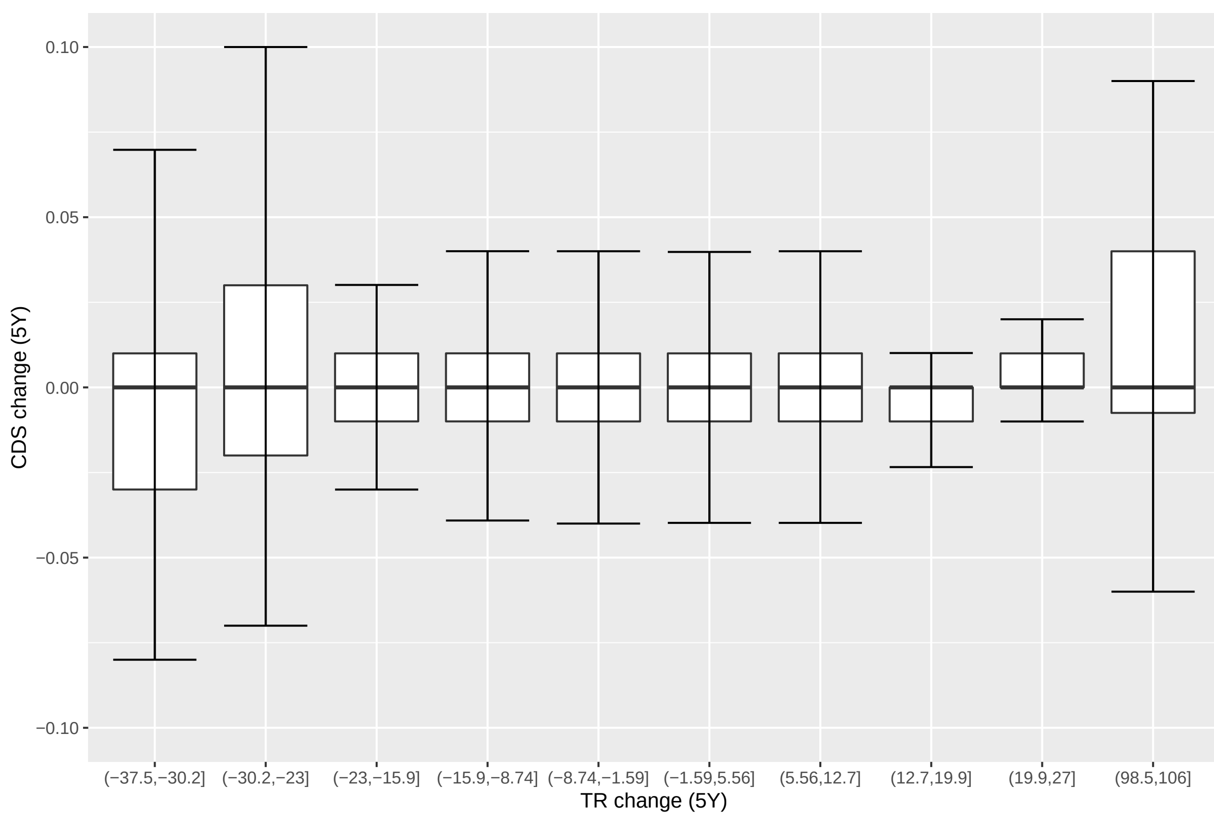

Figure 4: Boxplots of 5-year CDS spread change distributions for different levels of TR changes (5Y). The solid black line within each box indicates the median. The upper and lower limits of the boxes represent the first and third quartiles, respectively. The horizontal bars outside of the boxes represent the whiskers. For the sake of illustration, outliers outside of the whiskers are omitted.

3 Panel Quantile Regression Framework

Rather than solely modeling the conditional mean of the response within a standard regression framework, quantile regression (QR) allows us to characterize the effects on the entire conditional distribution. In particular, it relaxes the strong assumption of identically distributed error terms across all points of the conditional distribution and thus acknowledges heterogeneity of effects across different states. Figure 4 empirically illustrates the need to loose this assumption in our setting. QR can further mitigate some typical empirical problems frequently encountered in least squares models, like the presence of outliers and non-normal errors. In the CDS framework, these issues are of particular interest as Section 2.4 shows. In particular, the descriptive measures in Table 1 illustrate that CDS changes tend to be interspersed by occasional influential outliers making its distribution too heavy-tailed to be able to maintain the normality assumption. Even from a simplified structural perspective, a QR model would be the natural model choice, whereas a simple mean regression model would insufficiently describe the imposed causal dependence structure. Imposing the seminal Merton model Pires et al. (2015) show that the effect of volatility on the credit spread (i.e. the derivative of the spread with respect to volatility) is not constant but rather nonlinearly increases with the spread level.

Although theoretical postulations and empirical findings necessitate quantile regression models, their usage in the credit risk literature is scarce. Pires et al. (2015) examine CDS determinants using a pooled quantile regression approach and show that the effects of fundamental drivers differ across the conditional distribution. In a similar fashion, but only using a limited sample of 22 global systemically important banks (G-SIBs), Koutmos (2019) is able to back up the observed quantile heterogeneity and outlines consequences for risk management of G-SIBs. Recently, Barth et al. (2021) show that ESG ratings exhibit a U-shaped effect on the conditional distribution of logarithmized CDS spreads. Still, all but the last study lack any investigation of a linkage between credit risk and climate risk. Additionally, no study has yet examined any possibly persistent quantile heterogeneity in the term structure of CDS spreads.

To account for the presence of asymmetric patterns characterizing systemic tail-comovements in the data, we implement a quantile-regression estimator for panel data with fixed effects. Quantile regression models allow us to account for unobserved heterogeneity and heterogeneous covariates effects. The availability of panel data allows us to include fixed effects to control for firm-specific unobserved 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 some fixed quantile level $\tau \in (0, 1)$ we consider the panel quantile regression model

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

where $Q_{y_{i,t}}$ denotes the τ-th conditional quantile of $y_{i,t}$ given $\boldsymbol{x}_{i,t}$ and $\alpha_{\tau,i}$ are the firm-specific fixed effects parameters. We implement the two-stage quantile-regression model for panel data with fixed effects developed in Canay (2011) and further extended by Zhang et al. (2019) to estimate the parameter vector $\boldsymbol{\beta}_\tau$.[15] In a first stage, we run firm-specific quantile

[15]Initially introduced to model different effects across subgroups Zhang et al. (2019) propose a cluster-

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. In the second stage, we estimate

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

Quantile regression allows us to unfold different effects across the conditional distribution of the response. We test the robustness and persistence of our results with respect to quantile heterogeneity by employing the testing setup developed by Koenker and Bassett (1982). Specifically, for some fixed $\boldsymbol{\beta}_j = (\beta_j(\tau_1), \ldots, \beta_j(\tau_K))'$ we test the null

$$\mathbb{H}_0 : \beta_j(\tau_1) = \beta_j(\tau_2) = \ldots = \beta_j(\tau_K)$$

against the alternative

$$\mathbb{H}_1 : \beta_j(\tau_k) \neq \beta_j(\tau_l), \quad k \neq l$$

for at least one $k, l = 1, \ldots, K$.

based FE estimator for the group-specific slopes. Imposing the homogeneous slope assumption results in the Canay (2011) estimator but with quantile-specific fixed effects.

4 Empirical results

This section presents our empirical findings. We first present an analysis of the relationship between the transition risk factor (TR) and the changes in CDS spreads at the daily level (Section 4.1). This is followed by a sector analysis (Section 4.2) that allows us to explore how sectors are differently exposed to the costs and opportunities associated with a low-carbon transition. Finally, we explore short-term and long-term exposure to transition risk by examining the relationship between TR and the slope of the CDS spreads (Section 4.3).

4.1 Base Quantile Regression

In this subsection, we study the interaction between TR and the conditional quantiles of the CDS spread. Following prior literature on CDS spread and CDS spread changes (Galil et al., 2014), we include the most influential firm– and market-specific variables and examine the differential exposure to transition risk using a panel quantile regression model as follows:

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

where, for each firm $i = 1, \ldots, N$ and time $t = 1, \ldots, T$, we consider firm-specific variables (stock return $r_{i,t}$ and volatility $\Delta\sigma_{i,t}$), a common factor (market condition $\Delta\mathrm{MRI}_{i,t}$), and our TR factor designed to systematically measure the time-changing differential exposure of firms to transition risk. The slopes of the regressors are estimated at nine different quantiles $\tau \in \{0.1, \ldots, 0.9\}$ using the same set of explanatory variables for each quantile. For $\tau \in \{0.1, \ldots, 0.4\}$, CDS spreads decline as general credit-worthiness increases; these correspond to a downward moving CDS regime. For $\tau \in \{0.6, \ldots, 0.9\}$, CDS spreads increase as general credit-worthiness declines; these correspond to a upward moving CDS regime. Crucially, the quantile regression procedure yields a series of quantile coefficients, one for each sample quantile. In this way, we can examine the relevance of each control variable across the conditional distribution of CDS spread changes. It may be the case that the exposure to certain firm– and market-specific factors varies depending on the CDS regime, moving from tail to tail of the conditional distribution of CDS spreads.

