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Invited paper

Ask BERT: How Regulatory Disclosure of Transition and Physical Climate Risks Affects the CDS Term Structure*

Julian F. Kölbel[1], Markus Leippold [2], Jordy Rillaerts[3], and Qian Wang[4]

[1]Swiss Institute of Banking and Finance, University of St. Gallen, 9000 St. Gallen, Switzerland, [2]Department of Banking and Finance, Swiss Finance Institute (SFI), University of Zurich, Plattenstrasse 14, 8032 Zurich, Switzerland, [3]Department of Banking and Finance, Swiss Finance Institute (SFI), University of Zurich, Plattenstrasse 14, 8032 Zurich, Switzerland and [4]Department of Banking and Finance, University of Zurich, Plattenstrasse 14, 8032 Zurich, Switzerland

Address correspondence to Markus Leippold, Department of Banking and Finance, Swiss Finance Institute (SFI), University of Zurich, Plattenstrasse 14, 8032 Zurich, Switzerland, or e-mail: markus.leippold@bf.uzh.ch.

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Abstract

We use BERT, an AI-based algorithm for language understanding, to quantify regulatory climate risk disclosures and analyze their impact on the term structure in the credit default swap (CDS) market. Risk disclosures can either increase or decrease CDS spreads, depending on whether the disclosure reveals new risks or reduces uncertainty. Training BERT to differentiate between transition and physical climate risks, we find that disclosing transition risks increases CDS spreads after the Paris Climate Agreement of 2015, while disclosing physical risks decreases the spreads. In addition, we also find that the election of Trump had a negative impact on CDS

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spreads for firms exposed to transition risk. These impacts are consistent with theoretical predictions and economically and statistically significant.

Key words: climate risk disclosure, CDS spreads, 10-K filings, physical risks, transition risks, BERT model

JEL classification: G13, G28, M48

> Without effective disclosure of these risks, the financial impacts of climate change may not be correctly priced—and as the costs eventually become clearer, the potential for rapid adjustments could have destabilizing effects on markets.
>
> Michael Bloomberg, chairman on the TCFD, Financial Stability Board (2017)

Risk disclosure is a central problem in climate finance. The efficient pricing of climate risks in capital markets requires that companies provide adequate disclosure of firm-specific risks arising from climate change. Climate risks entail physical risks that emerge from extreme weather events and transition risks stemming from regulatory reforms intended to combat global warming. These two risks may affect companies in different ways. Most institutional investors believe that climate risks have significant financial implications for firms and argue for more climate risk disclosure (Krueger, Sautner, and Stark 2020). In response, regulators worldwide recognize the importance of mandating climate risk disclosure. Already in 2010, the US Securities and Exchange Commission (SEC) has adopted a principles-based approach in this regard,[1] requiring firms to self-identify climate-related risks that are material to their business in their 10-K report (SEC 2010).

While the importance of climate risk disclosure for market efficiency is agreed upon, the directional effect of disclosing climate risks on risk premia is not obvious. Risk disclosure may trigger two opposing effects, a risk-perception and an information-uncertainty effect. When disclosure reveals a novel risk factor, it increases investors' risk perception, leading to higher risk premia.[2] However, when disclosure reduces the information asymmetry between investors and companies (Campbell et al. 2014), it can resolve uncertainty around a risk factor and, as a consequence, leads to a decrease in risk premia (Duffie and Lando 2001; Yu 2005). We hypothesize that transition risk is likely to have a risk-perception effect because the prospect of tangible climate regulation emerged only recently, in particular with the Paris Agreement in 2015. In contrast, we hypothesize that the disclosure of physical risk has an uncertainty reduction effect since extreme weather events *per se* are a well-known risk factor.

1 In contrast, the Task Force on Climate-Related Financial Disclosures (TCFD), for example, adopts a standards-based approach that calls on firms to disclose a specific set of information and metrics. However, the application of TCFD guidelines is so far purely voluntary and their information content may be limited. For instance, 10 of the 36 pages of Morgan Stanley's inaugural TCFD report in 2020 are full-page photographs and there is no disclosure on carbon-related assets.

2 See, for example, Kothari, Li, and Short (2009) for bond markets. Also, Kravet and Muslu (2013) find that an annual increase in the number of risk sentences in a company's 10-K filing is associated with higher stock return volatility.

To test these hypotheses, we develop a novel firm-specific measure of climate risk based on regulatory disclosure in 10-K reports.[3] We use a powerful natural language processing (NLP) technique called bidirectional encoder representations from transformers (BERT), a deep neural network developed by researchers at Google (DevlIn et al. 2019).[4] BERT is superior to older NLP algorithms because it can interpret words in context. For complex topics such as climate change risks, this feature is a decisive advantage (Varini et al. 2020). We use BERT to classify sentences from the section Item 1.A of a firm's 10-K report and generate a firm-specific measure of both transition and physical risks. This novel method allows us to significantly improve upon older NLP methods that are commonly used in finance.[5]

To analyze the price impact of regulatory climate-risk disclosure as measured by BERT, we rely on credit default swaps (CDSs) at different maturities.[6] Climate risks primarily represent rare and tail risks. Therefore, we suspect that using derivative prices such as options and CDS offers some advantages over, for example, equity prices in identifying these risks. Compared with options, CDS provide a more accurate measure for long-term risks far in the tail. As CDS spreads theoretically represent a firm's pure credit risk, the analysis of the CDS term structure allows us to study the effects of climate risk on various maturities. Furthermore, the CDS market is dominated by professional investors with the analytical capacity to take climate risks into account. In addition, CDS contracts provide limited upside potential, making investors in this market particularly sensitive to negative news.[7]

We find that the CDS market responds distinctively to the disclosure of transition and physical risks captured by our firm-specific scores. After the Paris Climate Accord of 2015, the disclosure of transition risk increases credit spreads, which is consistent with the hypothesized risk-perception effect. However, with the election of Trump as president of the USA on November 8, 2016, this effect is reversed due to the perceived dismantling of major climate policies by the Trump administration and was particularly significant for the 1-year maturity CDS spread.[8] In contrast to transition risk, physical climate risks do not

3 Recently, Deng et al. (2022) use our measure to analyze the stock market reaction to the Ukraine war. They find that companies with high transition risk scores perform better than stocks with low transition risk and they relate this observation to a slow-down in the transition to a low-carbon economy.

4 On October 25, 2019, Google announced that it built BERT into the Google Search engine. See https://blog.google/products/search/search-language-understanding-bert/.

5 Extensions of the BERT methodology can be found in Webersinke et al. (2021) and Bingler et al. (2022b).

6 To mitigate concerns that we introduce a bias in our analysis due to some interference with determinants for CDS offerings, we also analyzed our climate scores for an equally sized sample of US stocks that we selected randomly from the Russell 3000 index. We find that the aggregate distributions of the climate scores are almost identical. Therefore, we think that there are no unwanted effects on climate risk disclosure generated by the fact that a company has issued CDS contracts.

7 Defond and Zhang (2014) find that bond price quotes impound bad earnings news on a more timely basis than good earnings news and that the bond market impounds bad news on a more timely basis than the stock market. Therefore, the risk-perception effect of annual reports' risk disclosure should be more significant for CDS than stock prices.

8 In particular, while a one standard deviation increase in transition risks leads to a 1.8% increase in the average 5-year CDS spread for the Paris Agreement, we find that the effect of the Trump election caused a one standard deviation increase to reduce the CDS spread by nearly 6%.

react to changing administrations. We find that the disclosure of physical risks has a negative effect on credit spreads, which is consistent with an uncertainty reduction effect. All these effects become (highly) significant only when restricting the sample to industries in which climate risks are deemed material, as defined by the Sustainability Accounting Standards Board (SASB).

Our paper addresses the fundamental problem of measurement in climate finance (Berg, Kölbel, and Rigobon 2022) by providing novel metrics of firm-specific transition and physical climate risk. With that, we contribute to a small but growing literature that uses NLP methods to identify climate-relevant information in text data (Grüning 2011; Berkman, Jona, and Soderstrom 2021; Luccioni and Palacios 2019; Engle et al. 2020; Sautner et al. 2022). Most closely related in this regard are Berkman, Jona, and Soderstrom (2021), who use a simple keyword-based approach to analyze 10-K reports, and Sautner et al. (2022), who use a more sophisticated keyword-based approach to analyze earnings call transcripts. The key innovation of our approach is that BERT is a more advanced NLP algorithm that is able to interpret words in their context. For instance, the word "climate" would have the same context-free interpretation in "business climate (BC)" and "climate change risk." BERT interprets "climate" using both its preceding and subsequent context, significantly improving the precision (Prec) of sentence classification (Varini et al. 2020). We benchmark BERT against these other NLP algorithms and demonstrate that BERT is substantially better in identifying climate-related sentences.[9]

Given that the measures of Sautner et al. (2022) are freely available, we use these to repeat our analyses as a robustness check.[10] Our results do not replicate when using these alternative measures, and they do not replicate when we use carbon emissions as a proxy for climate risk, which have been used in several other recent studies. We attribute this non-replication to the fact that our climate risk score is a more precise measure due to its reliance on standardized mandatory reporting and the BERT algorithm. Nevertheless, we recognize that further improving firm-specific climate risk scores is essential. Moreover, NLP and language understanding is a fast-moving research field. For these reasons, we make our scores on transition and physical climate risk disclosure publicly available for other researchers.[11]

Our paper also adds to the wider literature on the pricing of climate risks. Several studies suggest that transition risks are priced with a "carbon premium" in equity markets (Engle et al. 2020; Bolton and Kacperczyk 2021; Ramelli et al. 2021), in corporate credit markets (Delis, de Greiff, and Ongena 2019; Duan, Li, and Wen 2021), and option markets (Ilhan, Sautner, and Vilkov 2021). The impact of physical risks on the pricing of corporate securities is less explored and existing studies suggest that there may be mispricing (Bansal, Kiku, and Ochoa 2016; Hong et al. 2019). Our paper is unique in that it studies transition

9 While keyword-based approaches may still deliver reasonable results for simple tasks such as classifying a sentence into climate and non-climate, for more involved tasks such as differentiating between transition risk and physical risk, context-based approaches are by far outperforming these rule-based approaches.

10 In an earlier version, we also used the data in Berkman, Jona, and Soderstrom (2021) provided by CookESG that also relies on 10-K forms. However, these data are no longer available. Therefore, we dropped these results from our analysis.

11 Our data can be downloaded from the Open Science Framework; https://osf.io/pk2u9/.

and physical risk simultaneously and suggests that disclosure of transition and physical risk has differential effects.

