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Is Climate Transition Risk Priced into Corporate Credit Risk? Evidence from Credit Default Swaps

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Abstract

We study whether the credit default swap (CDS) spreads of firms reflect the risk from climate transition. We first construct a climate transition risk (CTR) factor by using information on the vulnerability of a firm's value to the transition to a low-carbon economy. We then document how this factor shifts the term structure of the CDS spreads of more vulnerable firms but not of less vulnerable firms. Considering the impact of different climate transition policies on the CTR factor, we find that these policies have asymmetric and significant economic impacts on the credit risk of more vulnerable firms, and negligible effects on other firms.

Topics: Climate change; Credit risk management; Econometric and statistical methods
JEL codes: C24, G12, G32, Q54

Résumé

Nous cherchons à savoir si les écarts sur les swaps sur défaillance des sociétés tiennent compte du risque associé à la transition climatique. Nous élaborons tout d'abord un facteur de risque lié à la transition climatique à l'aide de données sur la vulnérabilité de la valeur d'une société par rapport à la transition vers une économie à faibles émissions de carbone. Ensuite, nous mettons en évidence la façon dont ce facteur fait varier la structure par terme des écarts relatifs aux swaps sur défaillance des sociétés plus vulnérables, mais pas celle concernant les sociétés moins vulnérables. Nous étudions enfin l'incidence de différentes politiques de transition climatique sur le facteur de risque lié à la transition climatique. Nous constatons que ces politiques ont des effets économiques asymétriques et considérables sur le risque de crédit des sociétés plus vulnérables, et des effets négligeables sur les autres sociétés.

Sujets : Changements climatiques; Gestion du risque de crédit; Méthodes économétriques et statistiques
Codes JEL : C24, G12, G32, Q54

1. Introduction

Transitioning towards a low-carbon economy requires adjustments in regulations, technology, and consumer attitudes aimed at adapting economies to a new framework. Those changes entail risks, named climate transition risk (CTR), for the firm's cash flows and their volatility, which may impair the debt repayment capacity of firms and, therefore, increase their credit risk. CTR has been documented to be a relevant factor in private and institutional investor portfolio decisions (Krueger et al., 2020; Reboredo and Otero, 2021), as well as in the pricing of stocks and bonds (Ilhan et al., 2021; Bolton and Kacperczyk, 2020; Monasterolo and De Angelis, 2020; Painter, 2020; Reboredo and Ugolini, 2022). However, it is still unclear how credit risk across firms may be impacted according to their vulnerability to CTR, yet this information is crucial for business investment decisions aimed at mitigating the impact of climate change and developing optimal climate policies.

In this study, we examine whether CTR is reflected in the pricing of the credit risk of firms. We posit that changes in CTR should impact credit risk, with an intensity that varies depending on the firm's exposure to and management of that risk. In the transition to a low-carbon economy, some firms may face difficulties in running their business because of adverse climate policies, such as carbon taxes or carbon pricing or changes in consumer preferences, which have a direct impact on firms' cash flows, with ramifications on credit risk. Both exposure and management shape the impact of CTR on a firm's cash flows and thus on its capacity to repay debt. Exposure is delimited by a firm's emissions and intensive fossil fuel use, which both make cash flows more sensitive to carbon price risk and to oil price fluctuations, while carbon-intense assets are at risk of being stranded in the transition to cleaner energies. Management consists of all a firm's decisions aimed at mitigating adverse CTR effects, including policies to reduce emissions and develop greener products. Firms with greater exposure and poorer management of CTR should, *ceteris paribus*, exhibit greater credit risk.

To assess CTR, previous empirical studies have proxied risk in varying ways: portfolios based on information on firms' CO2 emissions (Alessi et al., 2021; Blasberg et al., 2022; Gourdel and Sydow, 2022), stranded asset portfolios (Jung et al., 2021), fund flows (Brière and Ramelli, 2021), green portfolio factors (Pastor et al., 2021; 2022), and a climate news sentiment index (Engle et al., 2020). In this article, in contrast, we use a CTR factor that is constructed from information on the vulnerability of a firm's value to the transition to a low-carbon economy, specifically, information on a firm's unmanaged risk, as rated annually by the Sustainalytics carbon risk score (CRS) with a number between 0 and 100, reflecting negligible (0), low (1 to 9.99), medium (10 to 29.99), high (30 to 49.99), and severe (50 or more) vulnerability. Our CTR factor uses this information, consistent with Pastor et al. (2022), to compute a green factor, created as a market portfolio composed of market-adjusted stock positions; each stock is weighted according to its CRS rating, with positive and negative weights reflecting relatively low and high vulnerability of a firm to CTR, respectively. As CTR has an asymmetric impact on a firm's value, with negative and positive effects on the value of firms more and less vulnerable to carbon risk, respectively, a downward (upward) movement in the value of the CTR factor therefore reflects a rise (fall) in transition risks.

We measure a firm's credit risk using market information on the firm's credit default swap (CDS) spread. This credit derivative protects against the risk of credit default: buyers pay a premium (CDS spread) to obtain insurance against default. The price of this financial instrument therefore reflects the market assessment of a firm's credit risk. Interestingly, from variations in this assessment across time scales we can obtain spreads for different time horizons for the same borrower. The term structure of CDS spread thus provides information on investor expectations regarding credit risk over longer and shorter periods, which essentially reflect perceptions on how a firm's short- and long-run cash flows could be affected by transition risks (Giglio et al., 2021).

Carney (2015) affirms that the impact of climate change may be felt at different horizons; therefore, information on the CDS term structure could reflect the effects of CTR depending on the time horizon. Further advantages are that CDS contracts are standardized (making them more easily comparable), traded in an active and liquid market (Zhang et al., 2009), and are very sensitive to new information (Blanco et al., 2005). Those features together make CDS more suitable for measuring credit risk than other financial information, such as corporate credit ratings or corporate bond spreads.

We study the relevance of the CTR factor for corporate CDS spreads using data for a sample of European firms for the period January 2014 to June 2022. Estimated values of the CTR factor—which comprise all stocks included in the STOXX 600 index with weights given by their relative CRS—show that the CTR factor has distinctive dynamics, and that the cumulative returns of the CTR factor rises over the sample period and, furthermore, are greater than the cumulative returns of the market index; this evidence is consistent with results for the green factor reported by Pastor et al. (2022) for the United States. Likewise, CDS spreads for more vulnerable firms are greater than for the remaining firms, especially over the long run, consistent with the fact that firms highly exposed to carbon risk pay higher risk premia.

Using a panel threshold regression model, we document that, for tenors of 1, 2, 5, 10, 20, and 30 years, the CTR factor has a significant and positive impact on the CDS spreads of firms highly vulnerable to CTR, but has no significant impact on CDS spreads of firms with low or negligible CTR. This evidence suggests that investors only pay a risk premium when buying credit protection for firms that are broadly affected by transition risks. This economically significant premium ranges between 12 and 20 basis points (bps) for short- and long-run maturities, accounting for 35%, 20%, and 13% of the average CDS spread value of the most vulnerable firms in the short-, medium-, and long-run horizons, respectively. Confirming this finding is a robustness analysis using different sampling frequencies, CTR measures, and empirical specifications.

We also explore how CTR would impact credit risk under different climate transition scenarios: hot house world, disorderly transition, and orderly transition to a low-carbon economy, reflecting the repricing effects of climate transition policies (Carney, 2015; NGFS, 2020) and the corresponding impacts on the CTR factor. We document that a disorderly transition, as given by downward CTR factor movement, shifts the term structure of the CDS spreads of the most vulnerable firms upwards, whereas a hot house scenario, featuring upward CTR factor movement, has the opposite effect. CDS spread differences between those scenarios are 40 to 66 bps for short- and long-run maturities. In contrast, an orderly transition, with average impacts on the CTR factor, has a negligible impact on credit risk, independently of the firm's vulnerability to CTR. This evidence shows that climate transition policies have asymmetric effects on credit risk—that is, a negligible impact for less vulnerable firms and a significant impact for highly vulnerable firms.

Our study is related to the growing literature on climate risks and credit risk. A set of studies examine the impact of carbon emissions on a firm's credit risk. Capasso et al. (2020) show that distance-to-default is negatively associated with a firm's emissions, whereas Kleimeier and Viehs (2018) show that a firm's CO2 emissions are negatively related to the cost of bank loans. Similarly, Vozian (2022) documents that European firms with higher emissions exhibit higher CDS spreads at different horizons; Seltzer et al. (2022) show that firms with higher emissions have lower credit ratings and exhibit higher yield spreads and that credit ratings and yield spreads are unfavourably affected by stringent environmental regulations; and Ilhan et al. (2021) show that firms with higher emissions experience greater downside risk. Carbone et al. (2021) show that firms with higher greenhouse gas emissions have worse credit risk estimates, and firms with emission reduction plans receive more favourable credit risk assessments.