Table 3 reports the estimated coefficients at different quantiles for CDS contracts with 1 year maturity – the shortest under investigation (the remainder of Table 3 will be discussed later). First, we observe that CDS spreads decrease with the firm-specific stock return, as predicted by theoretical structural models (Merton, 1974) and as observed in a number of empirical studies that use both CDS spreads (Pires et al., 2015) and changes in CDS spreads (Galil et al., 2014; Koutmos, 2019). An increase in the stock return would increase the firm's credit-worthiness, decrease the probability of default and decrease the CDS spread. All the estimated coefficients have the expected sign across all deciles and maturities: improved credit-worthiness has a negative impact on CDS spread changes. Unsurprisingly, the longer the maturity of the CDS contract, the larger the effect. Moreover, the effect is significantly larger in the tails of the conditional distribution: when the stock return increases, the likelihood of a sizable decline in the probability of default is significantly larger and the firm's credit-worthiness improves. Crucially, in other words, the effect is more pronounced when downward and upward CDS movements are larger, confirming the observations in Koutmos (2019).

Second, we consider firm-specific volatility and recall that, theoretically, higher volatility of a firm's assets, resulting from more asset value uncertainty, should lead to higher credit spreads (Merton (1974)). We observe that firm-specific volatility has a significant effect on the change of the CDS spread. Consistent with Koutmos (2019), firm-specific volatility is negatively related to CDS spread changes during CDS downward moving regimes, and positively related to CDS spread changes during CDS upward moving regimes. In between these two regimes, the sign and significance of the effect is unclear. Our findings are consistent with those of Koutmos (2019) and shed further light on the mixed empirical observations documented by Collin-Dufresne et al. (2001).

Third, market-wide conditions have a significant effect on CDS spreads (Galil et al., 2014). Deterioration of general market conditions, measured as an increased median CDS spread, decreases firms' credit-worthiness overall, increasing the probability of default and, ultimately, increasing the CDS spread. As global market conditions deteriorate, CDS spreads rise and vice versa. The positive effect holds regardless of the predominant CDS regime. Crucially, the effect is more pronounced in the tails of the conditional distribution. Worsening of market conditions can result in a sizable surge of default probabilities, affecting the extreme quantiles considerably more.

While these results confirm the importance of firm-specific and market-wide measures across the different quantiles – estimated coefficients are all statistically significant at the 1% level (except for the mid quantile) – we provide evidence of the differential exposure to transition risk. We uncover that, after controlling for those variables largely recognised to be the key drivers of CDS spread changes, there is a statistically significant positive relationship between the CDS spread changes and our aggregate transition risk factor TR_t. Moreover, we observe that this relationship varies depending on whether the CDS regime is downward or upward moving. The wider the distributional distance between CDS spreads of green and brown firms, which may indicate a higher aggregate exposure to transition risk, the stronger the positive effect on the CDS spread changes. In particular, when CDS spreads are declining (lower quantiles, CDS regime is downward moving), the relevance of the differential exposure to transition risk as a determinant of the change in CDS spreads is stronger. This effect is even stronger when CDS spreads are rising (higher quantiles, CDS regime is upward moving). In fact, a distinct U-shaped pattern of the estimated coefficients corresponding to $\Delta\mathrm{TR}_t$ is clearly observable.[16]

We re-estimate our baseline quantile regression separately for each maturity in our sample. The remainder of Table 3 presents the results for 3, 5, 10, and 30 years. The effect of differential exposure to transition risk is positive and significant for all maturities, i.e. transition risk is a determinant of CDS spread changes in both the short and long term. The coefficient estimates are larger for longer time horizons. The effects along the whole term structure reflect a market perception that the stringency of climate policies will continuously increase. A natural question is to test whether a differential exposure to transition risk has affected the slope of the CDS term structure. A positively sloped term structure would reflect the

[16] The observed heterogeneous effects across the conditional distribution are also confirmed by our test as the null of quantile homogeneity is strictly rejected. The same applies to all other control variables encountered before.

	1	2	3	4	5	6	7	8	9
					1Y				
StockReturn	−77.8667***	−28.7282***	−4.7073***	−0.2515***	−0.0081	−1.0397***	−10.3351***	−50.3998***	−120.2097***
	(2.0966)	(0.8671)	(0.1511)	(0.0583)	(0.0572)	(0.0781)	(0.4009)	(1.5887)	(3.1353)
ΔVolatility	−383.8992***	−82.4284***	−7.8621***	−0.0897	0.0112	6.6536***	62.3390***	297.8237***	771.5064***
	(20.4115)	(7.1953)	(1.2020)	(0.2964)	(0.2842)	(1.1643)	(5.9341)	(19.5851)	(33.0199)
ΔMRI	213.8703***	81.9464***	24.1946***	3.1982***	0.1390	11.1063***	51.9108***	185.5530***	543.3282***
	(8.9985)	(3.9686)	(1.2642)	(0.2785)	(0.0980)	(0.6983)	(3.1070)	(9.5383)	(23.3328)
ΔTR	3.3301***	1.1343***	0.4691***	0.0403*	0.0015	0.1836***	1.0579***	3.6947***	10.7681***
	(0.2980)	(0.1423)	(0.0472)	(0.0185)	(0.0154)	(0.0434)	(0.1496)	(0.3875)	(0.8702)
					3Y				
StockReturn	−200.6220***	−80.4492***	−43.0059***	−23.2803***	−11.2240***	−27.6472***	−59.7740***	−117.7203***	−256.8858***
	(4.6838)	(1.7321)	(1.0971)	(0.7117)	(0.4417)	(0.8535)	(1.6552)	(2.8540)	(8.3892)
ΔVolatility	−995.5050***	−272.9501***	−80.3410***	−15.2242**	8.0143*	95.1413***	290.2423***	752.5315***	1727.8946***
	(45.4348)	(15.3765)	(12.6305)	(5.4431)	(3.2819)	(11.4248)	(23.4699)	(48.6497)	(96.6924)
ΔMRI	212.3026***	113.2395***	63.9492***	42.3359***	28.1994***	61.9483***	121.0830***	253.5052***	528.3487***
	(9.5211)	(7.0739)	(4.1762)	(3.1481)	(2.5020)	(4.5798)	(7.4438)	(5.7514)	(28.5385)
ΔTR	26.6506***	10.3812***	5.4084***	3.9675***	2.8656***	4.3764***	6.7973***	14.2563***	39.0028***
	(1.1171)	(0.5385)	(0.3159)	(0.2552)	(0.1770)	(0.2904)	(0.4290)	(0.8320)	(1.8135)
					5Y				
StockReturn	−355.2438***	−140.6091***	−75.7607***	−45.8840***	−25.3300***	−48.7290***	−92.7075***	−182.8949***	−403.1630***
	(8.5740)	(3.2825)	(1.7964)	(1.2416)	(0.8177)	(1.3117)	(2.4275)	(5.6077)	(13.6711)
ΔVolatility	−1826.4503***	−523.6525***	−146.3518***	−28.3305***	7.1387·	151.8717***	420.2838***	1136.3432***	2859.0976***
	(90.7766)	(37.4063)	(22.7494)	(5.0402)	(4.2862)	(18.2599)	(32.3036)	(80.1294)	(162.5240)
ΔMRI	150.8786***	86.3638***	51.8349***	34.9969***	22.5276***	43.1855***	76.3632***	158.5290***	328.4251***
	(7.2925)	(5.0340)	(3.4653)	(3.0360)	(2.0383)	(3.6374)	(4.7859)	(9.7565)	(19.1394)
ΔTR	47.3913***	20.0024***	11.2499***	8.2239***	5.8891***	9.2364***	14.6667***	29.0845***	72.8638***
	(1.2198)	(0.8859)	(0.5587)	(0.4363)	(0.3489)	(0.5111)	(0.6503)	(1.3993)	(2.9928)
					10Y				
StockReturn	−497.0528***	−201.9507***	−109.5394***	−58.5909***	−30.4912***	−58.3667***	−112.0067***	−228.2433***	−514.5085***
	(9.8527)	(4.3751)	(2.5590)	(1.5923)	(1.0765)	(1.6076)	(2.9952)	(5.6277)	(11.9493)
ΔVolatility	−2466.6126***	−780.4818***	−230.2062***	−41.5673***	9.8961	182.6342***	508.4070***	1356.0210***	3448.3206***
	(109.6947)	(49.5282)	(32.5410)	(8.6324)	(7.6550)	(22.3968)	(39.6835)	(75.3623)	(177.2165)
ΔMRI	120.7161***	74.4651***	42.1123***	26.4601***	17.4573***	30.8234***	56.2227***	106.2174***	218.4690***
	(5.4608)	(4.4859)	(3.0728)	(2.2064)	(1.8821)	(2.5880)	(3.8852)	(6.1670)	(5.2686)
ΔTR	66.0931***	28.5337***	15.9232***	10.5595***	7.4816***	10.5191***	17.7432***	35.8642***	86.3224***
	(1.8518)	(1.1404)	(0.7152)	(0.5457)	(0.4191)	(0.5455)	(0.8010)	(1.3949)	(2.2625)
					30Y				
StockReturn	−710.9749***	−332.0532***	−187.8650***	−105.8961***	−59.1224***	−93.6610***	−179.6712***	−339.0502***	−743.8622***
	(12.9007)	(6.7215)	(4.2290)	(2.9453)	(2.0837)	(2.7404)	(4.1941)	(6.5733)	(13.3931)
ΔVolatility	−3070.7754***	−1217.7995***	−413.4754***	−97.4337**	16.7978	290.3628***	782.9947***	1873.2682***	4467.0704***
	(130.3765)	(78.2794)	(63.5055)	(31.3885)	(13.3321)	(33.3304)	(56.8785)	(103.6950)	(182.7203)
ΔMRI	134.8539***	83.1097***	50.1343***	32.9615***	22.5911***	34.9083***	64.6953***	123.2491***	250.4052***
	(4.9072)	(4.7235)	(3.8873)	(2.9152)	(2.4312)	(3.0034)	(4.7311)	(4.0402)	(9.1136)
ΔTR	91.7982***	45.0262***	26.7046***	17.3466***	12.7633***	15.2563***	24.7256***	46.3135***	111.4154***
	(2.5030)	(1.5861)	(1.1257)	(0.8804)	(0.6752)	(0.7781)	(1.0529)	(1.5403)	(2.9271)