Finally, our study is also related to general risk assessments based on 10-K filings (Hope, Hu, and Lu 2016; Friberg and Seiler 2017; Lopez-Lira 2019). Most of this literature finds a significant effect of the disclosed risks, proving that current disclosure methods provide relevant information and add value. However, we differentiate from these studies by analyzing the disclosure's effects through the risk perception and information uncertainty channels.

Our results imply that the climate risk disclosure mandated by the SEC fulfills, at least to some extent, its purpose of informing investors about material risks. However, regulators should note the difference between transition and physical risk. Our results suggest that firms actually have an incentive to disclose physical risks since this reduces their cost of debt. In contrast, firms appear to have a disincentive to disclose transition risks. This suggests that regulators may want to pursue different approaches to these two different types of risks. For example, disclosure of physical risks could evolve on a voluntary and flexible basis, whereas the disclosure of transition risk may require more coercion.

We organize the remainder of this article as follows. In Section 1, we argue theoretically why and how climate risk disclosures may impact CDS prices. Section 2 introduces our method to measure climate risk by quantifying climate-relevant information from 10-K filings. Then, in Section 3, we give an overview of the data, which underlies our study. Section 4 reports and discusses the main results. Finally, Section 5 concludes this article.

1 How Does Climate Risk Disclosure Affect Credit Spreads?

Before turning to the specific problem of climate risk disclosure, we review the theoretical expectations for risk disclosure in general. The literature suggests two opposing effects of risk disclosure on credit risk, a risk-perception effect, resulting in an increase of credit spreads, and an information-uncertainty effect, resulting in a decrease of credit spreads. Before we apply these theoretical expectations to the case of climate risk, we briefly revisit the underlying concepts in more detail.

1.1. Increasing Risk Perception

The risk-perception effect describes how investors' perception of corporate risk may increase following an increase in risk disclosure (Kothari, Li, and Short 2009). To analyze the impact of a change in risk perception on CDS prices, we develop our arguments based on the classical Merton (1974) model. Although it is a very stylized model, the financial industry often relies on this structural credit risk model to estimate the probability of default (PD) for a given company.[12] Studies such as Duffie, Saita, and Wang (2007) indicate that Merton's distance-to-default measure is a reasonable firm-specific dynamic quantity (defined by current observations of the firm) that correlates strongly with credit spreads and observed historical default frequency.

12 For instance, this model builds the backbone of Moody's KMV model and MSCI's CreditGrades. Recently, firms like Carbon Delta rely on a variant of Merton's model to assess the impact of transition costs on a firm's PD. To this end, Carbon Delta makes the hypothesis that emission reduction costs will be fully reflected in a reduction of the value of the company's assets (Monnin 2018).

Assuming that the firm's capital structure is composed by equity E_t and debt with face value of D payable at time T, we can interpret the firm's equity as a European call option with maturity T and strike price D on the firm's asset value A_t. For simplicity, we exclude dividends. In the classical Merton (1974) model, A_t evolves as

$$\frac{\mathrm{d}A_t}{A_t} = \mu_A \mathrm{d}t + \sigma_A \mathrm{d}W_t, \tag{1}$$

where μ_A and σ_A are the constant drift and volatility of the asset and W_t is a Brownian motion under the reference measure $\mathbb{P}$. Default can only happen at the maturity of the zero-coupon bond. Hence, the current equity price is

$$E_t = A_t N(d_1) - De^{-r\tau} N(d_2), \quad d_1 = \frac{\ln(e^{r\tau} A_t/D) + \frac{1}{2}\sigma_A^2 \tau}{\sigma_A \sqrt{\tau}}, \quad d_2 = d_1 - \sigma_A \sqrt{\tau},$$

where $N(\cdot)$ is the standard normal distribution function and $\tau = T - t$ is the time to maturity. Defining B_t as the market price of debt with implicit yield to maturity $y(t, T) = \ln(B_t/D)/\tau$, the Merton model implies a credit spread equal to

$$s(t, T) = y(t, T) - r = -\ln[N(d_2) + e^{r\tau} A_t/DN(-d_1)]/\tau. \tag{2}$$

The main determinants on the implied credit spread $s(t, T)$ are the leverage D/A_t and asset volatility σ_A. Zhou (2001) extends the classical Merton model by introducing Poisson jumps in the asset value process. The dynamics of the asset value in Equation (1) are adjusted to

$$\mathrm{d}A_t = \mu_A A_t \mathrm{d}t + \sigma_A A_t \mathrm{d}W_t + (e^{Z_t} - 1)A_{t-} \mathrm{d}N_t, \tag{3}$$

where N is a Poisson process under $\mathbb{P}$ with intensity $\lambda > 0$ and Z_t are independent normally distributed jump sizes with mean μ_J and variance σ_J^2. Under absence of jump-risk premia, we can derive the spread as

$$s(t, T) = y(t, T) - r = -\sum_{n=0}^{\infty} \frac{e^{-\lambda\tau}(\lambda\tau)^n}{n!} \ln[N(d_2; r_n, \sigma_n) + e^{r\tau} A_t/DN(-d_1; r_n, \sigma_n)]/\tau, \tag{4}$$

where $r_n = r - \lambda\overline{\kappa} + n\ln(1 + \overline{\kappa})/\tau$ with $\overline{\kappa} = \exp(\mu_J + \sigma_J^2/2) - 1$ and $\sigma_n^2 = \sigma^2 + n\sigma_J^2/\tau$.

Although the underlying assumptions for the credit spread in Equations (2) and (4) are highly restrictive, we can, at least qualitatively, discuss the risk-perception effect of climate risk disclosure. For physical climate risks such as, for example, natural catastrophes, we may argue that climate change is increasing the severity and frequency of such events. Since

$$\frac{\partial s(t, T)}{\partial \mu_J} > 0, \quad \frac{\partial s(t, T)}{\partial \lambda}\Big|_{\mu_J < 0} > 0,$$

the credit spread would increase. For transition risks, we may argue that a smooth transition to a new regulatory regime will reduce the value of the firm's asset. Since, in the absence of jumps,

$$\frac{\partial s(t, T)}{\partial A_t} = \frac{N(-d_1)}{s(t, T)} \geq 0,$$

a decrease of the assets due to transition risks will lead to an increase in credit spreads.

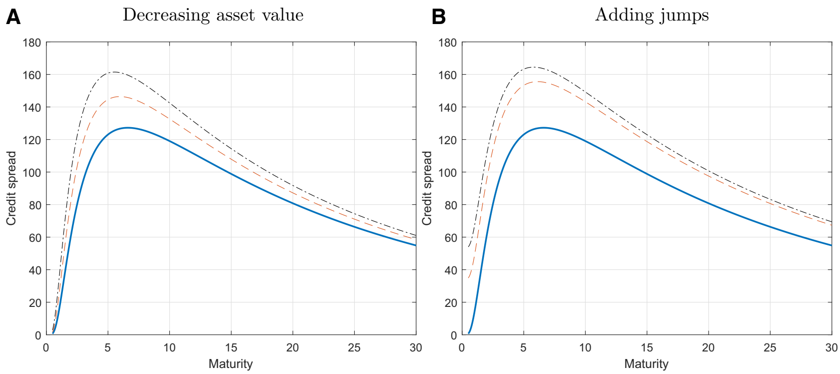

Figure 1 Theoretical predictions on credit spreads. (A) Decreasing asset value. (B) Adding jumps. The figure plots the risk-perception effect on credit spreads under different model specifications for maturities of up to 30 years. Panel A illustrates the impact of a decreasing asset value based on the standard Merton (1974) model. Panel B shows the impact when we add a jump component to the Merton model as in Zhou (2001) and vary the severity of the negative jump. In each panel, the solid line represents the base case, which corresponds to the classical Merton model, given the initial asset value.

We illustrate the risk-perception effect in Figure 1, where Panel A shows the impact of a decrease in asset value. The increase in CDS spreads turns out to be the largest for medium-term maturities. For short-term and long-term spreads, the rise in credit spreads due to decreased asset value is less severe. Panel B shows the impact of increasing the jump component. The presence of jumps remains noticeable for long maturities, implying that such an effect would be observable over the entire term structure.

1.2. Decreasing Information Uncertainty

The second effect of disclosure relates to a decrease of information uncertainty. Duffie and Lando (2001) find that incomplete and asymmetric information plays an essential role in credit risk. In particular, they show that when the true firm value is only partially observable, the credit spread remains strictly positive when maturity tends to zero. Consistent with this theory, Yu (2005) finds that firms with higher Association for Investment Management and Research disclosure rankings tend to have lower short-term credit spreads. For our setting, one may conjecture that, by disclosing additional climate-related risks, the information uncertainty associated with this risk factor is reduced and, consequently, credit spreads at the short end will decrease.

To explore the effect of an imperfectly observable firm value on credit spreads, we argue along the lines of Duffie and Lando (2001). Market participants have no access to managers' private information and must estimate today's asset value A^* based on publicly available information like accounting figures or regulatory disclosures.[13] Setting $\ln A = \ln A^* + u$, where $u \sim \mathcal{N}(-\frac{1}{2}\sigma_u^2, \sigma_u^2)$ is the normally distributed estimation error, the term σ_u captures the information uncertainty that can potentially be reduced by providing informative disclosures. In Figure 2, Panel A, we plot the credit spread for different levels of

13 Although Duffie and Lando (2001) assume that equity is not traded on the public market, the basic mechanisms also hold for publicly traded equity (Blöchlinger and Leippold 2018).

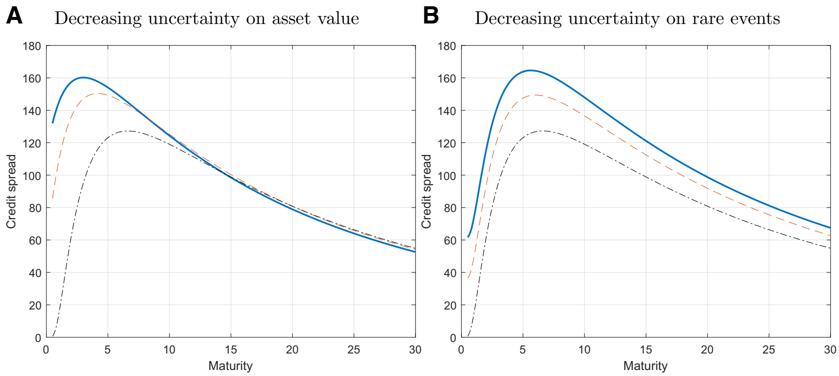

Figure 2 Theoretical predictions on credit spreads. (A) Decreasing uncertainty on asset value. (B) Decreasing uncertainty on rare events. The figure plots the information-uncertainty effect on credit spreads under different model specifications for maturities up to 30 years. Panel A illustrates the impact of reducing information uncertainty assuming a structural model as Lindset, Lund, and Persson (2014). Panel B shows the effect of reducing uncertainty about rare events in the model setting of Liu, Pan, and Wang (2005) for varying levels of the parameter β defining the extended entropy measure. In each panel, the solid line represents the base case, which corresponds to the case with the highest information uncertainty.

information uncertainty.[14] The solid line represents the base case for which information uncertainty is the highest. With decreasing uncertainty, the credit spread also decreases, notably at the short end of the term structure. There is no effect on the long end of the curve. Hence, arguing with the model of Duffie and Lando (2001), disclosure of climate risks must decrease short-term credit spreads while leaving long-term spreads unchanged.