Another set of studies assess the impact of CTR on credit risk by building a climate risk factor. Blasberg et al. (2022) describe a carbon risk factor that is computed as the difference between the median values of CDS spreads of firms with low and high emissions, showing that this factor affects the CDS spreads of European and US firms. Using text analysis of climate risks, Kölbel et al. (2023) build proxies for both climate transition and physical risks, documenting that disclosure of transition risks increases firms' CDS spreads, while the opposite occurs for physical risks.

Within a related strand of literature on climate risks, Huynh and Xia (2021) document that bond pricing varies with a firm's exposure to climate risks, while Jung et al. (2018) report evidence of a positive association between the cost of debt and carbon-related risks for firms. Duong et al. (2022), analysing firm-level carbon risk management association with a firm's CDS spreads, find that carbon management actions substantially reduce CDS spreads. Similarly, using information on environmental, social, and governance (ESG) practices, Barth et al. (2022) find that improved ESG ratings reduce firm credit risk as reflected in CDS spreads.

Our study contributes to this literature, first by measuring CTR through a new factor that considers the impact of CTR exposure and CTR management on the vulnerability of a firm's value, and second by providing evidence on the asymmetric effects of the CTR factor on firms' credit risk. Unlike previous studies, we assess how different transition scenarios, characterized by differing policy stances, impact the credit risk of firms, reporting evidence of significant economic and asymmetric effects. Our findings imply that firms that are better prepared for the transition to a low-carbon economy have a lower cost of capital and are more sheltered from the effects of transition policies. This is good news for ESG investors and has implications for investors in terms of hedging climate risks.

The remainder of the paper is laid out as follows. Section 2 describes firm-level CTR measurement and the construction of the CTR factor. Section 3 presents our data and provides a preliminary analysis on CTR and credit risk. Section 4 describes a threshold panel regression model and discusses estimations of the impact of the CTR factor on CDS spreads for different tenors. Section 5 discusses the impact of three climate transition scenarios on the credit risk of firms. Final conclusions are presented in Section 6.

2. The climate transition factor

Below we describe the framework we use to construct the CTR factor. We first describe the firm-level CRS measures that assess the vulnerability of a firm's value to the transition to a low-carbon economy, and then outline methods to construct the CTR factor.

2.1 Measuring firms' climate transition risk

To assess the firm's climate transition risk, we use information from Sustainalytics, a leading provider of ESG ratings and carbon information. Sustainalytics annually rates firms according to exposure and management factors.

Exposure evaluates to what extent carbon risks are materialized in the firm's operations, products, services, and supply chain, which largely depend on the firm's business sector. It is measured for 146 subindustries with differing degrees of exposure and is adjusted to take into account a firm's specific features, including (1) firm operations and product mix deviations from subindustry values, and (2) financial strength and geographical components shaping a firm's capacity to cope with carbon risks. Management reflects the firm's capacity to mitigate emissions and related carbon risks through a company's policies and programmes applied to the greening of operations, products, and services.

Climate transition risk beyond the firm's control or unaccounted for by the firm is considered to be unmanaged. Sustainalytics rates firm-level unmanaged climate transition risk with a CRS between 0 and 100 that reflects the extent to which a firm's value is at risk as negligible (0), low (1 to 9.99), medium (10 to 29.99), high (30 to 49.99), and severe (50 or more).[1] As a climate transition metric, the CRS accounts for the cost of the carbon externality by scoring its impact on the firm's value. Thus, given that the CRS specifically addresses risks to a firm's value caused by the transition to a low-carbon economy, the CRS provides more insightful information on climate transition risks than ESG indices or carbon emissions as reported by the Greenhouse Gas (GHG) Protocol Scopes 1, 2, and 3. Furthermore, CRS ratings are available for institutional and private investors to assess the resilience of their investments to climate transition risk (Reboredo and Otero, 2021; Reboredo and Ugolini, 2022).

2.2 Construction of a climate transition risk factor

Based on the CRS information, we construct the CTR factor following the method proposed by Pastor et al. (2022) to build a green factor that prices assets in equilibrium.

Specifically, based on the CRS for each firm *i* (*i*=1,…,N) at time *t* (*t*=1,…,T), we obtain a measure of the company's CTR relative to the market portfolio as $crs_{i,t} = -\left(CRS_{i,t} - \overline{CRS}_t\right)$, where $\overline{CRS}_t$ is the value-weighted average of $CRS_{i,t}$ across all firms: $\overline{CRS}_t = \sum_{i=1}^{N} w_{i,t}\, CRS_{i,t}$, with $w_{i,t}$ denoting the market value weighting of asset *i* at time *t*. Hence, the greater the value of $crs_{i,t}$, the lower the CTR of firm *i* relative to the market portfolio. Running a cross-sectional regression with no intercept of the firms' market-adjusted excess returns on their asset's CTR features, the slope of this regression represents the CTR factor at time *t*:

[1] For further information on the methodology to compute CRS values, see https://www.sustainalytics.com and https://www.morningstar.com/lp/low-carbon-economy.

$$CTR_t = \frac{crs'_{t-1} r_t}{crs'_{t-1} crs_{t-1}}, \tag{1}$$

where crs_t is a column vector containing the value of $crs_{i,t}$ for different firms, and r_t is the column vector of the stocks' market-adjusted excess returns for different firms, computed from a capital asset pricing model (CAPM) using rolling 60-monthly regressions as $r_{i,t} - \beta_{i,t-1} r_{m,t}$, where $r_{i,t}$ and $r_{m,t}$ are the stock i and market returns in excess of the risk-free rate, respectively, and where $\beta_{i,t-1}$ is the beta of stock *i* estimated using information until time *t*-1. Hence, the CTR factor is the return of a portfolio composed of stocks weighted by their CRS, with stocks with low and high risks receiving positive and negative weights, respectively. The CTR factor is a zero-cost long-short portfolio, as commonly used in the finance literature (Fama and French, 2017). As in Pastor et al. (2022), $\sum_{i=1}^{N} w_{i,t}\, crs_{i,t} = 0$, and the CTR portfolio differs from the return difference between low and high CTR stock returns.

3. Data

Below we describe data for the CTR factor, a firm's credit risk, and the control variables used in our empirical analysis.

3.1 Input data to build the climate transition risk factor

We compute monthly values of the CTR_t factor as per Eq. (1), including all European stocks included in the STOXX 600 index. For each month, we take the most recent annual firm-level information on the CRS rating from Sustainalytics and monthly stock returns from Refinitiv over the prior 5-year period to compute the beta of each stock. Using Eq. (1), we compute the values of CTR_t over the sample period January 2014, when data for credit and transition risk is available, to June 2022.

Referring to Figure 1, Panel A depicts the temporal dynamics of the CTR factor along with the STOXX 600 index, showing that both portfolios exhibit different return and volatility patterns, while Panel B graphically depicts cumulated returns of both the CTR factor and the STOXX 600 market index, revealing that the former gradually rose over the sample period and outperformed the latter. This evidence is consistent with the relatively good performance of green assets in recent years as documented in the literature (see, e.g., Pastor et al., 2022; Reboredo and Ugolini, 2022). Descriptive statistics for the CTR factor are reported in Table 1, showing this return factor has a near-zero monthly average, is volatile, and has a skewed and fat-tailed distribution, differing from the STOXX 600 index returns.

3.2 Credit risk measurement

Our sample includes month-end values of CDS spreads denominated in euros for European companies over the period February 2014 to June 2022, with the beginning of the sample determined by the availability of data for the CTR factor. We retrieved data from Refinitiv for single-name CDS and tenors of 1, 2, 5, 10, 20, and 30 years by considering the Modified-Modified Restructuring (2014 Protocol) clause. For each tenor, the sample includes CDS information for firms with data available for the whole sample period; hence, our panel is balanced, although the number of firms and observations may differ across tenors. To mitigate the impact of outliers, we only consider firms with CDS values below 1000 bps, and CDS data for each tenor is winsorized at the 99% level.

Referring to Table 2, Panel A presents descriptive statistics for the CDS data. Average spreads increase with maturity—from 23.27 bps for the 1-year period to 125.05 bps for the 30-year period—reflecting increasing uncertainty. Likewise, dispersion, minimum, and quantile values also rise with maturity. The number of firms (around 138) is quite similar across tenors.