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

Table 3: This table presents 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 changes. The sample comprises of data from 212 US firms from 2013/01/01 to 2018/12/31 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 1e04.

intuition that a longer time scale naturally increases the possibility of a decline in a firm's credit quality – there is greater uncertainty over longer periods of time; this can result in higher costs of default protection and CDS spreads. Later, we examine this relationship between changes in the slope-adjusted transition risk factor TRSlope_t and the changes in the slope of the CDS term structure.

4.2 Sector Analysis

The previous section provides evidence of a differential valuation of firms' exposure to transition risk as the global economy transitions away from carbon-intensive productions. As discussed in the first two sections, de-carbonising the economy will involve large-scale structural change, with some sectors having to rapidly expand their production and contribute to de-carbonisation goals, with others having to entirely transform their technological basis or, alternatively, shrink and potentially disappear.A growing body of empirical literature identifies this last category as comprising activities directly related to the production of energy and emission-intensive goods, especially steel and cement (Dietz et al., 2020). An inability to adapt will impact these industries' cash flows, compromising their ability to service their debt and thereby influencing their credit quality (Caldecott, 2018; Monasterolo, 2020). Fundamentally, this empirical literature concludes that a company's exposure to transition risk is proportional to the size of its emissions. The more carbon intensive the industry, the larger the exposure to transition risk (Bolton and Kacperczyk, 2020).

To empirically validate these findings and develop a more nuanced picture of differential intra-sectoral exposure explained in the previous section, we re-estimate our baseline quantile regression regrouping the firms using the 10-sector classification by Thomson Reuters (TRBC 2012). To the baseline quantile regression, we add sector dummies and interaction terms with our TR:

$$\begin{aligned}Q_{\Delta \mathrm{CDS}^m_{i,t}}(\tau|\boldsymbol{x}_{i,t}) = {} & \alpha_{\tau,i} + \beta_{\tau,1} r_{i,t} + \beta_{\tau,2}\Delta\sigma_{i,t} + \beta_{\tau,3}\Delta \mathrm{MRI}^m_{i,t} + \beta_{\tau,4}\Delta \mathrm{TR}^m_t \\ & + \sum_{j=5}^{14} \beta_{\tau,j}\mathrm{Sector}_i + \sum_{k=15}^{23} \beta_{\tau,k}\mathrm{Sector}_i \Delta \mathrm{TR}^m_t + \varepsilon_{i,t},\end{aligned}$$

where Sector_i indicates firm i's TRBC classification.

	1	2	3	4	5	6	7	8	9
				5Y					
BM × ΔTR	296.3713***	86.1295***	22.5244***	13.2128***	10.0142***	13.0525***	25.6751***	74.9132***	308.5004***
	(34.4290)	(14.7408)	(4.4383)	(3.1616)	(2.2277)	(3.2058)	(4.0767)	(11.2383)	(34.3729)
CCGS × ΔTR	78.3146·	214.8122***	99.6617***	44.9110***	22.3662***	43.8118***	87.4322***	237.2771***	220.9659***
	(42.0801)	(45.4554)	(15.3500)	(9.3411)	(5.9507)	(10.7235)	(18.9944)	(35.3475)	(42.8142)
Energy × ΔTR	896.2981***	464.5722***	157.0239***	71.9618***	33.5666***	89.3563**	227.2308***	733.8103***	1301.0794***
	(130.2447)	(118.5336)	(37.7601)	(17.8769)	(10.0390)	(27.6224)	(66.9018)	(150.0129)	(152.9782)
Financials × ΔTR	−244.6612***	−72.5697***	−16.8078***	−9.6947**	−7.5044***	−9.1834**	−18.2772***	−47.3987***	−196.3186***
	(34.5175)	(14.7762)	(4.5149)	(3.2150)	(2.2765)	(3.2589)	(4.1987)	(11.3940)	(34.5125)
Healthcare × ΔTR	−251.2124***	−74.9027***	−14.9613**	−5.8844·	−4.6802·	−5.2286	−14.1684**	−45.6027***	−194.7909***
	(34.7011)	(14.8829)	(4.6226)	(3.4079)	(2.4388)	(3.4538)	(4.4151)	(11.5708)	(35.4839)
Industrials × ΔTR	−276.0960***	−74.0124***	−16.4938***	−7.3279*	−5.4558*	−7.6108*	−18.2589***	−58.3785***	−262.1432***
	(34.5055)	(14.8952)	(4.5641)	(3.3043)	(2.3839)	(3.3359)	(4.2877)	(11.4320)	(34.5994)
NCGS × ΔTR	−283.8560***	−78.9079***	−16.7699***	−8.6049**	−5.9541*	−6.8983*	−15.9640***	−52.5699***	−251.8377***
	(34.5183)	(14.8710)	(4.5781)	(3.2689)	(2.3342)	(3.3973)	(4.3202)	(11.4549)	(34.6048)
Technology × ΔTR	−188.2395***	−45.1036**	−7.7651	−0.9304	0.4462	−0.3937	−7.0529	−24.1821·	−152.8365***
	(37.7395)	(15.8164)	(5.1407)	(3.9331)	(2.5963)	(3.9429)	(5.3321)	(13.1122)	(37.8205)
Tel. Services × ΔTR	−288.1630***	−85.2712***	−18.6779***	−8.2096*	−6.8998**	−7.2034*	−16.5504***	−56.1483***	−244.9540***
	(34.5166)	(14.8766)	(4.7257)	(3.4676)	(2.5799)	(3.5881)	(4.5148)	(11.5737)	(34.9823)
Utilities × ΔTR	−281.1555***	−83.3536***	−20.9145***	−12.0331***	−9.3479***	−11.7667***	−24.4555***	−65.9776***	−272.7884***
	(34.7015)	(14.8178)	(4.5267)	(3.2360)	(2.2769)	(3.2756)	(4.1389)	(11.3618)	(34.5676)

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

Table 4: This table presents the estimates of the interaction terms of the sector panel quantile regression for 5-year CDS spreads. The sample comprises of data from 212 US firms from 2013/01/01 to 2018/12/31 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 1e04.