In addition to the asymmetric information argument of Duffie and Lando (2001), we can also explore the impact of information uncertainty in a jump-diffusion framework, similar as in Equation (3). For this analysis, we build on Liu, Pan, and Wang (2005) who study the asset pricing implication of imprecise knowledge about rare events under ambiguity aversion.[15] In their setup, alternative models only differ in terms of the jump component. Given the reference measure $\mathbb{P}$, which defines the dynamics in Equation (3), the alternative model is specified by its probability measure $\mathbb{P}^* \sim \mathbb{P}$ with Radon-Nikodym derivative

$$\frac{\mathrm{d}\mathbb{P}^*}{\mathrm{d}\mathbb{P}} \stackrel{\text{def}}{=} \mathrm{d}\zeta_t = \left(e^{a+bZ_t-b\mu_J-\frac{1}{2}b^2\sigma_J^2} - 1\right)\zeta_{t-}\mathrm{d}N_t - (e^a - 1)\lambda\zeta_t\mathrm{d}t.$$

Here, the parameters a and b capture the concern for jump misspecification, are determined endogenously, and depend on the representative investor's risk and ambiguity aversion. In an exchange equilibrium and under constant relative risk aversion, the investor makes a robust decision respecting all candidate models $\mathbb{P}^* \in \mathcal{P}$ by penalizing the model's deviation from the reference model $\mathbb{P}$ using the distance measure,

$$\mathbb{E}_t^*[h\Big(\ln(\zeta_{t+1}/\zeta_t)\Big)], \quad h(x) = x + \beta(e^x - 1), \tag{5}$$

14 We base our implementation on the simplified model of Lindset, Lund, and Perssonv (2014).

15 In a recent paper, Augustin and Izhakian (2020) extend the framework of Liu, Pan, and Wang (2005) to pricing assets when net supply is zero.

which Liu, Pan, and Wang (2005) refer to as extended entropy. Under these assumptions, they derive the adjusted intensity $\lambda^{\mathbb{Q}}$ and the mean percentage jump size $\overline{\kappa}^{\mathbb{Q}}$ under the pricing measure $\mathbb{Q}$. The concern for the jump model misspecification is driven by the parameter β, which is essential in generating an uncertainty premium for rare events. Assuming a negative mean for the jump size, it follows that under uncertainty aversion we have $\lambda^{\mathbb{Q}} > \lambda$ and $\overline{\kappa}^{\mathbb{Q}} < \overline{\kappa}$.[16]

Given the role of β in defining an entropy bound for the jump misspecification in Equation (5), we plot in Panel B of Figure 2 the impact of varying levels of β on credit spreads. The solid line corresponds to when the value for β is the highest and the ambiguity-averse investor considers a broader range of potential models for robust decision-making. In contrast, the dash-dotted line corresponds to the case when β is close to zero. In this case, the investor chooses the reference model. For our analysis, we can represent a situation with highly informative risk disclosure with a low value of β and vice versa. Finally, we remark that, in comparison with Panel A of Figure 2, the impact of information uncertainty extends beyond the 10-year horizon. Nevertheless, the impact is highest in absolute terms at the short end of the credit spread curve.

In summary, there are competing mechanisms at play. Risk disclosure may either have a risk-perception effect that increases credit spreads or an uncertainty-reduction effect that decreases credit spreads. In the following section, we will apply these theoretical considerations to the case of climate risk disclosure, differentiating between transition and physical risks.

1.3. Climate Risk Disclosure: Risk Perception or Uncertainty Reduction?

We now formulate testable hypotheses related to transition and physical risks that align with the theoretical predictions for the CDS term structure as discussed above. To the extent that climate risk disclosure does affect credit spreads, the question is whether the risk-perception or the uncertainty-reduction effect dominates. These two mechanisms work in opposite directions and the effect of climate risk disclosure is not obvious. Moreover, although interlinked, transitional and physical risks have fundamentally different characteristics. Institutional changes within an economic system drive the former. The laws of physics drive the latter. Therefore, we distinguish between these two risks in the following discussion.

Transition risks of climate change are driven by politics. The general expectation is that governments will at some point intervene in the economy to curb CO_2 emissions. These interventions may take various forms, such as taxes on carbon emissions, emission trading systems, subsidies, and product standards.[17] While the regulatory approach varies, the Paris Agreement of 2015 resulted in a broad international consensus that some regulatory action must be taken. Given that transition risks change rapidly with the political process, disclosure mainly updates investors' views on risk exposure. Therefore, we expect that the

16 For more details, we refer to Liu, Pan, and Wang (2005), Proposition 3.

17 For example, the European Union implemented a cap-and-trade system of emission certificates in 2005, resulting in additional costs for emission-intensive industries in general. The governor of California recently determined that by 2035 only zero-emission vehicles will be allowed to be sold, putting car manufacturers that do not offer such vehicles at a disadvantage, see https://www.gov.ca.gov/wp-content/uploads/2020/09/9.23.20-EO-N-79-20-text.pdf.

Paris Agreement led to a risk-perception effect for transition risk and, hence, to an increase in risk premia (Hypothesis H_{Tr}). At the same time, we would expect a reversal of this effect with the election of Trump in late 2016.

The physical risks of climate change, as their name suggests, are driven by the physical processes of the earth's atmosphere. They materialize in extreme weather events, such as floods, storms, droughts, heatwaves, and knock-on effects such as wildfires, landslides, and crop failures. While none of these natural disasters are new phenomena,[18] the expectation is that they will become more frequent and more extreme due to climate change (Domeisen 2019; Domeisen and Butler 2020; IPCC 2022). Then, physical risk disclosure mainly updates investors' view of the firm's mitigation efforts. Therefore, the uncertainty reduction effect may dominate for physical risk disclosure, leading to a decrease in risk premia (Hypothesis H_{Ph}).

2 A Novel Disclosure-Based Measure of Climate Risk

Climate risk is a recent phenomenon in finance and there is to date no consensus on how to measure it empirically.[19] While the majority of recent studies use either carbon emissions or ESG scores to proxy for climate risk,[20] our approach to measuring climate risk relies on analyzing regulatory disclosure to the US SEC.

2.1. Regulatory Climate Risk Disclosure

Publicly listed companies in the USA are required to file audited annual reports in the form of 10-K filings. Since 2006, the SEC has required that the 10-K reports include a specific section (Item 1.A) for firms to self-identify those risks that they see as significant risk factors to their business. With the increasing awareness that climate risk may pose an economic threat to the corporate world, in 2010, the SEC provided some interpretive guidance, clarifying the existing disclosure requirements as they apply to business or legal developments

18 Arguably, this situation may change when the climate reaches a tipping point. However, even if a tipping point such as the disintegration of the Arctic Ice shield is reached, the consequences may take centuries to unfold (Lenton et al. 2019; Lenton 2021) and are thus unlikely to play a role in investor's considerations today.

19 Macro-economic studies have established the social cost of carbon as a central metric (see e.g., Cai and Lontzek 2019; van den Bremer and van der Ploeg 2021; Traeger 2021). In our case, however, we are concerned not with the aggregate social cost (or risk), but with the heterogeneous risks to individual firms.

20 Carbon emissions are used, for example, by Chen and Gao (2012); Andersson, Bolton, and Samama (2016); Liesen et al. (2017); Jung, Herbohn, and Clarkson (2018); In, Park, and Monk (2019); Ilhan, Sautner, and Vilkov (2021); and Ramelli et al. (2021) and ESG scores by Görgen et al. (2019). Examples of carbon emissions data providers are the Carbon Disclosure Project (CDP), Trucost, Clean Energy Regulator (Australia), South Pole Group, and MSCI. The primary ESG rating providers are the MSCI, Sustainalytics, Asset4, Vigeo Eiris, and Oekom ISS. Ginglinger and Moreau (2019) use a forward-looking measure, "Climate Risk Impact Screening," which was developed by the commercial data provider Carbone 4. Ramelli et al. (2021) complement carbon emissions with data on climate responsibility from the ESG rating agency Vigeo Eiris. Finally, Delis, de Greiff, and Ongena (2019) hand-collect data on fossil fuel reserves from the firm's annual reports.

relating to climate change. In that guidance, the SEC identified four existing items in Regulation S-K[21] that may require disclosure related to climate change, as follows: description of the business, legal proceedings, risk factors, and management's discussion and analysis of financial condition and results of operations, or MD&A.

Relying on regulatory filings to estimate climate risks offers several significant advantages over the available alternatives. First, companies are requested to disclose all kinds of climate-related risks in their 10-K filings. In contrast, carbon emissions do not capture all aspects of climate risk. Carbon emissions are probably a reasonable proxy for regulatory risk, given that a fundamental objective of future regulation is to drive emissions downward. However, carbon emissions do not indicate a firm's physical risk exposure. Regulatory filings reflect both the transition risks and the physical risks of climate change.

Second, 10-K filings contain a description of forward-looking risks, whereas carbon emissions data are backward-looking operational performance. Past emissions are not necessarily representative of future emissions and even less representative of future risk exposure. Firms may be able to outsource emission-intensive processes in the future or pass on cost increases to customers. In contrast, risks disclosed in SEC filings specifically refer to a company's forward-looking risk exposure. Therefore, they may provide a better proxy for future exposure. This forward-looking aspect of regulatory filings is deliberate because investors commonly seek to obtain and incorporate forward-looking information.