To assess whether CDS spreads differ across firms, we designate three CTR groups according to CRS values, depending on whether risk values are below the 25th quantile (low risk), between the 25th and 75th quantiles (average risk), or above the 75th quantile (high risk) of the CRS distribution.[2]

Panel B shows that firms with high CTR exhibit greater credit risk than firms with low or average CTR, independently of the tenor. Likewise, firms with low and average CTR show similar average levels of credit risk in the short run, while in the long run the CDS spreads of firms with average CTR are greater than for firms with low CTR. This descriptive analysis provides the first evidence on the pricing of CTR in credit markets considering different horizons, pointing to the fact that the market only discerns between highly exposed firms and the remaining firms (with low and average CTR). Figure 2 shows the time dynamics of average CDS spreads for firms in the three groups, documenting that firms with high CTR, independently of tenor, also exhibit greater credit risk over the whole sample period.

Panel C of Table 2 provides evidence on the stationarity properties of the CDS data, confirming that CDS data are stationary according to common and individual unit root panel tests, and allowing us to run our empirical analysis on the level of CDS spreads.

Concluding this section, Table 3 presents the distribution of our sampled firms across different sectors for the whole sample and for the three groups, showing that half of the firms are included in the industry, financial, and discretionary consumer sectors, and that most energy and industrial firms are included in the high CTR group.

[2] Average values for the 25th and 75th quantiles of the CRS distribution are 4.3 and 14.2, respectively.

3.3 Control variables

To isolate the impact of the CTR factor on CDS spreads, we consider a set of firm-specific and firm-shared (i.e., market-level) economic factors that the literature has identified as determinants of CDS spreads (e.g., Ericsson et al., 2009; Zhang et al., 2009; Han and Zhu, 2015; Bai and Wu, 2016; Augustin and Izhakian, 2020; Barth et al., 2022).

In line with structural credit risk models (Merton, 1974), firm-specific variables shaping credit risk include stock returns, returns volatility, leverage, and profitability. Stock returns are computed as the first difference of monthly log prices (retrieved from Refinitiv) in excess of the 1-month Euribor interest rates. Past stock returns are expected to have a negative impact on CDS spreads, as default probability decreases with the past return values (e.g., Galil et al., 2014). As in Campbell and Taksler (2003) and Kaviani et al. (2020), stock volatility is computed as the standard deviation of daily excess returns over the past 252 days (a trading year). As volatility increases default probability, a positive change in volatility is expected to have a positive impact on CDS spreads. A firm's leverage ratio, computed as debt over the sum of total debt at book value and equity at market value (data retrieved from Datastream), is expected to have a positive impact on CDS spreads (Ericsson et al., 2009). Finally, firm profitability, computed using the return on assets (ROA; retrieved from Datastream), is expected to have a negative impact on CDS spread as profitability reduces default risk (Bai and Wu, 2016).

Of market-level control factors expected to impact on CDS spreads, we consider stock market conditions, uncertainty in the treasury market, and the difference between 10-year and 3-month treasury yields. To reflect stock market conditions, we consider stock market returns and the Euro Stoxx 50 volatility index (VSTOXX), which are expected to have a negative and a positive impact, respectively, on the probability of default and, consequently, on CDS spreads. The effect of treasury market uncertainty is determined from the MOVE index, computed from treasury options in Europe by Bank of America Merrill Lynch. Finally, following Han and Zhou (2015), we account for the impact of the difference between 10-year and 3-month treasury yields, since a rise in market expectations regarding interest rates has a positive impact on default probabilities and thus raises CDS spread. Data for all variables at the market level were sourced from Refinitiv.

4. Empirical methods and results

4.1 Climate transition risk and CDS spreads

According to our descriptive evidence, cross-sectional variations in CDS spreads may be driven by firms' CTR vulnerability. As a result, to study the relationship between the CTR factor and the firm's CDS spread considering the firm's vulnerability, our modelling approach relies on threshold panel regression, in which the size effect of the CTR on CDS spreads differs according to the CRS of the firm as follows:

$$CDS_{i,t+1}^{m} = \alpha + \sum_{s=0}^{S} \mathbb{1}_{i,t,s}(\gamma_s \leq CRS_{i,t} \leq \gamma_{s+1})\delta_s CTR_t + \theta Controls_{i,t} + \varphi Controls_t + \varepsilon_{i,t+1} \quad (2)$$

where $CDS_{i,t+1}^{m}$ is the CDS spread of firm *i* at time *t*+1 for maturity m, and where *S* denotes the number of regimes in which the impact of the CTR factor on CDS spreads diverges according to the values of the δ_s parameters. Those regimes reflect the firm's vulnerability to CTR as given by the CRS of the firm and are delimited by the value of the indicator function $\mathbb{1}_{i,t,s}(\gamma_s \leq CRS_{i,t} \leq \gamma_{s+1})$, which takes the value 1 when firm *i* at time *t* has a transition risk in regime *s*, as given by a CRS value between the thresholds γ_s and γ_{s+1}, and zero otherwise. $Controls_{i,t}$ and $Controls_t$ include the firm-specific and firm-shared (market-level) variables, respectively, that may shape credit risk. Included, furthermore, as control variables are fixed effects as follows: sectoral fixed effects (see Table 3 for a sectoral classification) to account for unobserved heterogeneity by cross-section, yearly fixed effects to control for unobserved heterogeneity over time, and country fixed effects to control for differences in market credit conditions across countries. To mitigate reverse causality concerns, the values of independent variables are taken for the previous month. Using a sequential estimation procedure (Bai, 1997; Bai and Perron, 1998, Hansen, 1999), we estimate the model in Eq. (2) to determine the optimal number of regimes S, and thus the threshold values γ_s. Furthermore, to obtain cluster-robust inference, we compute standard errors by clustering at the sectoral, time, firm, and country level to account for cross-sectional and serial correlation in the error terms (Cameron and Miller, 2015).[3]

Table 4 presents the main regression results for different maturities. For all tenors, we identified two regimes delimited by a CRS value of around 16.5 ($\gamma_0 = 0,\ \gamma_1 = 16.5$): regime 1, which includes firms with high CTR (above the 86th percentile of the CRS), and regime 0, composed of the remaining firms, with negligible or average CTR. We observe that the estimated impact of the CTR factor on the CDS spreads of highly exposed firms is positive and significant at the 1% level across different tenors but has a greater impact for longer maturities (5 years or more). In contrast, for firms with negligible or average CTR exposure, our estimates indicate that the CTR factor has no significant effect in shaping a firm's credit risk, except for the 2- and 5-year tenors, for which the effects are positive and significant at the 10% level, with a size that is considerably lower than for firms in regime 1.

Our results point to the fact that CTR as given by the CTR factor is reflected in a firm's creditworthiness only when the firm is highly exposed, with no impact on the remaining firms. According to the magnitude of the estimated coefficients, the economic significance of a CTR factor increase of two standard deviations is reflected in a monthly CDS spread rise, for the more vulnerable firms, of about 12 bps over the short run and about 20 bps over the medium and long

[3] Appendix B provides details on the methodological approach.

runs. Our estimates also have implications for the impact of the hot house world, disorderly transition, and orderly transition scenarios on firm's funding costs, which we quantify in Section 5.

As for the control variables, for all tenors we find that the impact of firm stock returns on CDS spreads is negative and significant at the 1% level, indicating that bull stock market values reduce credit risk; this effect is, additionally, more intense for longer than for shorter tenors. However, independently of the tenor, firm volatility has negligible effects on the CDS spread. Leverage has a positive impact on credit risk for longer tenors, but an insignificant impact for shorter maturities. ROA has a significant negative impact on credit risk at the 10% level, and the impact becomes more pervasive as the tenor increases. This evidence is consistent with credit risk structural models (Ericsson et al., 2009) and previous empirical evidence on determinants of CDS spreads (Bai and Wu, 2016; Duong et al., 2021; Barth et al., 2022). Regarding market-level variables, our evidence indicates that market returns and market uncertainty have negligible impacts on a firm's credit risk, independently of the tenor, and that treasury market uncertainty has no effect on credit risk. Finally, the term spread has a positive impact on CDS spreads, consistent with the fact that an upwardly sloping term structure causes a firm's credit conditions to deteriorate, as reported in the literature (e.g., Duong et al., 2022).