Consistent with the argument that there is a strong relationship between transition risk exposure and total emissions, Table 4 shows that the coefficients on the interaction term between the sector and $\Delta \mathrm{TR}_t$ is positive and significant at the 1% level for Energy, Basic Materials and

CCGS, and it is negative and significant at the 1% level for most of the remaining sectors in our analysis. These results indicate that a wider distance between the CDS spreads of green and brown firms has a larger effect. A wider distance equally indicates (i) a decline of credit-worthiness of firms in carbon-intensive sectors and (ii) a rise of credit-worthiness of firms in less carbon-intensive sectors. These findings support the observations in recent literature: transition risk impacts firms' valuation differently, depending on their sector. Therefore, a growing difference in transition risk exposure could translate into higher credit risk for firms in carbon-intensive sectors like fossil fuels (Energy), construction materials (Basic Materials), and automobile and auto parts (CCGS). Conversely, businesses in sectors like industrial and commercial services (Industrials), technology equipment (Technology), and electric utilities (Utilities) are seen as capable of providing the innovation and technologies necessary to facilitate a low-carbon transformation. Moreover, and consistent with the findings in the previous section, the effect of a change in exposure to transition risk on the CDS spread changes is stronger during periods of extreme downward and upward movements in the CDS market. Table 4 reports coefficient estimates for CDS with 5 years maturity. Results do not qualitatively change when considering 1 year and 30 years maturities, as reported in Table 6 in Appendix C.

4.3 Term Structure

Our previous results provide empirical evidence of different repricing of CDS reflecting how individual firms and sectors may transition at different times. In this section, we empirically examine the different speed at which transition to a low-carbon economy occurs by examining the effect of transition risk on the term structure of CDS spreads. Specifically, we examine how a change in the expected temporal materialization of transition risk affects the term structure of a firm's credit risk. To that end, we adopt the empirical strategy proposed in Han and Zhou (2015). Accordingly, we construct the term structures of $\Delta\mathrm{MRI}_{i,t}$ and $\Delta\mathrm{TR}_t$ and re-examine our baseline quantile regression by including the risk-free interest rate $\Delta\mathrm{IR}_t$ and the risk-free yield curve Term_t:

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

The slope of the CDS spread is defined as the difference between the m-year and n-year CDS spread of firm i at day t. Analytically, we define $\mathrm{CDSSlope}^{m,n}_{i,t} = \mathrm{CDS}^m_{i,t} - \mathrm{CDS}^n_{i,t}$ with $(m > n)$. The slope of the CDS spread is not stationary and, again, we consider the first-difference of this time series defined as $\Delta\mathrm{CDSSlope}^{m,n}_{i,t} = \mathrm{CDSSlope}^{m,n}_{i,t} - \mathrm{CDSSlope}^{m,n}_{i,t-1}$.

We consider two slopes: the five-year minus one-year CDS term structure slope (5Y-1Y) and the thirty-year minus five-year CDS term structure slope (30Y-5Y). Table 5 reports the estimated results. Qualitatively, the sign of the coefficient estimates are largely aligned with Han and Zhou (2015). In particular, the slope of the CDS spread term structure decreases with interest rates, but increases with the level and slope of the Treasury yield curve. Table 7 in Appendix C reports the estimation results. We omit the examination of the IR, $\Delta\sigma_i$, $\Delta\mathrm{MRISlope}_i$, and ΔTerm control variables and concentrate our discussion on the effect of the change of the TR slope. To fix ideas, we recall that a positively sloped term structure reflects the intuition that the longer the maturity, the higher the uncertainty and, possibly, the higher the probability of default: this can result in higher costs of default protection and CDS spreads. We find that a steeper TR slope, reflecting that exposure to transition risk becomes comparatively more relevant for the longer term than the shorter term, has a positive effect on a firm's individual CDS slope in both 5Y-1Y and 30Y-5Y cases. In other words, differential exposure to transition risk increases with time and accelerates the decline in brown credit quality. Crucially, the coefficient estimate of the 5Y-1Y slope is larger than for the 30Y-5Y. This result indicates that a wider difference reflects investors' expectation that a faster transformation of the entire economic structure is required to achieve substantial emission reductions. A rapid acceleration of the transformation is likely to have significant and relatively larger financial impacts in the near future and, consequently, a faster decline in credit quality in the nearer- vs. longer-term.

The coefficient estimates are significant at the 1% level across all deciles except the mid decile for the 5Y-1Y slope. However, for the 30Y-5Y slope also the remaining central deciles are insignificant. This observation is consistent with the results in Kölbel et al. (2020) for their long-term slope – no prevalent transition risk effect is observed for the long-term part of the CDS spread curve. However, our 30Y-5Y results indicate that increasing exposure to transition risk affects the slope of the CDS spread during periods of extreme downward

	1	2	3	4	5	6	7	8	9
					5Y-1Y				
ΔTRSlope	34.8868***	13.4364***	5.8914***	0.4285***	0.0000	2.0750***	5.0405***	14.1183***	48.6431***
	(0.8998)	(0.4345)	(0.2823)	(0.1091)	(0.1021)	(0.1942)	(0.2464)	(0.5052)	(1.4807)
					30Y-5Y				
ΔTRSlope	23.6919***	8.2953***	2.8684***	0.1960	−0.0000	−0.0000	−1.9395***	−3.9765***	11.5876***
	(0.8272)	(0.6208)	(0.5207)	(0.4578)	(0.4709)	(0.4533)	(0.4726)	(0.5063)	(0.6545)

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

Table 5: This table presents the results (only TR slope) of the panel quantile regression for 5Y-1Y (top) and 30Y-5Y (bottom) CDS spread slopes. The sample comprises of data from 212 US firms from 2013/01/01 to 2018/12/31 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 1e04.

and upward movements in the CDS market. It seems that during times of credit-related financial distress, transition risk becomes more relevant for long-term risk estimations; the effect is still smaller than for short-term risk, however, given that most financial implications of transition risks will likely materialize within 5 years.

5 Conclusion

The transition to net zero will require an economic transformation extending in magnitude to the Industrial and Digital Revolutions. This decarbonisation of the economy will have substantial impacts on businesses, especially on firms that are unprepared to transition. Ultimately, a firms' ability to fulfill their financial obligations, and hence their creditworthiness, could be severely affected. To test the link between transition risk and credit risk, we first assess firms' exposure to transition risk by constructing a *transition risk factor* – a market-based measure of transition risk exposure – and examine how this risk affects firms' creditworthiness. A panel quantile regression is used to analyse the differential exposure to transition risk through changes in CDS spreads at varying maturities. Within our panel quantile regression model we control for well-known drivers of CDS spreads and augment it with our transition risk factor.

We show that the transition risk factor is a relevant determinant of CDS spread changes. We first provide evidence of the relationship between the differential exposure to transition risk and firms' cost of default protection. This effect is particularly pronounced during times of extreme credit events and is amplified for an upward moving credit risk regime. The effects vary substantially across industries. Whereas classical carbon-intensive sectors (e.g. Energy, Basic Materials) reveal a deteriorating effect as a result of an increased perception of transition risk, other less carbon-intensive industries exhibit a risk mitigation effect. We then examine how a change in the expected temporal materialization of transition risk affects the term structure of a firm's credit risk. We find that a steeper TR slope, reflecting that exposure to transition risk becomes comparatively more relevant for the longer term than the shorter term, has a positive effect on a firm's individual CDS slope in the near and further future. In other words, differential exposure to transition risk increases with time and accelerates the decline in creditworthiness of brown sector firms.

Overall, our results show that markets perceive transition risk to have a significant impact on firms' valuation. The relevance of differential exposure to transition risk as a determinant of changes in CDS spreads is stronger when CDS spreads are increasing (upper quantiles, CDS regime is upward moving). This speaks directly to the relevance of this work for the risk management practices of institutional investors and regulators. Moreover, unresponsiveness to the low-carbon transition may not only be financially detrimental for firms' everyday business, but may ultimately threaten their existence. This is especially true for firms in carbon-intensive sectors. As such, our findings are relevant for investors and regulators and illustrate the urgency for firms to manage a risk that will inevitably materialise in financial terms.