Third, and most importantly, 10-K filings are mandatory and enforceable. While an increasing number of companies report their carbon emissions, for example, via the CDP, such disclosure is voluntary. Also, ESG ratings are partially based on information that companies provide voluntarily. This raises two problems: first, companies may strategically choose not to disclose, especially when managers fear that the information will be perceived as unfavorable by investors (Lyon and Maxwell 2011) and second, voluntary disclosure is not routinely audited or enforceable, so that investors cannot be sure that the information is correct. Therefore, with voluntary disclosure, one might underestimate the risks of precisely those companies that have the highest risk exposure.[22] In contrast, the disclosure of climate risks in 10-K filings is legally required for all companies and a failure to report can have legal consequences.[23]

For our analysis, we focus on Item 1.A of the 10-K report, as it requires firms to specifically report risk factors and thus provides the most direct information about climate risk.[24]

21 Regulation S-K lays out a range of mostly qualitative reporting requirements under the SEC's purview. See also SEC (2010).

22 Indeed, in a recent study, Bingler et al. (2022a) find that TCFD-supporting companies tend to cherry-pick the most flattering aspects of how they cope with climate change.

23 For instance, in October 2018, a lawsuit was filed by the New York state attorney general against Exxon Mobil Corporation for understating their climate risk exposure in their annual report (10-K) and misleading investors. Consequently, the accompanying litigation risk serves as a third-party check for the quality and reliability of the disclosed information.

24 Matsumura, Prakash, and Vera-Muñoz (2018) have identified the management discussion in Item 7 as an additional source for climate-related disclosure, in which firms show their awareness and understanding of the risks at hand and elaborate on potential (future) actions. However, we argue that the discussion of climate risk in Item 7 is ambiguous, given that it might indicate not only the presence of a risk factor but also management's awareness and attention to that risk factor. For this reason, we restrict our analysis to Item 1.A.

Deriving a measure of climate risk from these regulatory filings is a subtle task. Companies are flexible in how they disclose and describe their climate risk exposure, which could make it difficult to compare the filings relative to each other. However, there is delicate legal reasoning that helps to discipline the disclosures. On the one hand, companies will take care to report the necessary minimum, so it will be difficult to sue them for misleading investors in a material way. Given the increasing number of climate-related cases against corporations,[25] they know that their disclosures might be scrutinized meticulously for completeness and accuracy (ACC) by prosecutors and courts, especially when certain risks materialize at a later point in time. On the other hand, companies will avoid overstating risks in mandatory disclosure since doing so would give the impression that the business is more exposed to risks than others, which might negatively affect the pricing of the corporation's securities. Thus, even though companies are flexible in their disclosure, all companies try to balance these competing considerations. As a result, a company that discloses more on climate risks relative to other companies most likely also has greater exposure to climate risks relative to other companies.

2.2. Analyzing Climate Risk Disclosure with BERT

Climate risk disclosure, as required by the SEC, is textual data, which calls for a method to create quantitative measures from textual data. With the introduction of pretrained neural language models such as BERT, we have recently witnessed enormous progress in such tasks. BERT is a contextual model, that is, the representation of a word is a function of the entire input text, respecting the word dependencies and sentence structures. BERT is pretrained on a large number of documents so that the contextual representations encode general language patterns. Contextual neural language models such as BERT have outperformed traditional word embeddings on various NLP tasks (see, e.g., Peters et al. 2018). Moreover, Varini et al. (2020) find that for topic classification of climate change, even a simple BERT model significantly outperforms keyword-based approaches, which tend to generate false positives, leading to low Prec, particularly for the analysis of 10-K reports. Motivated by these achievements, we leverage BERT to identify climate-risk relevant sentences in the 10-K reports.

We use BERT to classify sentences into three classes: sentences related to transition risk (labeled "transition"), sentences related to physical risk (labeled "physical"), and sentences related to neither of these risks (labeled "general"). Our algorithm builds on the pretrained Uncased-BERT-Base with two additional fully connected layers (both of size 128). For each sentence and each class, BERT calculates a score that indicates the probability that the sentence belongs to the class. Next, we aggregate these sentence-specific probabilities to obtain a document-level score. Then, using a threshold of 0.8, we determine whether a sentence is assigned to a class or not.[26] We then take the average of these binary values over all sentences of the document. This controls for the overall number of sentences in the document and

25 See http://climatecasechart.com/climate-change-litigation/.

26 We set this threshold to 0.8, which is a reasonable choice to avoid false positives. In additional experiments, we used thresholds ranging from 0.5 to 0.95, and our results remained robust, indicating that our BERT model discriminates well between non-climate and climate-related sentences.

yields a number that reflects the relative importance of transition risk or physical risk compared with other general risks disclosed in Item 1.A of the 10-K report.

We fine-tune the BERT model for the classification of climate-related text. To build a training set, we use the sample reports provided in the TCFD (2019) guidelines, which gives us almost a thousand example sentences for the classification task.[27] We add random sentences that are not climate related to the initial dataset. We then feed this data to our model and train the model for a few epochs. Next, we run the trained model on the 10-K dataset and collect the most confusing sentences, that is, sentences where the probabilities for different classes are similar. These confusing sentences were reviewed and labeled by human annotators with a background in finance and knowledge of the TCFD guidelines. We then add these confusing sentences to the training set, together with an equal number of the most confident sentences to preserve the probability distribution of the data. We perform this entire process for several rounds and end up with a data set of 3192 classified sentences. For further details on BERT and the fine-tuning of this algorithm for our purpose, we refer to the Online Appendix, where we also show some examples of text passages and how BERT classifies them.

2.3. Benchmarking BERT to Alternative Classification Methods

To demonstrate the advantages of using BERT, we compare it with three alternative methods, the bag-of-word (BoW) approach, the term frequency-inverse document frequency (tf-idf) approach, and the method used in Sautner et al. (2022). BoW and tf-idf are two of the most widely used approaches in the general finance literature,[28] and Sautner et al. (2022) perform a similar exercise in the context of climate risk.

To compare the different approaches, we use the annotated sentences from our training set described above. We split this data into a training and a test set. The training (test) data consist of 1699 (95) sentences labeled as “general”, 756 (58) sentences labeled as “transition”, and 536 (48) sentences labeled as “physical.” For the training of the BoW, tf-idf, and the dictionary approach, we use a random forest and we take the average of the results over 100 runs with different seed values.[29]

We create a list of unigrams (single words) and bigrams (combinations of two consecutive words) from the training set. We then vectorize these using the count-vectorizer (BoW) or the tf-idf vectorizer. BoW just creates a set of vectors containing the count of word occurrences in the document, while the tf-idf model contains, in addition, information about the relative importance of the words. To implement the dictionary approach from Sautner et al. (2022), we use their published list of bigrams that they use for differentiating

27 In particular, we selected the sentences from the original reports mentioned in the TCFD Good Practice Handbook and in Climate-related Financial Disclosures: Examples of Leading Practices in TCFD Reporting by Financial Firms.

28 We remark that we do not compare with word embedding models like Word2Vec, Glove, or fastText. This is because if the dataset is small BoW may work better than word embedding. Moreover, if the context is very domain-specific, which is the case for climate-related text; it is hard to find corresponding vectors from pretrained word embedding models.

29 In particular, we take the Random Forest Classifier using the Scikit-Learn library of Python programming language. We restrict the number of features N to consider when looking for the best split to $\sqrt{N}$, as suggested for classification problems (Hastie et al. 2009, p. 592).

between regulatory (transition) and physical climate risk exposures. However, these dictionaries alone are very sparse, that is, the bigrams are hardly ever found in the test set, resulting in inferior classification performance. A potential reason for this is that the dictionary has been developed for text from earnings call transcripts and does not perform as well in 10-K reports. Therefore, we use these bigrams to try to further improve on the BoW and tf-idf approach outlined above.[30]

To measure the performance in classification across methods, we use several scores that are common to the NLP literature, that is, the F1-score, ACC, Prec, recall (Rec), and Matthew's correlation coefficient (MCC).[31]

2.3.1. Results

Table 1 gives an overview of the results. BERT outperforms all other methods by a large margin. In terms of the relative increase in performance, we see that the BERT model increases in terms of the MCC by 22% relative to the best MCC of the traditional models (BoW using unigrams and bigrams, and including the bigrams of Sautner et al. (2022), Column D). In terms of the F1-score, the increase is more than 14% relative to the best F1-score of all other models (BoW, column D). The enlargement of the vocabulary with the dictionary of Sautner et al. (2022) improves performance in terms of F1. Nevertheless, also this augmented version of BOW and tf-idf remains substantially behind BERT in terms of performance. Interestingly, the performance gap between the traditional models and the BERT model in terms of Rec is large. For instance, BERT improves the Rec of the BoW in Column D by almost 26%.[32]

Hence, we conclude that BERT has a far better performance compared with traditional approaches like BoW or tf-idf and dictionary-based approaches for the classification task. In Appendix A, we provide additional diagnostics on the different models, showing confusion matrices and also some examples of where the prediction has failed on the training set. Keeping these drawbacks in mind, we use the firm-specific climate risk scores of Sautner et al. (2022) as a robustness check for our analysis (see Appendix C.2).

3 Data

Our study period is from February 2010 to October 2021. We start in 2010 after the SEC published its special guidance report on how to address climate change disclosure

30 In the Appendix, we also explore the classification into non-climate and climate risk, that is, we put all sentences related to transition and physical risks to the climate risk category. The reason is that for the physical and transition risk differentiation, we only have a very limited number of bigrams from Sautner et al. (2022), namely 150, which gives no valuable results. For the climate versus non-climate classification, we can use all the 750 bigrams that are published in Sautner et al. (2022). Our findings still indicate that BERT outperforms the dictionary-based approach.

31 While the F1-score is typically used in classification problems, the MCC, which ranges between –1 and 1, has the advantage that it can be generally regarded as a balanced measure which can be used in binary classification even if the classes are very different in size (Chicco 2017).

32 Models need high Rec when we need output-sensitive predictions. For example, predicting cancer needs a high Rec, that is, we need to cover false negatives as well: cancerous tumor should not be labeled non-cancerous.

Table 1 Performance statistics

	Bag-of-words				tf-idf				BERT
	(A)	(B)	(C)	(D)	(A)	(B)	(C)	(D)	
F1	81.278	67.647	78.791	83.637	80.467	67.205	78.628	80.059	94.665
Acc	82.718	72.272	80.471	84.481	82.136	71.743	80.252	81.112	95.154
Prec	86.880	80.030	86.090	85.021	86.545	78.602	86.386	83.335	94.473
Rec	79.132	65.280	76.329	75.280	83.465	64.999	76.066	79.020	94.932
MCC	0.736	0.584	0.707	0.761	0.730	0.572	0.704	0.708	0.925

Notes: The table reports the results for different performance measures for the transition-physical risk classification task. We use different specifications: (A) uses unigrams, (B) uses bigrams, (C) uses uni- and bigrams, and (D) uses the uni- and bigrams together with the bigrams from Sautner et al. (2022) to enlarge the vocabulary of the respective methods. We then compare the BoW and tf-idf vectorizers with the results from BERT. The training (test) data consist of 1699 (95) sentences labeled as "general," 756 (58) sentences labeled as "transition," and 536 (48) sentences labeled as "physical."