4.2 Robustness checks

We check whether our previous evidence changes with the sample frequency by running the regression model in Eq. (2) using quarterly data, as this frequency coincides with the accounting information used as control variables. Table 5 confirms the evidence reported for monthly data, indicating that the CTR factor has a sizeable impact on credit risk for firms with high CTR, and that this impact is greater for longer tenors.

We further check whether our previous evidence is consistent with alternative proxies for CTR. Berg et al. (2022) document that there is a wide dispersion in the measure of ESG, including carbon emissions; therefore, instead of using CRS information to construct the CTR factor, we use information on GHG Protocol Scopes 1, 2, and 3—sourced from Bloomberg—divided by revenues, which reflect exposure to emissions and thus indirect information on CTR. CRS and GHG Protocol Scopes contain different information, given that some firms may have low emissions by revenues but high CRS ratings due to their failure to implement carbon management actions. The CTR factor arising from CRS information may therefore differ from the information obtained using GHG Protocol Scopes by revenues. For our sample of European firms, Table 6 presents regression results for the CTR factor computed using information on emissions per unit of sales. The reported empirical evidence indicates that the CTR factor is greater for firms more exposed to carbon emissions, although the impact is significant for all firms, while firms with higher emissions also exhibit greater credit risk. This result is qualitatively similar to the evidence reported in Table 4, with differences in significance possibly explained by the fact that the CRS and carbon emissions reflect different CTR information.

Finally, we assess whether the effect of the COVID-19 pandemic had any influence on the size of the impact of the CTR on credit risk, using a proxy variable to delimit the period before and after the peak pandemic period. Table 7 shows that our evidence is fully consistent with the evidence reported in Table 4. Differences between the impact of the CTR factor for firms with high and low CTR exposure remained during the pandemic period, although the medium- and long-term impact was reduced for the more vulnerable firms, while the medium-term impact was reduced for the remaining firms.

5. The impact of climate transition policies on CDS spreads

Below we assess how different climate transition policies may impact a firm's credit risk. Specifically, we consider that different policies can be reflected in the average or quantile values of the CTR factor, which, in turn, has an impact on credit risk. Following the Network for Greening the Financial System (2020), those policies can be framed within the three scenarios of a hot house world, disorderly transition to a low-carbon economy, and orderly transition to a low-carbon economy.

The hot house world scenario is featured by climate policy inaction, growing emissions, and temperature rises above 3ºC in a 50-year period. Therefore, in this scenario more vulnerable firms to CTR will have more time to offload stranded assets, while less vulnerable firms will lose opportunities for business. Arguably, firms with high and low unmanaged CTR as measured by their CRS should experience upward and downward movements in their asset market returns, respectively. Thus, the relative price impact of a hot house world scenario is expressed in terms of a downward movement in the CTR factor, which can be described by its α-quantile, CTR_{α}, given by $P(CTR \leq CTR_{\alpha}) = \alpha$.

In a disorderly transition scenario, polices to reduce emissions and keep temperatures below 2ºC in the next 50 years are introduced abruptly, resulting in high CTR. While policy constraints on emissions and on the use of carbon-intense technologies will support the business of less vulnerable firms, those policies may cause operational difficulties for more vulnerable firms. Therefore, firms with low and high unmanaged CTR as measured by their CRS should experience upward and downward movements, respectively, in their asset market returns. This relative price movement is expressed in terms of an upward movement in the CTR factor, which can be described by its β-quantile, CTR_{β}, given by $P\left(CTR \geq CTR_{\beta}\right) = 1 - \beta$.

Finally, in the orderly transition scenario, climate policies to reduce emissions and keep global warming below 2ºC in the next 50 years are gradually implemented, so all firms will be able to progressively adapt, and consequently, their market returns are not expected to experience abrupt changes. Consistently, the value of all firms, independently of their CTR, is expected to hover around the median value, which can be described by the median value of the CTR, $CTR_{0.5}$, given by $P(CTR \leq CTR_{0.5}) = 0.5$.

We compute quantile values of the CTR factor that reflect the three transition scenarios as $CTR_{\alpha,t} = \mu_t + t_{\upsilon}^{-1}(\alpha)\sigma_t$, where μ_t and σ_t are the conditional mean and standard deviation of the CTR factor at time *t* that can be obtained from a threshold generalized autoregressive conditional heteroscedasticity (TGARCH) moving average model, and where $t_{\upsilon}^{-1}(\alpha)$ denotes the α-quantile of the Student-t distribution of the CTR factor.[4] To assess how a specific climate transition scenario as given by $CTR_{\alpha,t}$ impacts a firm's credit risk, instead of CTR_t we plug $CTR_{\alpha,t}$ into the estimated panel regression in Eq. (2) to obtain the estimated value of $CDS_{i,t+1}^{m}$ in a specific transition scenario.

Figure 3 displays, for different tenors, the impact of the three transition scenarios on firm credit risk over the sample period, considering the two regimes identified in the estimation process, that is, firms with high and firms with average-low CTR (regime 1 and 0, respectively; see Table 4). CDS spreads under different transition scenarios are computed for quantiles $CTR_{0.01,t}$, $CTR_{0.5,t}$, and $CTR_{0.99,t}$. Empirical estimates point to prominent differences in credit risk between scenarios and across firms depending on their CTR vulnerability. Thus, for firms with CRS values below 16.5, CDS spreads have similar values under different transition scenarios and across different tenors. While CDS spreads for the orderly transition are similar to average values, differences for the disorderly and hot house scenarios are around 7 bps for all tenors. Thus, the credit risk of firms

[4] Detailed explanations of CTR factor modelling and computation of quantiles are provided in Appendix A.

with relatively low or average unmanaged CTR are only slightly affected by smooth or abrupt implementation of climate transition policies.

In contrast, for all tenors, firms with high CTR experience a notable rise in CDS spreads in a disorderly transition scenario, and a significant reduction in CDS spreads in a hot house scenario. Average CDS values in those scenarios are 40 bps for the 1-year tenor, rising to 66 pbs for the 30-year tenor. Moreover, CDS spread values in a disorderly transition are more than double the average values, while CDS spreads in a hot house scenario fall to 70% of average values. As for an orderly transition scenario, we find no relevant differences in credit risk effects for the estimated CDS spreads compared to average CDS values.

Overall, our evidence points to the fact that climate transition policies have asymmetric effects on firms' credit risk, with asymmetries determined by a firm's CTR vulnerability. In particular, firms that are highly vulnerable are greatly affected by climate transition policies, while the impact for the remaining firms is negligible. In other words, CTR only shifts the term structure of credit risk for highly vulnerable firms, while there is no significant impact on the term structure of credit risk for the remaining firms. This evidence has implications for both the design and implementation of climate transition policies with specific effects on the credit risk of firms, and for the hedging of climate risks by investors.

6. Conclusions

We have explored whether CTR is reflected in the pricing of credit risk of firms. To that end, we constructed a CTR factor as a portfolio composed of traded assets; each asset is weighted according to its CTR, with positive and negative weights reflecting relatively low or high firm CTR vulnerability, respectively. Changes in the value of the CTR factor are consistent with the repricing effects of CTR, with upward and downward movements reflecting the market pricing effects of high and low CTR, respectively. We measure credit risk using market information on CDS spreads, as this credit derivative echoes the market assessment of a given firm's credit risk and of variations in time, since CDS spread information is available for different time horizons.

Using a panel threshold regression model and a sample of European firms, we find that the CTR factor has an asymmetric impact on credit risk, with positive and significant effects on the credit risk of firms that are highly vulnerable to CTR and with negligible effects for the remaining firms. This evidence points to the fact that investors pay a CTR premium when buying credit protection for firms that are greatly affected by CTR; this premium is economically sizeable, ranging between 12 and 20 bps for short- and long-run maturities, accounting for 35%, 20%, and 13% of the average CDS spread value of the most vulnerable firms in the short-, medium-, and long-run horizons, respectively. Thus, the term structure of CDS spreads of firms more vulnerable to CTR shift upward when the CTR factor increases, with stronger impacts for longer than for shorter tenors.

We also assess how CTR would impact credit risk under three climate transition scenarios (hot house world, disorderly and orderly transition to a low-carbon economy), each characterized by different climate transition policy pricing effects on the CTR factor. In a disorderly transition, featured by downward CTR factor movement, the CDS spread term structure for the most vulnerable firms shifts upward, whereas the opposite occurs in a hot house scenario. Differences in CDS spreads between those scenarios are 40 bps to 66 bps for the short- and long-run maturities, respectively. In an orderly transition, featured by median CTR factor values, CTR has a negligible impact on credit risk, independent of the firm's vulnerability to CTR. Our evidence thus points to an asymmetric effect of climate transition policies: the impact on credit risk of the less vulnerable firms is negligible, but it is significant for highly vulnerable firms.