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A Theoretical Considerations

As often in the context of credit risk we use the Merton model to gain qualitative insights. We denote with $V(t)$ the firm value, F the face value of outstanding debt, T the maturity of the debt. For the dynamics of the firm value (under a suitable pricing measure) we assume

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

where σ is the firm value volatility, r the interest rate and $0 < \delta < r$ a carbon tax rate.

We assume that the carbon tax rate δ is a random variable and smaller for green than for brown firm. To be more precise we assume

$$\delta^G \leq \delta^B \Rightarrow F_B \geq F_G,$$

where $F_{G,B}$ are the corresponding cumulative distribution functions. Observe that we use stochastic dominance of order 1 here.

For δ given Merton's model implies for the corresponding (bond) spreads at time $t = 0$

$$s(\delta) = -\frac{1}{T}\log\left\{V_0 e^{-\delta T}\Phi(-d_1) + F e^{-rT}\Phi(d_2)\right\}, \tag{2}$$

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

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

As expected the spreads are monotonic in the tax rate, that is $\delta^G \leq \delta^B$ implies $s^G \leq s^B$. To see this, observe that

$$\frac{\partial s(\delta)}{\partial \delta} = -\frac{1}{T}\frac{-V_0 T e^{-\delta T}\Phi(-d_1)}{V_0 e^{-\delta T}\Phi(-d_1) + F e^{-rT}\Phi(d_2)} > 0.$$

Now as markets are uncertain about possible implications of transition risk they assess different distributions on tax rates on green and brown firms. However, it is clear that $\delta^G \leq \delta^B$ hence $F_B \geq F_G$.
To calculate the spreads under uncertainty, we simply have to integrate the spread formula (A) with respect to the relevant distribution, so

$$s^G = \int_0^r s(\delta)\mathrm{d}F_G(\delta) \text{ and } s^B = \int_0^r s(\delta)\mathrm{d}F_B(\delta).$$

By stochastic dominance (or simply observing that the arguments of the integrals are non-negative and bounded, so that we can use dominated convergence) the relation of the spreads obtains, i.e. $s^G \leq s^B$.

Using the Wasserstein metric of order 1 we can discuss the difference of the spreads. Recall the first order Wasserstein distance between the CDFs F and G

$$\mathrm{W(F,G)} = \int_0^1 \left|F^{-1}(u) - G^{-1}(u)\right| \mathrm{d}u.$$

In fact, we can use continuity of the integral operator to infer that

$$W(F^B, F^G) \downarrow \Rightarrow s^B - s^G \downarrow .$$

So periods where transition risk is assumed to be low (green and brown are treated similarly) will reduce the spread difference.

B Construction of Green/Brown Groups

Formally, let $\mathrm{ES}_{i,t}$ and $\mathrm{CR}_{i,t}$ be firm i's emission intensity value and S&P credit rating, where $i = 1, \ldots, N$ at time t and $t = 1, \ldots, T$. Further, let $\mathrm{ES}_t^{(q)}$ and $\mathrm{CR}_t^{(q)}$ be the corresponding q-quantile at time t for the emission intensity and credit rating, respectively. We assign each firm to a specific group based on the ES and CR quantiles separately. Let $\mathcal{G}_{t,j}^{m}$ be the set of firms at time t where the value m lies within the jth quantile. Formally, we sort firms from the least emission intensive to the most emission intensive into three buckets:

$$\begin{aligned}
\mathcal{G}_{t,1}^{\mathrm{ES}} &= \left\{ i \mid \mathrm{ES}_{i,t} \leq \mathrm{ES}_t^{(1/3)} \right\} \\
\mathcal{G}_{t,2}^{\mathrm{ES}} &= \left\{ i \mid \mathrm{ES}_t^{(1/3)} < \mathrm{ES}_{i,t} \leq \mathrm{ES}_t^{(2/3)} \right\} \\
\mathcal{G}_{t,3}^{\mathrm{ES}} &= \left\{ i \mid \mathrm{ES}_{i,t} > \mathrm{ES}_t^{(2/3)} \right\},
\end{aligned}$$

where 1 corresponds to low carbon intensity and 3 to high carbon intensity. Similarly, we obtain three buckets for credit rating:

$$\begin{aligned}
\mathcal{G}_{t,1}^{\mathrm{CR}} &= \left\{ i \mid \mathrm{CR}_{i,t} \leq \mathrm{CR}_t^{(1/3)} \right\} \\
\mathcal{G}_{t,2}^{\mathrm{CR}} &= \left\{ i \mid \mathrm{CR}_t^{(1/3)} < \mathrm{CR}_{i,t} \leq \mathrm{CR}_t^{(2/3)} \right\} \\
\mathcal{G}_{t,3}^{\mathrm{CR}} &= \left\{ i \mid \mathrm{CR}_{i,t} > \mathrm{CR}_t^{(2/3)} \right\},
\end{aligned}$$

where 1 corresponds to low credit rating and 3 high credit rating. By considering each combination of these buckets, we obtain nine possible final groups:

$$\mathcal{G}_{t,jk} = \mathcal{G}_{t,j}^{\mathrm{ES}} \cap \mathcal{G}_{t,k}^{\mathrm{CR}} \quad \text{for } j = 1,2,3 \quad \text{and } k = 1,2,3.$$

Using this notation, we define green firms and brown firms at time t as

$$\mathcal{G}_t^{\text{green}} = \{\mathcal{G}_{t,13}, \mathcal{G}_{t,12}\} \quad \text{and} \quad \mathcal{G}_t^{\text{brown}} = \{\mathcal{G}_{t,31}, \mathcal{G}_{t,32}\},$$

respectively.