(SEC 2010). In addition to the BERT-based climate risk scores, we collect data on CDS spreads, control variables for our regression, and sector classifications.

3.1. CDS Spreads and Control Variables

We collect CDS spreads from Thomson Reuters Datastream. CDS are fixed-income derivative instruments, offering protection buyer insurance against a contingent credit event on an underlying reference entity. CDSs are traded over the counter (OTC) and quoted by the annuity premium the protection buyer pays the protection seller, the CDS spread, expressed in basis points with respect to the insured notional amount. Our CDS dataset contains daily spreads for single-name CDS contracts for maturities ranging from 1 to 30 years. We filtered out observations that are likely to be data errors.[33]

In the selection of control variables, we chose macroeconomic and firm-specific variables that have been shown to have a potential effect on credit spreads in prior literature.[34] For macroeconomic controls, we include the general BC in the form of S&P500 returns and the risk-free rate (IR) proxied by the 10-year constant maturity Treasury yield. We allow for the possibility of non-linear dependency on the interest rate by including IR^2 in the model (Collin-Dufresne, Goldstein, and Spencer 2001; Han and Zhou 2015). As firm-specific controls, we include leverage, return-on-assets, and asset volatility. We obtain the book value of total liabilities, net income, and total assets from Compustat to construct the leverage ratio (Lev) and return-on-assets (ROA). The leverage ratio is defined as the ratio between the book value of total liabilities and the sum of the book value of total liabilities and the market value of equity. We obtain the total market value of equity from CRSP by

33 Specifically, we filter out negative CDS spreads and observations with values of 0 for all maturities except for the 5-year maturity. Following Barth, Hübel, and Scholz (2019), we also drop CDS observations with spreads above 2000 basis points on any maturity below 7 years. More details on the collection process can be found in Section 2 of the Online Appendix.

34 See Collin-Dufresne, Goldstein, and Spencer (2001); Ericsson, Jacobs, and Oviedo (2009); Zhang, Zhou, and Zhu (2009), and Han and Zhou (2015).

multiplying the total shares outstanding with the stock price. ROA is the ratio of net income to total assets. We collect Compustat data on a quarterly frequency, while CRSP data are daily. We align Compustat with CRSP, taking into account the reporting delay by looking for each company separately at its quarterly filing dates and using the values reported as new values from the moment they are reported.

As a proxy for the asset volatility (Vol), we follow Campbell and Taksler (2003) by computing the standard deviation of stock returns using the most recent 180 days. By relying on historical volatility, the results are in line with those of Han and Zhou (2015) using the stock-specific implied volatility. We remark that as an additional alternative, Collin-Dufresne, Goldstein, and Spencer (2001) use the VIX as a proxy for the individual firm's expected volatility because most of the firms in their sample do not have traded options. However, when we use VIX for our data sample, we get the counter-intuitive result that the VIX has a negative impact on CDS spreads. Therefore, we keep the method of Campbell and Taksler (2003).

By matching the CDS data with the data from all the other sources, we have observations for 418 different CDS contracts from February 2010 to October 2021. Because data are collected at different frequencies, we make a compromise to the frequency trade-off between these different frequencies and decide on performing monthly regressions. Hence, we resample higher frequency data by taking the average for each month, we repeat and forward till lower frequency data by taking the last observation for each month. Finally, we have data for at least 767 different CDS contracts at each point in time and we have a total of 50,278 firm-month observations. For the descriptive statistics of the independent variables and the CDS spreads, we refer to Section 2 of the Online Appendix.

3.2. Industry Classification

In our panel regression analysis, we opt to use for industry classification the SASB's Sustainable Industry Classification System (SICS) in favor of other conventional practices for the following reason. According to the SASB, the SICS does not focus solely on the common market and financial characteristics, unlike many traditional classifications, but it also emphasizes a company's sustainability profile, such as sustainability-related risks and opportunities. Given that our primary focus is on climate risk exposure, such a sustainability-oriented industry classification is perfectly suited for our purpose. In Appendix B, we present the distribution of our sample across industries.

Another reason to use SICS is that the SASB provides a so-called materiality map. Based on the US Supreme Court's definition of materiality,[35] SASB's materiality map indicates for each SICS industry which sustainability issues are considered material from an investor's point of view. We use the SASB materiality map to identify those SICS industries for which climate risk is considered a material risk.[36]

35 See BASIC INC. v. LEVINSON (1988) "a substantial likelihood that the disclosure of the omitted fact would have been viewed by the reasonable investor as having significantly altered the total mix of information made available."

36 See also, for example, Matsumura, Prakash, and Vera-Muñoz (2018). The most recent version of the SASB materiality map can be found under https://materiality.sasb.org/.

4 Regression Results

We analyze how the regulatory disclosure of transition and physical risks impacts CDS spreads over various maturities. Specifically, we estimate the following one-month ahead forecasting regressions:

$$\Delta S^{m}_{i,t+1} = \beta_T \Delta \text{CR-Transition}_{i,t} + \beta_P \Delta \text{CR-Physical}_{i,t} + \Phi \Delta X_{i,t} + \Theta \Delta Y_t + \epsilon_{i,t+1}, \qquad (6)$$

where by $S^{m}_{i,t+1}$ we denote the next month's (average) m-year spread and $X_{i,t}$ and Y_t are firm-specific and macro-economic control vectors, respectively.[37] By CR-Trans$_{i,t}$ and CR-Phys$_{i,t}$, we denote our BERT-based proxies for transition and physical risk discussed in Section 2. Since we predict counteracting effects for transition risk and physical risk, we estimate these two risk components separately. A significant coefficient β would indicate that regulatory climate risk disclosure carries relevant information for the determination of CDS spreads. If positive, empirical evidence supports the risk-perception effect. If negative, empirical evidence favors the information-uncertainty effect.

The regression Equation (6) represents a panel first-difference (FD) model by focusing on the effect of changes in the exogenous variables on changes in the endogenous variable. However, we obtain estimates for our regression coefficients by performing simple (pooled) OLS on the differences series and exploiting our data's panel structure. By taking the first difference in each firm's time series, we can effectively control for any time-invariant, unobserved heterogeneous effect. Also, we allow for arbitrary correlations in the standard errors for firms with similar sustainability profiles by clustering on SASB industries. By clustering on industry instead of on an entity level, we take a conservative stance. The SICS's industry classification identifies a sufficiently high number of clusters to render unbiased standard errors (Petersen 2009).

As highlighted by Kravet and Muslu (2013), companies are likely to repeat a significant portion of their risk disclosures over consecutive annual reports. Therefore, to address concerns related to correlated omitted variables and reverse causality, it is crucial to employ first differences. This point was also made by Li (2010), who calls for using a change specification whenever appropriate in textual analysis research to mitigate endogeneity concerns. Besides, an FD model is similar in spirit to a panel model for the levels, including (firm)-fixed effects (FEs), where the firm FEs are differenced away.[38] Both the

37 As in Zhang, Zhou, and Zhu (2009), we use lagged explanatory variables mainly to avoid the simultaneity problem, see their footnote 8. In their paper, they use weekly data combined with lower-frequency macro variables. Here, we use monthly data with lower-frequency disclosure data. As robustness checks, we also performed the same regressions based on yearly data. We opted for monthly regressions to find a balance between the different frequencies of the different data sources. We do not find a substantial difference from the regressions based on yearly data. Also, we performed contemporaneous regressions. Results do not change. These results can be obtained from the authors.

38 For a model with only two time periods, the FD estimate and the FEs regression are even identical. For $T > 2$, the FD and FE estimators are very much related. The choice between an FE or FD model depends mostly on notions of relative efficiency, which depends on the assumption one is willing to make on the error term in the FE regression (Wooldridge 2010). As a robustness check, we also perform FE regressions on the levels, which give us estimates that are qualitatively similar to those reported for the FD regressions. Therefore, we are even more convinced about the robustness of our results. These tables for the FE regressions are available on request.

forecasting element and the focus on changes in our panel setting allow us to emphasize the causal inference.

4.1. Base Results

For our analysis, we account for the fact that not all firms are exposed to climate risk. Therefore, we split the sample into firms where climate risks are deemed material and where they are deemed non-material. To perform this split, we rely on the SASB's materiality map that identifies 26 sustainability-related business issues that are likely to affect companies' financial conditions or operating performance within an industry. From those 26 issues, 7 are climate risk related. Following Matsumura, Prakash, and Vera-Muñoz (2018), climate risk is considered material for an industry if four out of seven issues apply to that industry.[39]

The control variables of our regressions in Table 2 are directionally consistent with expectations from previous literature throughout all the specifications and are often strongly significant.[40] Changes in business conditions, leverage, and interest rates are found to be the main drivers of CDS spreads.

With regard to climate risk, in the full sample (Columns I–IV), physical risk has a negative effect across all maturities, but only marginally significant at the 10% level. Whereas for transition risk the marginally significant negative effect is only present for the 1-year maturity. When looking at the sub-sample of companies for which climate risks are deemed material (Columns IX–XII), both risks are insignificant. These results only marginally suggest an information uncertainty reduction effect, for physical risk especially.

We cannot comfortably reject the hypothesis that climate risk disclosure does not affect CDS spreads in light of these results. In the following sections, we attempt to answer whether this is because 10-K filings are pure boilerplate or this general setup cannot correctly identify the effects at play. To provide more elaborate tests of our hypotheses about transition risk and physical risk, we explore the influence of both the Paris Agreement in 2015 and the election of Donald Trump as President of the USA on November 8, 2016. However, before we do so, we first narrow down on physical risk by revisiting the definition of materiality for physical risk.

4.2. Narrowing Down on Physical Risk

The finding that we do not find a substantial impact of physical risks at any maturity may be due to the definition of materiality, which does not properly distinguish between transition and physical risk so far. Therefore, instead of covering the whole materiality map, we select only companies within industries for which the physical impacts of climate change are deemed material.[41] For this category, we end up with 73 companies and the corresponding results are in Table 3. In this case, the material firms (Columns IX–XII)

39 Table B.1 of the Appendix denotes industries classified as material with the superscript ($*$).

40 See, for example, Han and Zhou (2015). We remark that the sample contains a larger number of firms and covers a different period than that of Ericsson, Jacobs, and Oviedo (2009) and Han and Zhou (2015), which includes the recent financial crisis. Hence, our results may differ in terms of the control variables.