Our findings suggests that firms better prepared for the transition to a low-carbon economy have a lower cost of capital and are more sheltered from the effects of climate transition policies. This is relevant CTR information for investors in terms of portfolio design and hedging decisions and for policymakers in terms of channelling the financial funding necessary to facilitate the transition to a low-carbon economy. It also relevant for the manner in which climate transition polices are implemented, as aggregate CTR has a minor impact on credit risk when polices are introduced smoothly and a sizeable asymmetric impact when they are not.

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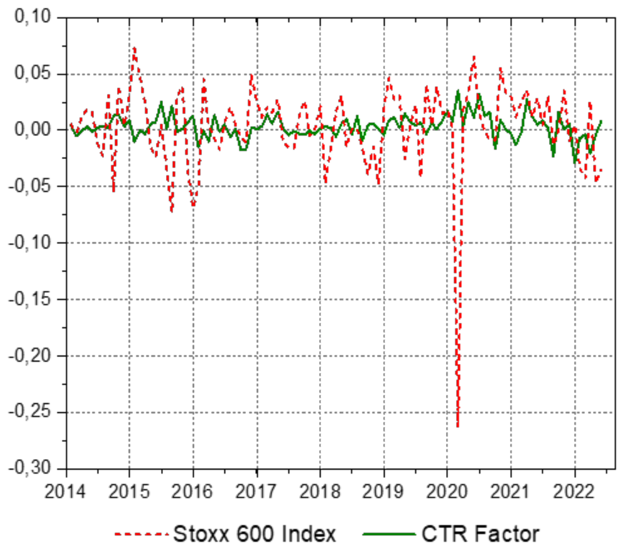
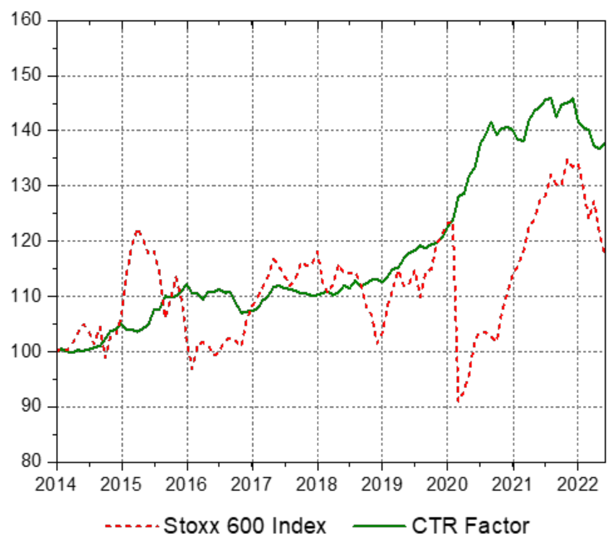
Figure 1. The CTR factor and the STOXX 600 index.



Panel A. Time series plot of the CTR factor and the STOXX 600 index log-returns.



Panel B. Cumulative returns of the CTR factor and the STOXX 600 index (initial value 100).

Figure 2. Average CDS spreads (tenors 1 to 30 years) for firms with low (G1, in green), average (G2, in blue), and high (G3, in red) CTR.

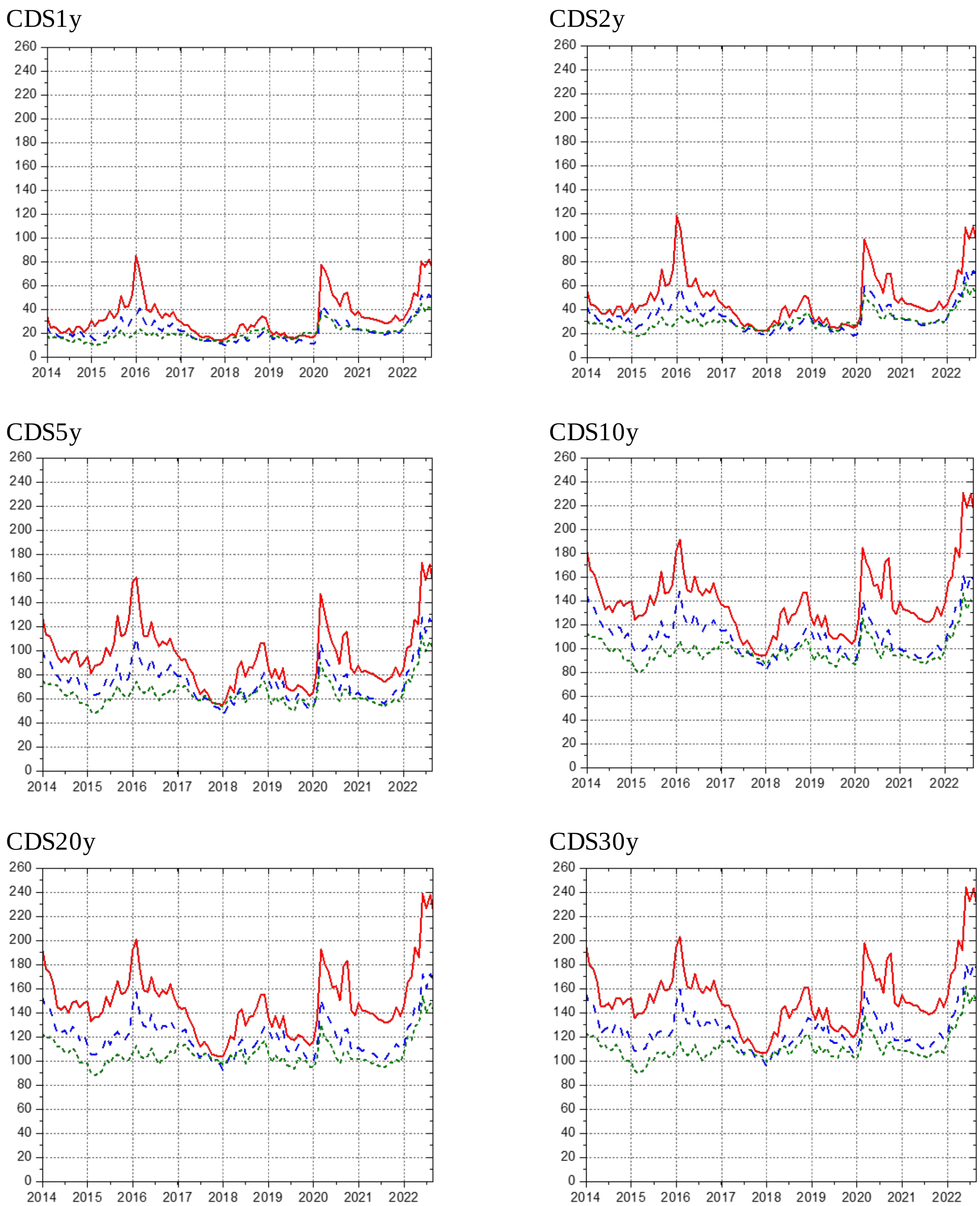
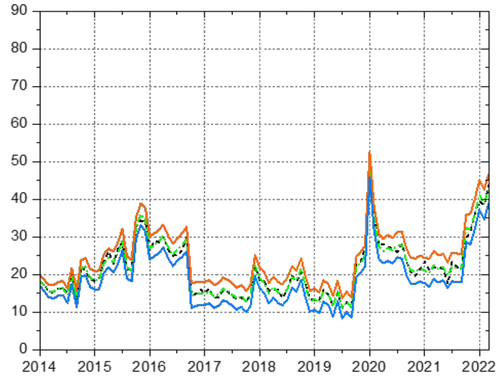


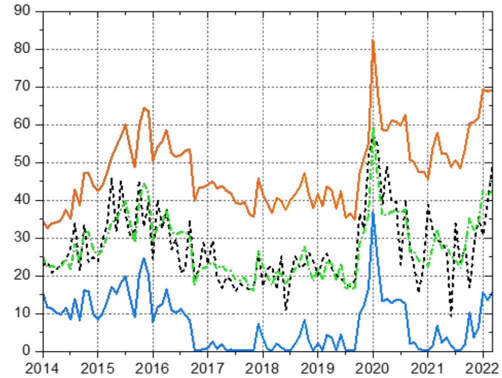
Figure 3. The effect of climate transition scenarios on CDS spreads (tenors 1 to 30 years).