C Additional Tables

	1	2	3	4	5	6	7	8	9
					1Y				
BM × ΔTR	20.1966$^{\cdot}$	2.8875$^{\cdot}$	1.3514*	0.1641	0.0089	0.4794*	2.0663**	4.3518**	28.1363***
	(10.7210)	(1.5735)	(0.6889)	(0.1468)	(0.0507)	(0.2017)	(0.7470)	(1.4450)	(6.7642)
CCGS × ΔTR	1.1575	14.1031**	3.1046*	0.4758*	0.0335	1.6780*	8.9908**	29.0996**	57.3277***
	(12.1344)	(5.0056)	(1.3001)	(0.2232)	(0.0891)	(0.8200)	(3.2208)	(9.6317)	(13.3088)
Energy × ΔTR	105.4213**	18.5156*	1.8995	−0.1055	−0.0073	0.0787	6.0464$^{\cdot}$	50.1512*	225.2696***
	(36.5246)	(8.0622)	(1.5810)	(0.1573)	(0.0636)	(0.3467)	(3.5583)	(22.9518)	(21.4513)
Financials × ΔTR	−16.6318	−2.4700	−1.0313	−0.1318	−0.0074	−0.3720$^{\cdot}$	−1.1770	0.6738	−0.7494
	(10.8122)	(1.5846)	(0.7067)	(0.1502)	(0.0591)	(0.2100)	(0.7971)	(1.5855)	(7.2119)
Healthcare × ΔTR	−7.1626	−0.9168	−0.2334	−0.0246	−0.0046	0.0444	0.0078	2.2056	−10.4269
	(11.1848)	(1.7547)	(0.8173)	(0.1949)	(0.0913)	(0.2225)	(0.9760)	(2.5047)	(7.6609)
Industrials × ΔTR	−18.7053$^{\cdot}$	−2.2134	−0.8492	−0.1297	−0.0075	−0.3555	−1.3731	−3.2706$^{\cdot}$	−26.3213***
	(10.7777)	(1.6354)	(0.7057)	(0.1546)	(0.0613)	(0.2272)	(0.8574)	(1.7542)	(6.8507)
NCGS × ΔTR	−24.9888*	−3.1397$^{\cdot}$	−1.0509	−0.1214	−0.0065	−0.1813	−0.8824	1.3135	−6.3272
	(10.9082)	(1.6559)	(0.7480)	(0.1692)	(0.0947)	(0.2516)	(0.8263)	(1.8020)	(7.1363)
Technology × ΔTR	−11.2263	−1.9898	−0.9076	−0.1368	−0.0078	−0.3390	−1.5839$^{\cdot}$	−2.9871*	−25.7707***
	(11.4199)	(1.8171)	(0.7485)	(0.1680)	(0.0834)	(0.2584)	(0.8659)	(1.4983)	(7.3326)
Tel. Services × ΔTR	−27.0319*	−2.7552	−0.9452	−0.1251	−0.0066	−0.2082	−1.4478$^{\cdot}$	−2.7012	−29.7384***
	(11.1916)	(1.9265)	(0.8097)	(0.1853)	(0.1192)	(0.3170)	(0.8297)	(2.6944)	(6.8525)
Utilities × ΔTR	−17.3650	−2.2803	−1.3354$^{\cdot}$	−0.1653	−0.0090	−0.4978*	−1.9870**	−3.8906**	−28.2916***
	(11.4189)	(1.7026)	(0.6910)	(0.1510)	(0.0602)	(0.2058)	(0.7591)	(1.5025)	(6.7993)
					30Y				
BM × ΔTR	493.1102***	165.1615***	69.5861***	43.8821***	35.7702***	42.8803***	59.7291***	157.9209***	507.0180***
	(34.6188)	(19.2673)	(8.5773)	(6.4906)	(5.3510)	(6.4543)	(5.8690)	(21.3418)	(32.3213)
CCGS × ΔTR	−72.2778$^{\cdot}$	117.4583***	67.1750***	20.1830$^{\cdot}$	6.6228	8.5310	56.5442***	143.1715***	16.9519
	(40.7064)	(25.1520)	(18.1153)	(10.4413)	(7.7610)	(9.4080)	(14.2975)	(30.3217)	(44.6443)
Energy × ΔTR	1012.4728***	517.1081***	259.6919***	121.3273***	62.7923**	105.4455***	254.6129***	718.1268***	1438.3439***
	(75.2721)	(79.1840)	(45.9991)	(30.3344)	(22.0348)	(25.6158)	(37.7695)	(108.7933)	(122.5092)
Financials × ΔTR	−418.9202***	−132.8765***	−54.2499***	−32.8278***	−28.4920***	−33.5145***	−45.0289***	−122.0259***	−387.0009***
	(34.8948)	(19.4817)	(8.7664)	(6.6346)	(5.5118)	(6.6001)	(6.1648)	(21.5376)	(32.6121)
Healthcare × ΔTR	−407.8372***	−136.6285***	−55.3385***	−33.7661***	−27.7498***	−33.5629***	−49.4466***	−130.9695***	−353.9568***
	(35.9717)	(19.6784)	(8.7910)	(6.8129)	(5.6390)	(6.7787)	(6.1674)	(21.7842)	(33.9804)
Industrials × ΔTR	−438.5259***	−142.2247***	−55.7986***	−35.2354***	−28.6406***	−35.1578***	−48.3869***	−134.7475***	−417.5142***
	(35.0120)	(19.5413)	(8.7638)	(6.7411)	(5.5732)	(6.6665)	(6.1013)	(21.5151)	(33.0725)
NCGS × ΔTR	−471.3364***	−150.9174***	−54.7047***	−34.9447***	−28.0048***	−34.6392***	−45.1642***	−132.0258***	−413.8281***
	(34.7312)	(19.4038)	(8.8067)	(6.7125)	(5.5790)	(6.6646)	(6.2563)	(21.5018)	(32.8019)
Technology × ΔTR	−374.8808***	−108.7503***	−39.2861***	−24.3153**	−21.1985***	−27.7896***	−31.9875***	−90.3865***	−320.9448***
	(36.3567)	(20.3859)	(9.9362)	(7.5277)	(5.8416)	(6.9264)	(7.8971)	(22.8243)	(35.3633)
Tel. Services × ΔTR	−466.3759***	−133.7344***	−47.7542***	−24.7621**	−23.9650***	−27.3465***	−44.7473***	−126.8411***	−450.0888***
	(35.8082)	(20.3153)	(9.7784)	(7.6624)	(6.4738)	(7.4914)	(7.0693)	(21.8482)	(33.8259)
Utilities × ΔTR	−445.4739***	−150.9732***	−63.4957***	−41.3342***	−34.1411***	−41.2574***	−56.3298***	−146.4039***	−468.6683***
	(35.1088)	(19.4234)	(8.7484)	(6.5712)	(5.4176)	(6.5149)	(6.0404)	(21.4375)	(32.8908)

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

Table 6: This table presents the estimates of the interaction terms of the sector panel quantile regression for 1-year (top) and 30-year (bottom) CDS spreads. The sample comprises of data from 212 US firms from 2013/01/01 to 2018/12/31 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 1e04.

	1	2	3	4	5	6	7	8	9
					5Y-1Y				
ΔVolatility	−614.0469***	−125.2807***	−32.7578***	−0.7311	0.0000	17.2388***	110.1421***	362.7548***	1446.9441***
	(26.8899)	(9.9924)	(4.2813)	(0.9517)	(0.8573)	(3.6757)	(10.3413)	(23.4439)	(63.4364)
ΔMRISlope	58.7995***	24.9151***	7.7446***	0.6713*	0.0000	3.3673***	12.9884***	43.5195***	131.7257***
	(2.3020)	(1.4591)	(0.7711)	(0.2712)	(0.1407)	(0.5025)	(0.6417)	(2.2922)	(4.6833)
ΔIR	−12224.6922***	−3848.0991***	−1282.2749***	−61.4182***	−0.0001	−235.4486***	−592.5380***	−2050.2054***	−12446.7595***
	(227.0861)	(67.1086)	(40.7497)	(17.6123)	(18.3324)	(23.0523)	(31.2944)	(56.5826)	(288.5556)
ΔIR^2	−116447.4666***	−14404.2382***	−3208.3339***	−119.8934	0.0004	2933.5765***	5984.1498***	23235.4458***	273760.3631***
	(3032.1221)	(427.6513)	(184.2193)	(79.6648)	(82.1314)	(131.4450)	(191.5596)	(504.7838)	(6316.8031)
ΔTerm	7086.8412***	2885.4030***	991.0229***	45.1584*	0.0000	26.4392	8.4228	76.7190	486.4513***
	(122.8190)	(60.7925)	(39.3838)	(18.8153)	(19.5998)	(23.0264)	(29.3956)	(46.6805)	(104.7896)
ΔTRSlope	34.8868***	13.4364***	5.8914***	0.4285***	0.0000	2.0750***	5.0405***	14.1183***	48.6431***
	(0.8998)	(0.4345)	(0.2823)	(0.1091)	(0.1021)	(0.1942)	(0.2464)	(0.5052)	(1.4807)
					30Y-5Y				
ΔVolatility	−685.4659***	−235.8622***	−90.4720***	−11.3318*	0.0000	0.0000	93.2193***	318.7744***	922.9083***
	(32.1654)	(17.9007)	(11.7533)	(5.7315)	(2.7261)	(2.6065)	(14.3408)	(22.9406)	(40.4129)
ΔMRISlope	72.2614***	24.1570***	7.0075***	1.0483*	0.0000	0.0000	4.3217***	16.7584***	55.2710***
	(1.4708)	(0.9892)	(0.6333)	(0.4132)	(0.3991)	(0.3833)	(0.5646)	(0.7876)	(1.3553)
ΔIR	−11889.7577***	−2554.8879***	−625.0650***	4.2739	0.0000	0.0000	836.5326***	1989.1155***	4548.4067***
	(142.1877)	(73.1734)	(58.5658)	(52.5836)	(53.1549)	(51.1362)	(56.4983)	(66.2628)	(94.2545)
ΔIR^2	−65272.7840***	−15413.3019***	−8935.2357***	−2406.7712***	−0.0000	0.0000	7244.5342***	14669.7023***	74003.8712***
	(880.5906)	(421.8787)	(346.7422)	(264.5610)	(273.2477)	(263.6979)	(395.4290)	(468.2778)	(1233.7671)
ΔTerm	11742.6209***	2859.2439***	868.8613***	62.1172	−0.0000	−0.0000	−713.7976***	−2042.8712***	−5960.8456***
	(144.8130)	(78.9484)	(63.3853)	(56.6498)	(57.4904)	(55.3291)	(59.6913)	(70.0126)	(102.9779)
ΔTRSlope	23.6919***	8.2953***	2.8684***	0.1960	−0.0000	−0.0000	−1.9395***	−3.9765***	11.5876***
	(0.8272)	(0.6208)	(0.5207)	(0.4578)	(0.4709)	(0.4533)	(0.4726)	(0.5063)	(0.6545)

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

Table 7: This table presents results of the panel quantile regression for 5Y-1Y (top) and 30Y-5Y (bottom) CDS spread slopes. The sample comprises of data from 212 US firms from 2013/01/01 to 2018/12/31 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 1e04.