41 Table B.1 denotes industries classified as physical material with the superscript ($+$).

Table 2 Monthly FD regression results, when separating physical and transition climate risk, controlling for materiality

	(I) All ΔS^{1Y}	(II) All ΔS^{5Y}	(III) All ΔS^{10Y}	(IV) All ΔS^{30Y}	(V) Non-Mat ΔS^{1Y}	(VI) Non-Mat ΔS^{5Y}	(VII) Non-Mat ΔS^{10Y}	(VIII) Non-Mat ΔS^{30Y}	(IX) Mat ΔS^{1Y}	(X) Mat ΔS^{5Y}	(XI) Mat ΔS^{10Y}	(XII) Mat ΔS^{30Y}
ΔTransition	–57.972*	–41.321	–36.433	–33.023	–102.564	–69.984	–58.086	–49.495	–35.151	–26.131	–24.830	–23.817
	(34.965)	(29.471)	(28.043)	(27.139)	(92.149)	(57.260)	(49.790)	(46.929)	(31.696)	(38.451)	(37.931)	(36.384)
ΔPhysical	–25.580*	–25.378*	–25.867*	–24.819*	–26.176*	–33.309	–31.978	–31.495	–12.648	–0.655	–6.976	–6.807
	(13.928)	(14.051)	(13.840)	(14.077)	(15.381)	(20.319)	(19.883)	(20.373)	(32.313)	(20.269)	(20.086)	(20.390)
ΔLev	1.485***	2.483***	2.335***	2.208***	1.377***	2.243***	2.100***	1.977***	1.757***	3.066***	2.906***	2.772***
	(0.246)	(0.325)	(0.298)	(0.278)	(0.304)	(0.378)	(0.344)	(0.321)	(0.389)	(0.551)	(0.507)	(0.476)
ΔROA	0.031	0.145	0.104	0.106	0.072	0.158	0.114	0.086	–0.156	0.066	0.044	0.163
	(0.108)	(0.113)	(0.099)	(0.095)	(0.112)	(0.109)	(0.096)	(0.092)	(0.289)	(0.356)	(0.309)	(0.298)
ΔVol	2.729	1.536	1.139	1.076	4.520**	3.270**	2.752*	2.753*	–3.996***	–4.877***	–4.823***	–5.108***
	(1.792)	(1.462)	(1.298)	(1.255)	(2.087)	(1.653)	(1.476)	(1.407)	(1.452)	(1.063)	(1.040)	(1.041)
ΔBC	–0.202***	–0.250***	–0.241***	–0.233***	–0.208***	–0.246***	–0.240***	–0.236***	–0.178	–0.261*	–0.244**	–0.223***
	(0.049)	(0.054)	(0.048)	(0.044)	(0.053)	(0.057)	(0.053)	(0.051)	(0.118)	(0.138)	(0.107)	(0.085)
ΔIR	–16.267**	–0.030	3.658	7.899*	–16.569*	–0.437	2.647	6.224	–16.345**	–0.100	5.460	11.681*
	(7.070)	(5.059)	(4.741)	(4.475)	(9.176)	(6.367)	(6.095)	(5.783)	(7.293)	(7.167)	(6.131)	(6.119)
ΔIR2	2.567*	–0.267	–0.916	–1.809*	2.427	–0.389	–0.866	–1.633	3.076**	0.254	–0.919	–2.184*
	(1.478)	(1.104)	(1.059)	(1.034)	(1.925)	(1.397)	(1.377)	(1.352)	(1.325)	(1.357)	(1.095)	(1.132)
Number of observations	49,783	49,828	49,783	49,783	37,423	37,504	37,423	37,423	12,360	12,324	12,360	12,360
R-squared	0.019	0.038	0.038	0.034	0.017	0.031	0.031	0.029	0.032	0.062	0.060	0.054

Notes: This table shows the regression results for a panel first difference regression of the form: $\Delta S^{m}_{i,t+1} = \beta \Delta \mathrm{CR}_{i,t} + \Phi \Delta X_{i,t} + \Theta \Delta Y_t$, where $\mathrm{CR}_{i,t}$ is the vector containing both *Physical* and *Transition*. Both physical and transition climate risk are based on Item 1.A in firms' 10-Ks. Coefficients are estimated by performing pooled OLS using the difference and this for different subsamples. Materiality subsamples are determined on expected climate change materiality on an industry level based on Matsumura, Prakash, and Vera-Muñoz (2018) and the SASB's materiality map. Standard errors are clustered on an industry level. The sample period ranges from February 2010 to October 2021. By *, **, and *** we denote *p*-levels below 10%, 5%, and 1%, respectively.

Table 3 Monthly FD regression results, controlling for physical materiality

	(I) All ΔS^{1Y}	(II) All ΔS^{5Y}	(III) All ΔS^{10Y}	(IV) All ΔS^{30Y}	(V) Non-Mat ΔS^{1Y}	(VI) Non-Mat ΔS^{5Y}	(VII) Non-Mat ΔS^{10Y}	(VIII) Non-Mat ΔS^{30Y}	(IX) Mat ΔS^{1Y}	(X) Mat ΔS^{5Y}	(XI) Mat ΔS^{10Y}	(XII) Mat ΔS^{30Y}
ΔTransition	–57.972*	–41.321	–36.433	–33.023	–60.213*	–43.902	–38.620	–35.687	102.249***	99.204*	70.744	84.659
	(34.965)	(29.471)	(28.043)	(27.139)	(36.222)	(30.396)	(28.917)	(27.878)	(19.651)	(51.853)	(66.877)	(75.354)
ΔPhysical	–25.580*	–25.378*	–25.867*	–24.819*	–22.062	–18.051	–18.603	–16.612	–125.764***	–107.727	–110.804	–120.281
	(13.928)	(14.051)	(13.840)	(14.077)	(14.449)	(12.364)	(12.200)	(11.906)	(21.442)	(69.833)	(90.617)	(103.117)
ΔLev	1.485***	2.483***	2.335***	2.208***	1.505***	2.568***	2.413***	2.276***	1.570***	2.122**	1.970**	1.740**
	(0.246)	(0.325)	(0.298)	(0.278)	(0.253)	(0.328)	(0.305)	(0.286)	(0.570)	(0.825)	(0.778)	(0.803)
ΔROA	0.031	0.145	0.104	0.106	0.025	0.134	0.083	0.085	0.214	0.499*	0.731**	0.782**
	(0.108)	(0.113)	(0.099)	(0.095)	(0.113)	(0.117)	(0.100)	(0.096)	(0.181)	(0.285)	(0.359)	(0.367)
ΔVol	2.729	1.536	1.139	1.076	1.411	0.535	0.200	0.194	15.202***	13.803***	12.741***	11.246***
	(1.792)	(1.462)	(1.298)	(1.255)	(2.009)	(1.665)	(1.469)	(1.419)	(1.090)	(1.466)	(1.490)	(1.446)
ΔBC	–0.202***	–0.250***	–0.241***	–0.233***	–0.178***	–0.225***	–0.214***	–0.206***	–0.418***	–0.495***	–0.473***	–0.455***
	(0.049)	(0.054)	(0.048)	(0.044)	(0.057)	(0.064)	(0.055)	(0.051)	(0.041)	(0.046)	(0.046)	(0.043)
ΔIR	–16.267**	–0.030	3.658	7.899*	–25.010***	–5.819	–2.658	1.955	27.274***	30.357***	39.486***	41.815***
	(7.070)	(5.059)	(4.741)	(4.475)	(7.043)	(5.090)	(4.428)	(4.145)	(9.792)	(10.464)	(8.846)	(5.703)
ΔIR2	2.567*	–0.267	–0.916	–1.809*	4.511***	1.143	0.602	–0.366	–4.042*	–4.252**	–6.941***	–8.124***
	(1.478)	(1.104)	(1.059)	(1.034)	(1.396)	(1.067)	(0.925)	(0.871)	(2.291)	(2.062)	(1.466)	(0.906)
Number of observations	49,783	49,828	49,783	49,783	40,795	40,813	40,795	40,795	8963	8990	8963	8963
R-squared	0.019	0.038	0.038	0.034	0.020	0.041	0.041	0.037	0.032	0.047	0.043	0.037

Notes: This table shows the regression results for a panel first difference regression of the general form: $\Delta S^{m}_{i,t+1} = \beta \Delta \mathrm{CR}_{i,t} + \Phi \Delta X_{i,t} + \Theta \Delta Y_t$, where $\mathrm{CR}_{i,t}$ is the vector containing both *Physical* and *Transition*. X and Y are vectors of firm-specific and macro-economic controls, respectively. Coefficients are estimated by performing pooled OLS using the difference and this for different subsamples. Materiality subsamples are based on the "Physical Impacts of Climate Change" point in the SASB's materiality map on an industry level. Standard errors are clustered on an industry level. The sample period ranges from February 2010 to October 2021. By *, **, and *** we denote p-levels below 10%, 5%, and 1%, respectively.

experience a much larger negative effect of physical risk disclosure versus the non-material firms, though the effect on material firms is only highly significant for the 1-year maturity.

These results lend support to Hypothesis H_{Ph}, stating that the disclosure of physical risks results in a decrease in CDS spreads due to an uncertainty-reduction effect. It suggests that investors reward the disclosure of physical climate risks because it resolves a risk factor that is not new but difficult for outsiders to quantify. As we have argued, the risks due to extreme weather events have always been present and are routinely covered by the re-insurance industry. However, outsiders cannot easily assess a firm's vulnerability to extreme weather events. Thus, the results are consistent with the view that disclosure of physical risks reduces CDS spreads because it reduces uncertainty for investors.

The effects of physical risk disclosure are also economically significant. In Column IX of Table 3, a one standard deviation in physical risks results in a decrease of CDS spreads of 2.33 bps, which amounts to a change of –2.9% for the average 1-year CDS contract in our sample. This decrease is economically substantial and comparable in size to the effects of transition risk disclosure. It is also noteworthy that in Table 3, the effect of transition risk disclosure is also significant, suggesting that for this sample, the counteracting effects of risk-perception and uncertainty-reduction are present at the same time. However, calculating its economic significance turns out to be lower than the impact of physical risk. In particular, the effect of transition risk for the 1-year contract is 1.81, which is a 2.26% increase. Given that transition risk is always linked to climate policy and, therefore, has a strong political component, we next analyze the impact of two critical events, namely the Paris Agreement and the election of Trump.