CDS1y

Firms with $CRS < \gamma_1$

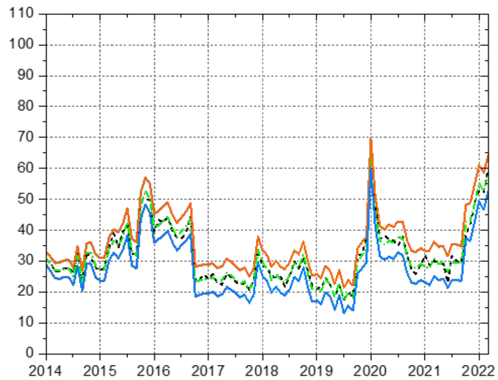


Firms with $CRS \geq \gamma_1$

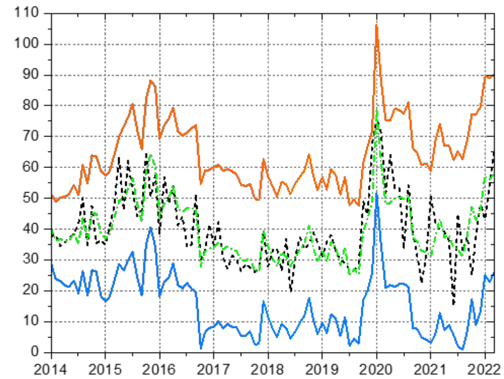


CDS2y

Firms with $CRS < \gamma_1$

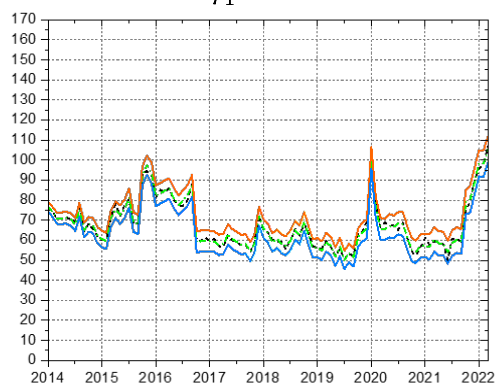


Firms with $CRS \geq \gamma_1$

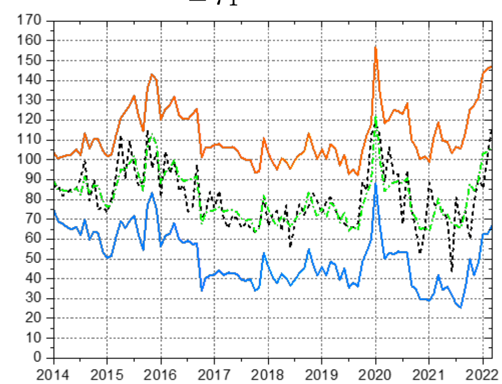


CDS5y

Firms with $CRS < \gamma_1$



Firms with $CRS \geq \gamma_1$

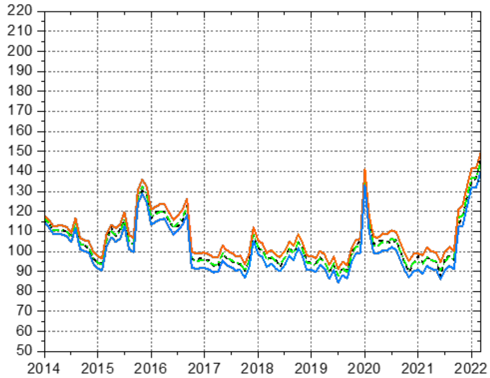


Mean Orderly Disorderly Hot House

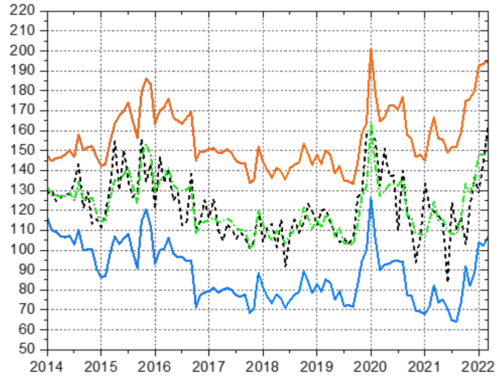
Figure 3, Cont.

CDS10y

Firms with $CRS < \gamma_1$

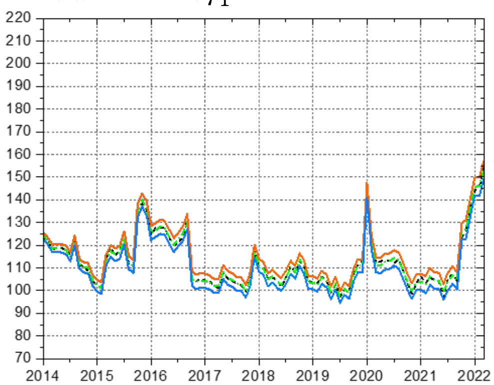


Firms with $CRS \geq \gamma_1$

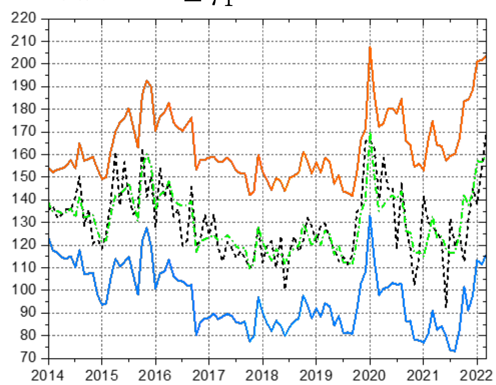


CDS20y

Firms with $CRS < \gamma_1$

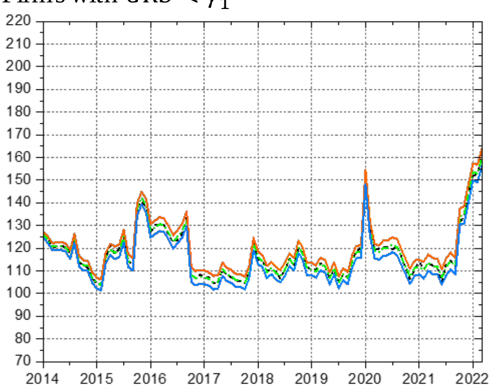


Firms with $CRS \geq \gamma_1$

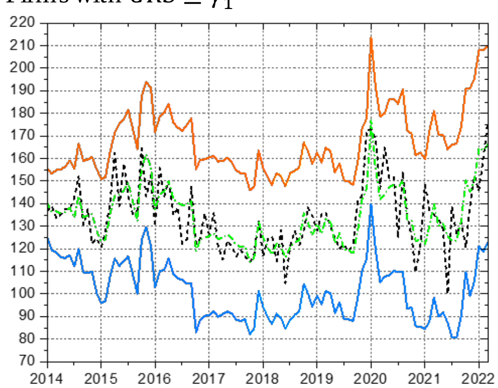


CDS30y

Firms with $CRS < \gamma_1$



Firms with $CRS \geq \gamma_1$



Mean Orderly Disorderly Hot House

Note: The value of γ_1 for each tenor is provided in Table 4.

Table 1. Descriptive statistics for the CTR factor and the STOXX 600 index returns.

	CTR	STOXX 600
Mean	0.003	0.002
St. Dev.	0.011	0.039
Skewness	0.036	-3.134
Kurtosis	1.263	18.733
Max	0.035	0.073
Min	-0.029	-0.263
p1	-0.023	-0.073
p5	-0.017	-0.048
p50	0.003	0.005
p95	0.022	0.046
p99	0.032	0.065

Notes. This table presents summary statistics for the monthly CTR factor (log) returns and STOXX 600 index (log) returns: mean, standard deviation, skewness, kurtosis, maximum, minimum, and percentiles 1 (p1), 5 (p5), 50 (p50), 95 (p95), and 99 (p99).

Table 2. Descriptive statistics for CDS spreads.