D Constituents of Green/Brown Class

Table 8 displays all firms that were constituents of the green resp. brown class at some point during our sample period from 2013 to 2018. In total, 57 and 70 firms entered the green resp. brown class at least once. The majority of the green firms originates from the financial sector with a share of 42% which represents nearly 60% of all financial firms in the sample. In the brown class energy firms dominate with a share of 24% making up 85% of all energy firms in the sample.

Sunrise	Sunset
Torchmark Corporation, GATX Corporation, Emerson Electric Co., Bunge Limited Finance Corp., D.R. Horton Inc., Xerox Corporation, Rogers Communications Inc., Assurant, Inc., Aon Corporation, Loews Corporation, Humana Inc., International Business Machines Corporation, NIKE Inc., McKesson Corporation, Cardinal Health Inc., Cisco Systems Inc., Anthem Holding Corp., Marsh & McLennan Companies Inc., Oracle Corporation, Unum Group, UnitedHealth Group Incorporated, W. R. Berkley Corporation, CBS Corporation, American International Group Inc., Rockwell Automation Inc., American Express Company, Time Warner Cable Inc., Masco Corporation, Johnson & Johnson, Agilent Technologies Inc., Citigroup Inc., Omnicom Group Inc., JPMorgan Chase & Co., Prudential Financial Inc., CNA Financial Corporation, Morgan Stanley, Berkshire Hathaway Inc., MBIA Inc., Amgen Inc., BCE Inc., The Thomson Corporation, Brunswick Corporation, Boston Scientific Corporation, Time Warner Inc., Altria Group Inc., Capital One Financial Corporation, Microsoft Corporation, AmerisourceBergen Corporation, DIRECTV Holdings LLC, CA Inc., Allergan, Assured Guar, Equity One, Fidelity Nat, Keycorp, Mack-Cali Realty LP, Genworth Financial Inc.	Enbridge Inc., DTE Energy Company, GATX Corporation, YRC Worldwide Inc., Sempra Energy, Marathon Oil Corporation, MeadWestvaco Corporation, Cytec Industries Inc., American Axle & Manufacturing Inc., Apache Corporation, Spectra Energy Capital LLC, Pepco Holdings Inc., Camden Property Trust, Con-way Inc., RPM International Inc., Olin Corporation, Anadarko Petroleum Corporation, Domtar Corporation, Highwoods Realty Limited Partnership, Diamond Offshore Drilling Inc., UDR Inc., CenterPoint Energy Resources Corp., Murphy Oil Corporation, Ryder System Inc., FedEx Corporation, Worthington Industries Inc., Hess Corporation, Molson Coors Brewing Company, Commercial Metals Company, Delta Air Lines Inc., Textron Inc., CMS Energy Corporation, NRG Energy Inc., Halliburton Company, EOG Resources Inc., Service Corporation International, Unisys Corporation, Rock-Tenn Company, Norfolk Southern Corporation, Cooper Tire & Rubber Company, Sonoco Products Company, Mohawk Industries Inc., Enterprise Products Partners L.P., Supervalu Inc., TECO Energy Inc., EnCana Corporation, Talisman Energy Inc., Barrick Gold Corporation, Agrium Inc., Tyson Foods Inc., United States Steel Corporation, Republic Services Inc., Chesapeake Energy Corporation, Weyerhaeuser Company, Alcoa Inc., American Electric Power Company Inc., Time Warner Inc., Altria Group Inc., Teck Resources Limited, YUM Brands Inc., CSX Corporation, Ball Corporation, Noble Energy, Transalta, American Axle & Manufacturing Holdings Inc., Avis Budget Grp Inc, Barrick Gold Fin Co, ENSCO, Husky Energy Inc., Bombardier Inc.

Table 8: This table displays all firms that were constituents of the sunrise resp. sunset class. at some point time (2013-2018).

E Robustness Checks

E.1 Emission TR

To check the robustness of the TR and its effect on CDS spread changes, we additionally provide a variant of the TR that solely depends on emission data and incorporate it in our base model. Any credit data that possibly contains unrelated but influential information is omitted. Concretely, we use the emission intensity to build up green and brown groups and then proceed in the same manner to compute the TR. Table 9 reports the results of the base model with the new TR for all maturities. Noticeably, we observe a decrease in the size of the effects which may be caused by a less dynamic TR due to the annual frequency of the emission data (changes in the composition of green and brown groups hence only happen annually). Nevertheless, the observed effects remain significant.

E.2 Sector Dominance

Appendix D reveals the dominance of financial and energy firms in the green/brown class. Although this composition is plausibly explained by the disparities in the emission intensity of their respective business models, it raises the question whether the results are solely driven by stereotyped high and low emitters. Additionally, each sector-wide CDS spread level is heavily influenced by external factors (strict solvency regulations resp. commodity price shocks) which possibly causes problems to attribute changes in the TR to a changing market perception of transition risk. To investigate this issue, we rerun the base model for the 5-year CDS spreads without the aforementioned sectors.[17] In particular, we exclude both sectors – individually and jointly – from our sample, build a new TR and conduct the same analysis from Section 4.1.

The results are displayed in Table 10. In terms of the general direction and significance of the TR no qualitative changes can be observed. Excluding energy firms slightly increases the TR estimates for all deciles, whereas the size difference is negligible for the other two analyses.

[17]The results for all other models and maturities resemble the displayed results and are available upon request.