4.3. The Impact of the Paris Agreement

Both Ilhan, Sautner, and Vilkov (2021) and Delis, de Greiff, and Ongena (2019) find that the 2015 Paris Agreement was a pivotal point and that only afterward, climate change did become price- and risk-relevant. In our case, the Paris Agreement should be relevant for transition risk, since the Paris agreement accelerated the global push for climate regulation. As a result, disclosure of transition risk after the Paris Agreement should have a strong risk-perception effect, leading to a positive effect on CDS spreads. To test this, we introduce a dummy variable into our baseline regression that marks the period after the Paris Agreement in December 2015, resulting in the following regression equation:

$$\begin{aligned}\Delta S^m_{i,t+1} = {} & \beta_T \Delta\text{CR-Transition}_{i,t} + \gamma_T(\Delta\text{CR-Transition} \times \text{Paris})_{i,t} \\ & + \beta_P \Delta\text{CR-Physical}_{i,t} + \gamma_P(\Delta\text{CR-Physical} \times \text{Paris})_{i,t} \\ & + \eta\Delta\text{Paris}_{i,t} + \Phi\Delta X_{i,t} + \Theta\Delta Y_t + \epsilon_{i,t+1},\end{aligned} \tag{7}$$

where Paris is a dummy for the period after the Paris agreement.

As Table 4 suggests, we find a stronger impact of transition risk after the Paris Agreement in 2015, and more importantly for material industries only. The impact is positive and significant for all maturities beyond the 1-year maturity, that is, transition climate risk disclosure leads to higher credit spreads. The coefficient is largest (48.88) at the 5-year horizon. Moreover, the impact is economically relevant. A one standard deviation increase in transition risk leads to an increase of 2.88 bps in the post-Paris period, a relative increase of 1.77% in the average 5-year CDS spread in our sample. In alignment with our classification, there is no significant effect for industries that are non-materially exposed to climate risk.

Table 4 Monthly FD regression results, when separating physical and transition climate risk, controlling for both materiality and the Paris agreement

	(I) All ΔS^{1Y}	(II) All ΔS^{5Y}	(III) All ΔS^{10Y}	(IV) All ΔS^{30Y}	(V) Non-Mat ΔS^{1Y}	(VI) Non-Mat ΔS^{5Y}	(VII) Non-Mat ΔS^{10Y}	(VIII) Non-Mat ΔS^{30Y}	(IX) Mat ΔS^{1Y}	(X) Mat ΔS^{5Y}	(XI) Mat ΔS^{10Y}	(XII) Mat ΔS^{30Y}
ΔTransition	−51.632	−53.029	−45.870	−40.355	−62.547	−45.820	−37.971	−30.465	−39.744	−47.129	−41.561	−38.294
	(35.742)	(36.841)	(35.101)	(33.213)	(60.210)	(37.111)	(32.401)	(30.767)	(37.878)	(44.333)	(43.060)	(40.703)
ΔPhysical	−10.438	−13.951	−11.592	−8.572	−19.916*	−16.127	−15.731	−14.490	11.640	−0.317	2.667	6.489
	(20.945)	(13.112)	(11.268)	(10.815)	(10.307)	(10.727)	(9.896)	(10.734)	(51.816)	(28.373)	(25.031)	(24.376)
Transition Δ × Paris	−14.828	28.208	22.846	17.860	−100.339	−60.019	−49.814	−47.057	10.827	48.876**	38.976**	33.739**
	(37.372)	(31.465)	(28.012)	(25.133)	(84.745)	(54.617)	(49.290)	(47.209)	(22.421)	(19.515)	(18.530)	(16.626)
ΔPhysical ×Paris	−31.971	−25.724	−31.710	−35.785	−6.099	−28.968	−27.885	−29.454	−78.533	0.496	−30.078	−42.120
	(30.029)	(28.626)	(27.724)	(28.643)	(24.904)	(36.119)	(35.264)	(36.588)	(79.825)	(33.189)	(29.216)	(31.446)
ΔParis	1.969	7.135***	8.450***	8.791***	2.195	8.109***	8.977***	9.183***	4.714	7.508	10.309*	10.641**
	(1.720)	(2.028)	(2.300)	(2.522)	(2.322)	(2.490)	(2.768)	(2.985)	(5.765)	(5.633)	(5.515)	(5.379)
ΔLev	1.485***	2.477***	2.328***	2.201***	1.380***	2.238***	2.094***	1.970***	1.757***	3.066***	2.904***	2.770***
	(0.246)	(0.324)	(0.297)	(0.278)	(0.305)	(0.378)	(0.344)	(0.320)	(0.388)	(0.548)	(0.505)	(0.474)
ΔROA	0.031	0.145	0.105	0.106	0.071	0.157	0.113	0.085	−0.151	0.069	0.047	0.167
	(0.108)	(0.113)	(0.098)	(0.095)	(0.113)	(0.109)	(0.096)	(0.092)	(0.290)	(0.358)	(0.310)	(0.299)
ΔVol	2.733	1.457	1.055	0.994	4.506**	3.215*	2.689*	2.689*	−4.040***	−5.168***	−5.087***	−5.346***
	(1.797)	(1.472)	(1.305)	(1.264)	(2.080)	(1.648)	(1.472)	(1.403)	(1.373)	(1.022)	(0.977)	(1.089)
ΔBC	−0.202***	−0.245***	−0.235***	−0.227***	−0.208***	−0.243***	−0.235***	−0.231***	−0.177	−0.248*	−0.232**	−0.213***
	(0.048)	(0.053)	(0.047)	(0.043)	(0.053)	(0.056)	(0.053)	(0.051)	(0.113)	(0.131)	(0.100)	(0.080)
ΔIR	−16.269**	0.338	4.058	8.294*	−16.629*	−0.207	2.930	6.518	−16.117**	0.595	6.181	12.368**
	(7.075)	(5.074)	(4.776)	(4.519)	(9.199)	(6.409)	(6.143)	(5.830)	(7.146)	(7.060)	(6.146)	(6.229)
ΔIR2	2.565*	−0.300	−0.952	−1.845*	2.436	−0.408	−0.889	−1.657	3.050**	0.199	−0.981	−2.245**
	(1.478)	(1.106)	(1.061)	(1.037)	(1.927)	(1.400)	(1.380)	(1.355)	(1.311)	(1.357)	(1.097)	(1.138)
Number of observation	49,783	49,828	49,783	49,783	37,423	37,504	37,423	37,423	12,360	12,324	12,360	12,360
R-squared	0.019	0.038	0.038	0.035	0.017	0.032	0.032	0.029	0.032	0.064	0.062	0.056

Notes: This table shows the regression results for a panel first difference regression of the form: $\Delta S^{m}_{i,t+1} = \beta\Delta \mathrm{CR}_{i,t} + \eta\Delta \mathrm{Paris}_{i,t} + \gamma\Delta(\mathrm{Paris} \times \mathrm{CR})_{i,t} + \Phi\Delta X_{i,t} + \Theta\Delta Y_t$, where $\mathrm{CR}_{i,t}$ is the vector containing both *Physical* and *Transition*. Both physical and transition climate risk are based on Item 1.A in firms' 10-Ks. Coefficients are estimated by performing pooled OLS using the difference and this for different subsamples. Materiality subsamples are determined on expected climate change materiality on an industry level based on Matsumura, Prakash, and Vera-Muñoz (2018) and the SASB's materiality map. To measure the impact of the Paris agreement, we include "Paris" as a dummy for the subsequent period and interact this dummy with our climate risk exposure variable. Standard errors are clustered on an industry level. The sample period ranges from February 2010 to October 2021. By *, **, and ***, we denote *p*-levels below 10%, 5%, and 1%, respectively.

These results lend support to Hypothesis H_{Tr}, stating that the regulatory disclosure of transition risks increases credit spreads through a risk-perception effect—at least for those industries where climate risks are deemed material. The fact that the significant response of CDS spreads to transition risk disclosure starts after the Paris agreement is in line with the argument that CDS investors view climate risk as a novel risk factor that emerges from political developments. The effects along the whole term structure are qualitatively consistent with the theoretical prediction of a risk-perception effect via updated beliefs about asset value. In Table 4, the effect of transition climate risk disclosure is relatively small (10.83) and not significant for the 1-year maturity, whereas it is equally significant across larger maturities with the largest effect for the 5-year maturity compared with the longer maturities. This is most consistent with the change in the term structure shape suggested in Figure 1, Panel A.

4.4. Trump Election and Its Impact on Transition Risk

Transition risk arises from political processes in which governments impose additional regulations on business to mitigate climate change risks. It is therefore not surprising that the willingness to impose more regulation under the Paris Agreement stalled with the election of Donald Trump as President of the USA on November 8, 2016. Even during his election campaign, Trump threatened to withdraw the USA from the 2015 Paris Agreement and eventually announced that withdrawal on June 1, 2017.

We examine how Trump's election affects investor perceptions of the impact of transition risks on CDS spreads.[42] To do so, we add the Trump dummy while at the same time accounting for the Paris Agreement, that is, we estimate the regression:

$$\begin{aligned}\Delta S^m_{i,t+1} = {} & \beta_T \Delta\text{CR-Transition}_{i,t} + \beta_P \Delta\text{CR-Physical}_{i,t} \\ & + \gamma_T(\Delta\text{CR-Transition} \times \text{Paris})_{i,t} + \gamma_P(\Delta\text{CR-Physical} \times \text{Paris})_{i,t} \\ & + \psi_T(\Delta\text{CR-Transition} \times \text{Trump})_{i,t} + \psi_P(\Delta\text{CR-Physical} \times \text{Trump})_{i,t} \\ & + \eta\Delta\text{Paris}_{i,t} + \zeta\Delta\text{Trump}_{i,t} + \Phi\Delta X_{i,t} + \Theta\Delta Y_t + \epsilon_{i,t+1},\end{aligned} \tag{8}$$

Table 5 reports the results. We observe that Trump elect had a highly significant impact on how transition risk affects CDS spreads. While we have found that the Paris Agreement was causing an increase in the spreads for companies materially exposed to transition risk, we now observe, maybe not surprisingly, a reversal of this effect. Moreover, the Trump election is also affecting the short end of the CDS term structure, that is, it has already an immediate effect, while we do not observe such an immediate effect for the Paris Agreement. At the same time, comparing the transition risk coefficients in Table 5 with the one in Table 4 for the Paris Agreement, we observe that these coefficients become even more significant and almost twice as large when we take also the Trump election into account.