	CDS1y	CDS2y	CDS5y	CDS10y	CDS20y	CDS30y
Panel A. Full sample						
Mean	23.266	34.972	74.068	111.268	120.268	125.052
St. Dev.	32.101	38.645	52.880	64.141	65.323	65.559
kurtosis	79.270	80.142	24.071	16.716	13.948	13.071
Skewness	6.868	6.401	3.377	2.919	2.703	2.619
Max	683.875	950.150	955.909	986.459	930.625	912.953
Min	1.000	2.410	6.480	25.980	33.720	36.590
p10	6.560	11.110	28.770	52.595	58.760	63.222
p25	9.380	16.310	42.705	72.308	80.125	84.290
p50	14.590	24.690	61.480	96.470	105.845	111.070
p75	24.420	38.740	85.300	129.135	139.445	145.070
p90	44.110	64.934	132.244	183.135	192.135	197.514
# firms	140	137	139	136	136	137
Panel B. Firms grouped by their CTR						
Group G1: firms within the first CRS quartile						
Mean	20.152	30.193	63.602	97.483	105.174	110.446
St. Dev.	28.400	30.988	42.215	50.575	52.335	53.014
Min	1.210	3.050	10.360	25.980	33.720	36.590
Max	476.390	456.623	438.065	556.080	491.082	460.182
Obs.	3870	3674	3876	3674	3674	3775
Group G2: firms within the interquartile range						
Mean	20.460	31.494	69.978	105.771	115.474	120.513
St. Dev.	23.214	29.981	44.310	52.968	54.546	55.266
Min	1.000	2.410	6.480	29.830	37.360	36.650
Max	665.990	850.090	437.930	487.810	500.300	510.040
Obs.	6607	6512	6549	6489	6489	6489
Group G3: firms within the last CRS quartile						
Mean	31.617	45.985	92.706	135.425	144.495	148.725
St. Dev.	45.390	54.088	69.998	85.202	85.581	85.484
Min	2.079	3.430	15.090	39.250	40.070	40.170
Max	683.875	950.150	955.909	986.459	930.625	912.953
Obs.	3663	3651	3614	3573	3573	3573
Panel C. Panel unit root test						
Common test						
LHC	-3.936	-2.403	-1.710	-4.143	-2.757	-2.101
	[0.00]	[0.01]	[0.04]	[0.00]	[0.00]	[0.02]
Individual tests						
IPS	-12.941	-12.701	-9.779	-10.604	-10.358	-10.104
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
ADF	769.077	733.316	602.331	626.056	619.674	616.722
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
PP	789.711	698.944	626.233	641.905	611.312	602.543
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]

Notes. This table presents summary statistics for monthly CDS spreads of European companies for tenors of 1, 2, 5, 10, 20, and 30 years (CDS1y, CDS2y, CDS5y, CDS10y, CDS20y, and CDS30y) over the period February 2014 to June 2022. For the full sample, Panel A reports mean, standard deviation, maximum, minimum, percentiles 10 (p10), 25 (p25), 50 (p50), 75 (p75), and 90 (p90), and number of firms. Panel B reports summary statistics for CDS spreads considering three groups: firms with a CRS lower than the first quantile of the CRS (G1), firms with a CRS between the 25th and 75th quantile of the CRS (G2), and firms with a CRS above the 75th quantile of the CRS (G3). Panel C reports the panel unit root tests for monthly CDS spreads: LHC (Levin, Lin, and Chu t); IPS (Im, Pesaram, and Shin), ADF (Augmented Dickey Fuller), and PP (Phillips and Perron).

Table 3. Distribution of sampled firms across sectors and countries.

	CDS1y			CDS2y			CDS5y			CDS10y			CDS20y			CDS30y		
	G1	G2	G3	G1	G2	G3	G1	G2	G3	G1	G2	G3	G1	G2	G3	G1	G2	G3
Consumer discretionary	14	7	4	12	7	4	14	7	4	12	7	4	12	7	4	13	7	4
Consumer staples	13	2		13	2		13	2		13	2		13	2		13	2	
Energy			4			4			4			4			4			4
Financials	6	19		6	19		6	19		6	19		6	19		6	19	
Healthcare	8			8			8			8			8			8		
Industrials	5	10	8	5	9	8	5	9	8	5	9	9	5	9	9	5	9	9
Information technology	3			3			3			3			3			3		
Materials	1	8	3	1	8	3	1	7	3	1	7	2	1	7	2	1	7	2
Real estate	1	1		1	1		1	1		1	1		1	1		1	1	
Telecommunication	1	8		1	8		1	8		1	8		1	8		1	8	
Utilities	2	12		2	12		2	13		2	12		2	12		2	12	
Total	54	67	19	52	66	19	54	66	19	52	65	19	52	65	19	53	65	19

Notes. For the European CDS market over the period February 2014 to June 2022, this table shows the number of firms in our sample from 2014 to 2022 by sector (based on the Sustainalytics industry classification), considering tenors of 1, 2, 5, 10, 20, and 30 years (CDS1y, CDS2y, CDS5y, CDS10y, CDS20y, and CDS30y) and three groups: firms with low CTR (G1), average CTR (G2), and high (G3) CTR.

Table 4. Estimates of the impact of the CTR factor on CDS spreads for different tenors.

	CDS1y	CDS2y	CDS5y	CDS10y	CDS20y	CDS30y
γ_1	16.996	17.784	16.512	16.512	16.512	16.388
δ_0	82.942	124.886*	138.616*	102.371	83.724	81.051
	(1.56)	(1.77)	(1.73)	(0.92)	(0.73)	(0.71)
δ_1	575.684***	689.067***	867.049***	950.073**	941.487**	931.025**
	(3.47)	(3.20)	(3.68)	(2.30)	(2.22)	(2.20)
Control variables						
Constant	13.369*	20.422**	49.174***	70.494***	81.140***	89.023***
	(1.69)	(2.24)	(4.13)	(5.94)	(6.97)	(7.80)
Stock return	-41.678***	-55.444***	-68.156***	-71.055***	-73.472***	-74.027***
	(-2.94)	(-3.07)	(-5.35)	(-6.52)	(-6.32)	(-6.07)
Stock volatility	1.155	1.316	0.698	0.049	-0.015	-0.024
	(1.24)	(1.12)	(0.74)	(0.08)	(-0.02)	(-0.04)
Leverage	-1.099	2.732	10.841	80.872**	81.645**	82.543**
	(-0.12)	(0.30)	(0.61)	(2.22)	(2.21)	(2.24)
ROA	-0.744**	-1.043**	-1.640*	-2.278*	-2.400*	-2.390*
	(-2.05)	(-2.12)	(-1.72)	(-1.74)	(-1.78)	(-1.75)
Market returns	5.866	8.540	10.009	17.118	21.864	22.072
	(0.39)	(0.44)	(0.40)	(0.71)	(0.90)	(0.92)
Market volatility	0.374	0.482*	0.497	0.494	0.456	0.441
	(1.56)	(1.66)	(1.35)	(1.41)	(1.47)	(1.48)
Move	0.036	0.042	0.099	0.085	0.088	0.091
	(0.66)	(0.61)	(0.99)	(0.83)	(0.92)	(0.97)
Term	5.554**	9.200**	16.515***	18.067***	18.026***	17.060***
	(2.04)	(2.46)	(3.18)	(4.07)	(4.05)	(3.74)
Sector FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
R^2	0.17	0.20	0.28	0.30	0.31	0.31

Notes. This table presents estimates for the response of monthly CDS spreads to the CTR factor for European firms as per Eq. (2). Columns 2 to 7 include estimates for tenors of 1, 2, 5, 10, 20, and 30 years (CDS1y, CDS2y, CDS5y, CDS10y, CDS20y, and CDS30y) over the period February 2014 to June 2022. γ_1 denotes the threshold value for the CRS, while δ_0 and δ_1 denote the parameter values for the CTR factor in regimes 0 and 1, respectively. The model includes firm-specific (stock returns, return volatility, leverage, and ROA) and market-level (market returns, volatility, treasury market volatility (MOVE), and term spread) control variables, and also Sustainalytics industry classification fixed effects (Sector FE), yearly fixed effects (Time FE), and country fixed effects (Country FE). t-statistics—reported in parentheses—are computed using standard errors clustered by firm, time, sector, and country. The asterisks ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Estimates of the quarterly impact of the CTR factor on CDS spreads for different tenors.

	CDS1y	CDS2y	CDS5y	CDS10y	CDS20y	CDS30y
γ_1	475.347	489.497	398.030	453.202	453.202	453.202
δ_0	91.474***	121.814***	150.089**	105.026	99.379	107.097
	(2.78)	(2.65)	(2.35)	(1.27)	(1.19)	(1.26)
δ_1	297.477*	407.918*	543.177*	696.644	715.698	716.671
	(1.65)	(1.67)	(1.69)	(1.30)	(1.27)	(1.27)
Control variables	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
R^2	0.20	0.25	0.33	0.32	0.33	0.33

Notes. See notes for Table 4.

Table 6. Estimates of the impact of the CTR factor on CDS spreads for different tenors using carbon emissions data to obtain the value of the CTR factor.