	1	2	3	4	5	6	7	8	9
					1Y				
StockReturn	−78.6349***	−29.0986***	−4.7215***	−0.2075***	−0.0015	−0.8679***	−10.3527***	−50.9134***	−121.4971***
	(2.1573)	(0.8902)	(0.1515)	(0.0573)	(0.0571)	(0.0740)	(0.4013)	(1.5322)	(3.1540)
ΔVolatility	−385.4458***	−83.9065***	−7.3975***	−0.0357	0.0023	5.3303***	61.3330***	294.8198***	774.2842***
	(19.6956)	(7.5879)	(1.6616)	(0.2893)	(0.2841)	(1.0945)	(5.8543)	(20.2492)	(33.6705)
ΔMRI	218.6282***	82.7464***	24.6021***	2.6038***	0.0222	10.1739***	52.6527***	187.2051***	546.1486***
	(9.2648)	(4.1009)	(1.3093)	(0.2496)	(0.0942)	(0.6969)	(3.1833)	(8.9516)	(22.4116)
ΔTR	1.2099***	0.3934***	0.0506	0.0044	0.0000	0.0294	0.3684***	1.0421***	4.7487***
	(0.1439)	(0.0861)	(0.0315)	(0.0215)	(0.0207)	(0.0241)	(0.0797)	(0.1391)	(0.3864)
					3Y				
StockReturn	−201.2797***	−81.5489***	−42.7498***	−22.2156***	−9.7969***	−26.8104***	−59.2221***	−116.3933***	−256.2204***
	(4.8361)	(1.7459)	(1.0754)	(0.6862)	(0.4019)	(0.8284)	(1.6135)	(2.9041)	(8.2260)
ΔVolatility	−973.2290***	−275.3691***	−76.7647***	−12.9225**	7.8854*	92.1760***	283.8412***	740.7140***	1715.5433***
	(54.4676)	(15.7549)	(11.8999)	(4.5695)	(3.2097)	(10.4608)	(22.0371)	(46.2116)	(95.8932)
ΔMRI	223.4540***	115.2765***	65.0755***	43.2412***	28.0993***	61.8873***	121.5114***	253.2455***	540.8681***
	(10.1375)	(6.6473)	(3.8513)	(3.1241)	(2.0480)	(4.0400)	(7.9063)	(9.6684)	(28.2627)
ΔTR	3.5026***	1.6049***	0.9712***	0.8625***	0.6141**	1.4721***	2.2360***	4.0472***	13.3480***
	(0.4105)	(0.3163)	(0.2765)	(0.2536)	(0.2028)	(0.2684)	(0.3333)	(0.4697)	(1.0250)
					5Y				
StockReturn	−357.2863***	−140.7529***	−74.9753***	−44.0121***	−22.9355***	−46.7178***	−91.2376***	−182.3271***	−397.5438***
	(8.7982)	(3.3284)	(1.7918)	(1.1803)	(0.7606)	(1.2486)	(2.3899)	(5.4933)	(13.2119)
ΔVolatility	−1825.7634***	−519.3800***	−137.6123***	−26.2063***	7.3567·	142.3430***	410.7345***	1124.2258***	2791.8455***
	(91.3348)	(37.1255)	(21.7308)	(4.6806)	(4.0459)	(17.1315)	(33.5760)	(78.7165)	(167.8022)
ΔMRI	156.0269***	87.1931***	53.0727***	34.6712***	21.9241***	41.0551***	76.3303***	159.3504***	336.9151***
	(7.2776)	(5.0774)	(3.6808)	(2.9032)	(1.9065)	(3.2852)	(5.2737)	(9.8074)	(17.7695)
ΔTR	12.0499***	3.9511***	2.6887***	2.2364***	1.9850***	3.3947***	5.8891***	11.7439***	25.8426***
	(0.6834)	(0.4088)	(0.3323)	(0.2815)	(0.2636)	(0.3578)	(0.5162)	(0.8446)	(1.6207)
					10Y				
StockReturn	−511.7342***	−202.1691***	−109.7679***	−56.2683***	−28.1080***	−55.0749***	−109.8447***	−224.2027***	−504.6410***
	(10.3465)	(4.3511)	(2.5758)	(1.4967)	(1.0062)	(1.5066)	(2.8991)	(5.7295)	(11.6211)
ΔVolatility	−2501.9932***	−777.8220***	−222.5463***	−40.4656***	8.5644	163.6761***	496.6495***	1320.5554***	3347.7572***
	(111.9179)	(51.5399)	(28.9212)	(9.1106)	(6.2782)	(19.9919)	(39.1077)	(87.1761)	(171.6218)
ΔMRI	125.0571***	77.2294***	44.3692***	25.7665***	17.1962***	29.7629***	55.4591***	109.4038***	218.5459***
	(5.3030)	(3.6644)	(3.4241)	(1.7026)	(1.8190)	(2.4119)	(3.8222)	(6.4405)	(4.5655)
ΔTR	17.8905***	6.3845***	3.6832***	1.9443***	1.0401***	1.5713***	2.5845***	4.3526***	14.6479***
	(0.9365)	(0.4951)	(0.4277)	(0.3551)	(0.2990)	(0.3479)	(0.4179)	(0.4611)	(0.8296)
					30Y				
StockReturn	−727.5989***	−338.9551***	−190.2333***	−104.0037***	−58.1794***	−90.8957***	−179.4912***	−339.7287***	−745.8244***
	(12.8206)	(6.3792)	(4.2171)	(2.8528)	(2.0115)	(2.6366)	(4.1554)	(6.8571)	(14.0949)
ΔVolatility	−3122.9152***	−1225.8299***	−398.0533***	−91.0484**	19.5287	277.9716***	774.1661***	1866.1317***	4493.5010***
	(146.9456)	(65.2986)	(61.9531)	(28.9503)	(12.7241)	(31.9738)	(59.9988)	(107.4355)	(203.1130)
ΔMRI	141.3800***	87.9735***	52.4345***	33.7068***	23.6606***	34.8476***	66.2135***	126.2169***	262.8045***
	(5.8791)	(4.3078)	(3.8018)	(2.9259)	(2.0923)	(2.9090)	(4.5851)	(6.4007)	(10.2788)
ΔTR	33.0433***	12.6417***	7.1359***	4.2279***	2.6552***	3.5695***	5.8296***	9.4040***	26.4358***
	(1.8756)	(1.0158)	(0.8383)	(0.6836)	(0.5687)	(0.6506)	(0.7945)	(0.9429)	(1.8100)

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

Table 9: This table presents 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 changes. Within the construction of the TR we only use the emission intensity to determine green and brown firms. The sample comprises of data from 212 US firms from 2013/01/01 to 2018/12/31 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 1e04.

	1	2	3	4	5	6	7	8	9
				Without Energy					
StockReturn	-318.3846^{***}	-134.7608^{***}	-73.3882^{***}	-46.8185^{***}	-26.8962^{***}	-47.7951^{***}	-89.3057^{***}	-171.1303^{***}	-357.1531^{***}
	(6.3127)	(3.1699)	(1.7414)	(1.2421)	(0.8690)	(1.2796)	(2.3596)	(4.9347)	(9.3950)
ΔVolatility	-1544.7218^{***}	-462.7689^{***}	-133.4980^{***}	-29.4406^{**}	6.8278	148.3803^{***}	396.4265^{***}	1000.4144^{***}	2377.1492^{***}
	(41.9528)	(40.0393)	(21.4046)	(9.4199)	(5.7272)	(17.7019)	(35.3174)	(73.5850)	(102.9133)
ΔMRI	137.2038^{***}	84.3255^{***}	50.1550^{***}	33.7929^{***}	21.4784^{***}	37.9465^{***}	65.1641^{***}	136.6296^{***}	275.6724^{***}
	(6.8026)	(5.1559)	(3.5384)	(3.0368)	(2.2261)	(3.2837)	(3.9228)	(7.8649)	(14.9207)
ΔTR	74.0000^{***}	34.0141^{***}	19.8147^{***}	13.7549^{***}	9.2401^{***}	14.0423^{***}	23.1596^{***}	43.2705^{***}	101.4573^{***}
	(1.9663)	(1.1435)	(0.7183)	(0.5914)	(0.4875)	(0.6031)	(0.8526)	(1.5406)	(2.6883)
				Without Financials					
StockReturn	-398.9466^{***}	-161.8197^{***}	-85.0447^{***}	-51.7266^{***}	-30.7017^{***}	-55.4944^{***}	-108.6112^{***}	-203.6243^{***}	-438.2321^{***}
	(10.7253)	(4.2596)	(2.1438)	(1.4934)	(1.0686)	(1.6423)	(3.3229)	(7.0623)	(15.8496)
ΔVolatility	-1989.6412^{***}	-572.8673^{***}	-158.1265^{***}	-20.3962^{**}	14.4489^{*}	179.9208^{***}	507.2120^{***}	1278.4590^{***}	3110.1396^{***}
	(106.6702)	(49.0849)	(27.3550)	(6.7753)	(6.5449)	(22.7720)	(42.5930)	(76.1881)	(185.4286)
ΔMRI	131.3963^{***}	72.1861^{***}	44.1407^{***}	33.8418^{***}	24.5597^{***}	47.3229^{***}	86.2996^{***}	172.3643^{***}	365.1154^{***}
	(7.4531)	(5.1004)	(2.0241)	(3.5455)	(2.5958)	(4.1775)	(7.4977)	(15.5485)	(23.0904)
ΔTR	48.3781^{***}	21.0268^{***}	12.4012^{***}	8.5545^{***}	6.7126^{***}	10.0583^{***}	16.5239^{***}	32.5458^{***}	68.7863^{***}
	(2.0416)	(1.0489)	(0.7214)	(0.5183)	(0.3980)	(0.5179)	(0.9309)	(1.7765)	(3.2369)
				Without Energy and Financials					
StockReturn	-350.0675^{***}	-160.9287^{***}	-89.1543^{***}	-54.8440^{***}	-33.7369^{***}	-56.8049^{***}	-105.3999^{***}	-190.9131^{***}	-388.7687^{***}
	(9.9301)	(4.4340)	(2.4800)	(1.6545)	(1.2135)	(1.7644)	(3.3717)	(6.7824)	(13.3516)
ΔVolatility	-1623.1874^{***}	-530.9274^{***}	-155.3427^{***}	-21.7817^{***}	8.2832	165.4198^{***}	439.8435^{***}	1107.9180^{***}	2636.2589^{***}
	(106.4166)	(34.8379)	(25.2732)	(6.0312)	(7.5828)	(22.2445)	(44.1204)	(106.1445)	(157.4550)
ΔMRI	171.1927^{***}	100.9850^{***}	61.9731^{***}	46.5311^{***}	31.4699^{***}	58.5291^{***}	98.6639^{***}	189.8934^{***}	391.1620^{***}
	(9.2523)	(7.4892)	(4.9600)	(4.2194)	(3.5837)	(5.0943)	(8.9288)	(15.0593)	(24.8974)
ΔTR	44.3992^{***}	21.5663^{***}	13.7308^{***}	9.3759^{***}	6.8851^{***}	10.4229^{***}	16.7103^{***}	30.2913^{***}	62.4804^{***}
	(1.6490)	(0.9209)	(0.6543)	(0.5556)	(0.4535)	(0.5919)	(0.7950)	(1.3519)	(2.5878)

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

Table 10: This table presents results of the panel quantile regression for 5-year CDS spreads without energy firms (top), financial firms (center) and firms from both sectors (bottom). The sample comprises of data from 2013/01/01 to 2018/12/31 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 1e04.