	CDS1y	CDS2y	CDS5y	CDS10y	CDS20y	CDS30y
γ_1	11.760	11.700	11.200	11.200	11.650	11.300
δ_0	231.257***	321.085***	406.626***	316.346*	302.017*	307.950*
	(2.84)	(2.92)	(3.06)	(1.83)	(1.74)	(1.78)
δ_1	837.871*	1003.996*	1171.212*	1442.624	1433.745	1408.094
	(1.67)	(1.75)	(1.78)	(1.46)	(1.41)	(1.40)
Control variables	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
R^2	0.17	0.20	0.28	0.30	0.31	0.31

Notes. See notes for Table 4.

Table 7. Effects of COVID-19 on the impact of the CTR factor on CDS spreads for different tenors.

	CDS1y	CDS2y	CDS5y	CDS10y	CDS20y	CDS30y
γ_1	16.996	17.512	16.512	16.512	16.512	16.388
δ_0	129.845*	200.644**	241.273**	191.666	160.111	150.598
	(1.88)	(2.16)	(2.27)	(1.23)	(1.00)	(0.94)
δ_1	714.881***	899.363***	1179.269***	1222.118***	1206.206***	1189.521***
	(3.08)	(3.25)	(3.92)	(2.97)	(2.84)	(2.81)
$d_{COVID}\delta_0$	-110.617	-178.069*	-241.461*	-210.031	-180.157	-164.340
	(-1.55)	(-1.86)	(-1.88)	(-1.29)	(-1.05)	(-0.96)
$d_{COVID}\delta_1$	-332.838	-499.038	-771.563	-676.277***	-658.504***	-643.240**
	(-0.98)	(-1.22)	(-1.53)	(-2.79)	(-2.57)	(-2.51)
Control variables	Y	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y
R^2	0.17	0.20	0.28	0.30	0.31	0.31

Notes. See notes for Table 4. d_{COVID} denotes a dummy variable that takes the value of 1 if the CDS observation is later than 15/03/2020. $d_{COVID}\delta_j$ is the estimated parameter value for $d_{COVID}\delta_j CTR_t$ in regime j=0,1.

Appendix A

This appendix provides information on the modelling approach for the CTR in order to compute quantiles that are consistent with the three climate transition scenarios. We assume that the time dynamics of the CTR is described by an autoregressive (AR) moving average (MA) model:

$$CTR_t = \phi_0 + \sum_{q=1}^{m} \phi_q CTR_{t-q} + \sum_{k=1}^{k} \varphi_k \varepsilon_{t-k} + \varepsilon_t, \tag{A1}$$

where ϕ_q and φ_r denote the parameters of the AR and MA components, and ε_t is a stochastic zero mean variable with variance given by a threshold generalized autoregressive conditional heteroskedasticity (TGARCH) model:

$$\sigma_t^2 = \omega_0 + \sum_{k=1}^{K} \beta_q \sigma_{t-k}^2 + \sum_{h=1}^{H} \alpha_h \varepsilon_{t-h}^2 + \sum_{h=1}^{H} \delta_h 1_{t-h} \varepsilon_{t-h}^2, \tag{A2}$$

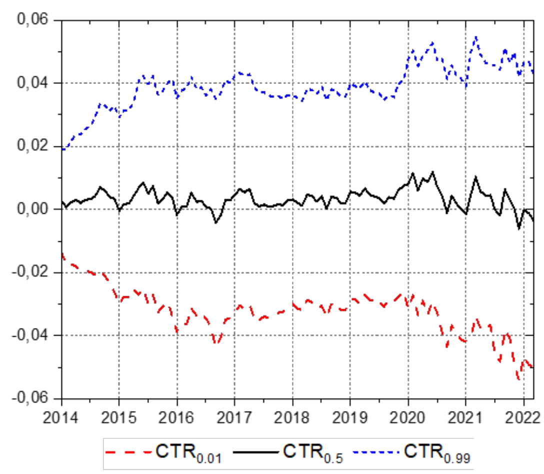
where ω_0, β_q, and α_h are the parameters of the volatility model. $1_{t-h} = 1$ if $\varepsilon_{t-h} < 0$ and otherwise is zero, so the parameter δ_h accounts for the asymmetric effect of shocks: negative shocks have more (less) impact on variance than positive shocks when $\delta_h > 0$ (< 0). When $\delta_h = 0$, we have the standard GARCH model. To account for fat tails and asymmetries in the distribution of CTR, the distribution of ε_t is assumed to be given by Student-t density. Hence, we compute the α-quantile values of the CTR factor at time *t* as $CTR_{\alpha,t} = \mu_t + t_{\upsilon,\eta}^{-1}(\alpha)\sigma_t$, where $\mu_t = \phi_0 + \sum_{q=1}^{m} \phi_q CTR_{t-q} + \sum_{k=1}^{k} \varphi_k \varepsilon_{t-k}$, σ_t is the root square of Eq. (A2), and where $t_{\upsilon,\eta}^{-1}(\alpha)$ denotes the α-quantile of the Student-t distribution. Table A1 shows the parameter estimates of the ARMA TGARCH model for the CTR factor, while Figure A1 shows the dynamics of the quantiles of the CTR factor that reflect the three climate transition scenarios: $CTR_{0.01}$, $CTR_{0.5}$, and $CTR_{0.99}$ for the hot house, orderly transition, and disorderly transition scenarios, respectively.

Table A1. Maximum likelihood estimates of the distribution of the CTR factor.

Mean equation		
ϕ_0	ϕ_1	ϕ_2
0.002*	0.113	0.256*
(2.146)	(1.115)	(2.750)
Variance equation		
ω	α_1	β_1
0.000	0.053	0.903*
(0.840)	(0.650)	(8.005)
υ	4.724	
	(2.220)	
LogLik.	320.26	
LJ	10.376	
	[0.96]	
LJ 2	25.061	
	[0.16]	
ARCH	1.187	
	[0.29]	

Notes. This table reports empirical estimates for the CTR model and the corresponding z-statistics (in parentheses). An asterisk (*) indicates significance at 5%. LogLik is the log-likelihood value, and LJ and LJ2 denote the Ljung-Box statistics for serial correlation in the (squared) residual model calculated with 20 lags. ARCH is Engle's LM test for the ARCH effect in residuals computed with 20 lags.

Figure A1. Times series plot of the CTR quantiles.



Appendix B: Threshold Model

In threshold regression modelling, the number of thresholds, denoted by m, partitions the observed range of a continuous variable into $m + 1$ regions. The regions are indexed by $S = 1, \ldots, m + 1$. The threshold regression model can be expressed as a linear combination of regressors and indicator functions of the observed variable falling within each of the $m + 1$ regions. The model can be represented as

$$y_t = \mathbf{x_t}\boldsymbol{\beta} + \sum_{S=1}^{m+1} \mathbf{z_t}\boldsymbol{\delta_j}\, I_S(\gamma_S, w_t) + \epsilon_t, \tag{1}$$

where $\gamma_1 < \gamma_2 < \cdots < \gamma_m$ are ordered thresholds with $\gamma_0 = -\infty$ and $\gamma_{m+1} = \infty$. $I_S(\gamma_S, w_t) = I(\gamma_{S-1} < w_t \leq \gamma_S)$ is an indicator for the Sth region. The ordered thresholds $\gamma_1 < \gamma_2 < \cdots < \gamma_m$ are estimated sequentially, starting from a model with two regions and then extending to a model with $m + 1$ regions.

The threshold estimator is obtained by minimizing the sum of squared errors (SSE) over all observations in the corresponding region. The estimator of the lth threshold γ_l^*, conditional on the previous $l - 1$ estimated thresholds $\widehat{\gamma_1^*}, \ldots, \widehat{\gamma_{l-1}^*}$, is given by

$$\widehat{\gamma_l^*} = \arg\min_{\gamma_l^* \in \Gamma_l} SSE_{T_l}\left(\gamma_l^* \mid \widehat{\gamma_1^*}, \ldots, \widehat{\gamma_{l-1}^*}\right), \tag{2}$$

where $SSE_{T_l}\left(\gamma_l^* \mid \widehat{\gamma_1^*}, \ldots, \widehat{\gamma_{l-1}^*}\right)$ is the SSE of a regression with l regions. The set Γ_l denotes the range of the lth threshold, which excludes the previously estimated thresholds. The number of thresholds is determined by selecting the optimal value of m that minimizes a criterion such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), or Hannan-Quinn Information Criterion (HQIC), which are defined in terms of the SSE and the number of parameters.