For visual comparison, we present the empirically derived effect of transition risk disclosure on the yield curve in Figure 3 for the materially affected firms, including the

42 In a first regression, we account for the Trump election in an identical fashion as we did for the Paris agreement, that is, introducing a Trump dummy. We find highly significant results for the materiality subsample. Trump's election led to a sharp decline in credit spreads for firms exposed to transition risk. We do not reproduce the table of regression results here, but it is available upon request.

Table 5 Monthly FD regression results, when separating physical and transition climate risk, controlling for materiality and both the Paris agreement and the Trump election

	(I) All ΔS^{1Y}	(II) All ΔS^{5Y}	(III) All ΔS^{10Y}	(IV) All ΔS^{30Y}	(V) Non-Mat ΔS^{1Y}	(VI) Non-Mat ΔS^{5Y}	(VII) Non-Mat ΔS^{10Y}	(VIII) Non-Mat ΔS^{30Y}	(IX) Mat ΔS^{1Y}	(X) Mat ΔS^{5Y}	(XI) Mat ΔS^{10Y}	(XII) Mat ΔS^{30Y}
ΔTransition	–37.009	–32.322	–26.309	–21.930	–44.706	–35.619	–27.661	–19.890	–25.224	–21.922	–18.612	–17.004
	(29.441)	(29.362)	(28.211)	(26.834)	(44.488)	(27.561)	(23.886)	(22.448)	(29.923)	(34.260)	(33.498)	(32.008)
ΔPhysical	–6.791	–9.353	–8.180	–5.456	–18.877**	–13.314	–14.838	–14.003	17.968	8.952	12.390	15.948
	(18.402)	(9.705)	(8.544)	(8.590)	(9.330)	(9.639)	(9.542)	(10.715)	(41.761)	(12.663)	(12.429)	(12.983)
ΔTransition × Paris	–1.493	47.324	41.340	35.322	–72.037	–44.430	–33.632	–30.373	32.303	86.951***	73.103***	65.211**
	(37.129)	(35.757)	(32.240)	(29.028)	(57.446)	(38.961)	(37.319)	(36.897)	(27.564)	(28.392)	(28.114)	(25.577)
ΔTransition×	–55.880**	–79.171***	–75.140***	–70.793***	–82.127	–46.413	–47.014	–48.206	–64.987**	–113.481***	–102.969***	–95.402***
Trump	(22.225)	(26.145)	(24.042)	(22.388)	(74.870)	(49.700)	(44.554)	(43.842)	(27.482)	(34.797)	(33.467)	(30.859)
ΔPhysical × Paris	–24.490	–17.294	–27.624	–32.321	–2.012	–18.531	–24.406	–27.441	–57.821	27.560	1.833	–9.936
	(33.710)	(31.942)	(29.514)	(29.748)	(20.136)	(32.335)	(32.129)	(33.373)	(122.192)	(98.994)	(83.309)	(78.468)
ΔPhysical×	–24.696	–30.214	–20.188	–18.174	–11.768	–24.484	–8.997	–5.730	–61.091	–89.753	–96.760	–95.292
Trump	(25.689)	(33.071)	(29.842)	(29.520)	(13.482)	(21.024)	(17.332)	(18.361)	(122.201)	(151.710)	(136.106)	(130.448)
ΔParis	0.814	5.674***	7.186***	7.625***	1.215	7.397***	8.449***	8.692***	–0.102	–0.399	2.858	3.655
	(1.693)	(2.154)	(2.426)	(2.640)	(1.769)	(2.326)	(2.741)	(3.009)	(4.225)	(2.720)	(3.346)	(3.802)
ΔTrump	7.742***	3.351	1.958	0.906	7.169**	1.270	0.073	–0.675	13.831	15.296	12.835	10.573
	(2.944)	(3.217)	(3.030)	(2.755)	(2.909)	(2.339)	(2.362)	(2.281)	(12.741)	(15.835)	(14.229)	(12.699)
ΔLev	1.480***	2.477***	2.329***	2.202***	1.375***	2.239***	2.095***	1.972***	1.757***	3.070***	2.909***	2.775***
	(0.245)	(0.322)	(0.295)	(0.276)	(0.305)	(0.378)	(0.344)	(0.321)	(0.383)	(0.539)	(0.496)	(0.465)

(continued)

Table 5 Continued

	(I) All ΔS^{1Y}	(II) All ΔS^{5Y}	(III) All ΔS^{10Y}	(IV) All ΔS^{30Y}	(V) Non-Mat ΔS^{1Y}	(VI) Non-Mat ΔS^{5Y}	(VII) Non-Mat ΔS^{10Y}	(VIII) Non-Mat ΔS^{30Y}	(IX) Mat ΔS^{1Y}	(X) Mat ΔS^{5Y}	(XI) Mat ΔS^{10Y}	(XII) Mat ΔS^{30Y}
ΔROA	0.037	0.152	0.111	0.112	0.074	0.157	0.112	0.084	–0.132	0.111	0.089	0.207
	(0.105)	(0.109)	(0.095)	(0.092)	(0.112)	(0.109)	(0.096)	(0.092)	(0.274)	(0.325)	(0.278)	(0.271)
ΔVol	2.670	1.412	1.018	0.965	4.460**	3.215*	2.694*	2.699*	–4.168***	–5.388***	–5.290***	–5.536***
	(1.786)	(1.473)	(1.306)	(1.269)	(2.065)	(1.643)	(1.468)	(1.400)	(1.305)	(1.017)	(0.946)	(1.167)
ΔBC	–0.206***	–0.242***	–0.232***	–0.223***	–0.214***	–0.242***	–0.234***	–0.229***	–0.176	–0.238*	–0.221**	–0.201***
	(0.049)	(0.053)	(0.047)	(0.043)	(0.054)	(0.057)	(0.053)	(0.051)	(0.113)	(0.129)	(0.098)	(0.077)
ΔIR	–17.143**	0.909	4.826	9.239**	–17.740*	–0.023	3.293	7.046	–16.265**	2.281	8.118	14.536**
	(7.226)	(5.147)	(4.837)	(4.552)	(9.370)	(6.496)	(6.220)	(5.867)	(7.725)	(7.594)	(6.557)	(6.561)
ΔIR2	2.693*	–0.381	–1.062	–1.980*	2.598	–0.434	–0.940	–1.732	3.072**	–0.043	–1.260	–2.558**
	(1.498)	(1.112)	(1.064)	(1.034)	(1.951)	(1.409)	(1.386)	(1.353)	(1.397)	(1.438)	(1.158)	(1.182)
Number of observation	49,783	49,828	49,783	49,783	37,423	37,504	37,423	37,423	12,360	12,324	12,360	12,360
R-squared	0.019	0.039	0.039	0.036	0.017	0.032	0.032	0.029	0.033	0.067	0.065	0.058

Notes: This table shows the regression results for a panel first difference regression of the form: $\Delta S^{m}_{i,t+1} = \beta \Delta \mathrm{CR}_{i,t} + \eta \Delta \mathrm{Paris}_{i,t} + \gamma \Delta(\mathrm{Paris} \times \mathrm{CR})_{i,t} + \zeta \Delta \mathrm{Trump}_{i,t} + \psi \Delta(\mathrm{Trump} \times \mathrm{CR})_{i,t} + \Phi \Delta X_{i,t} + \Theta \Delta Y_t$, where $\mathrm{CR}_{i,t}$ is the vector containing both *Physical* and *Transition*. Both physical and transition climate risk are based on Item 1.A in firms' 10-Ks. Coefficients are estimated by performing pooled OLS using the difference and this for different subsamples. Materiality subsamples are determined on expected climate change materiality on an industry level based on Matsumura, Prakash, and Vera-Muñoz (2018) and the SASB's materiality map. To measure the impact of the Paris agreement and the Trump election, we include "Paris" and "Trump" as dummies for the respective subsequent periods and interact these dummies with our climate risk exposure variable. Standard errors are clustered on an industry level. The sample period ranges from February 2010 to October 2021. By *, **, and *** we denote *p*-levels below 10%, 5%, and 1%, respectively.

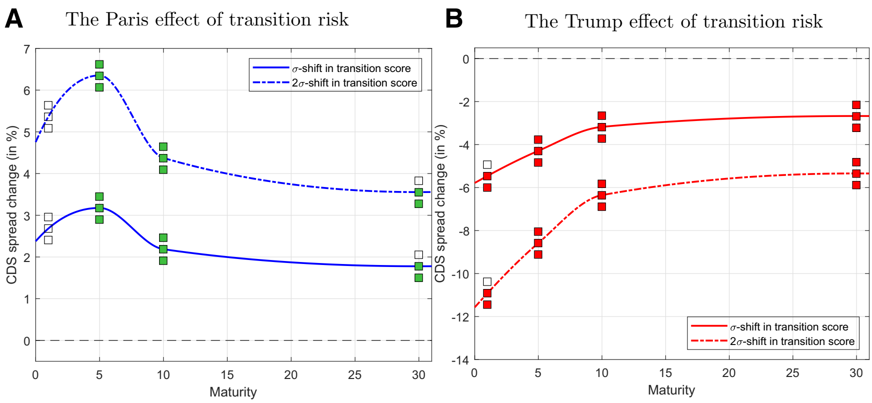

Figure 3 Impact of transition and physical climate risk on credit spreads. (A) The Paris effect of transition risk. (B) The Trump effect of transition risk. The figure plots the effect of transition risk disclosure in the 10-K filings. In Panel A, we illustrate the effect of the Paris Agreement. In particular, we plot the relative change in the CDS curve when we multiply the regression coefficient for the Paris Agreement with a one standard (solid line) and two standard deviation (dash-dotted line, 2SD) increase in the exposure to transition risk. In Panel B, we perform the same analysis for the Trump effect, that is, we plot the relative change in the CDS curve when we multiply the regression coefficient for the Trump presidency with a one standard (solid line) and two standard deviation (dash-dotted line, 2SD) increase in the exposure to transition risk. We only plot the results for the respective materiality subsample. The squares represent the significance levels of the impact of climate risk on the CDS spreads. Three, two, and one filled square represent the 1%, 5%, and 10% significance levels, respectively. The numbers used for the plots are from Table 5.

significance levels for the different maturity ranges. In Panel A, we present the impact of the Paris Agreement on the CDS term structure. We find that the Paris effect is strongest at 5-year maturities, leading to an increase of >3% for a one standard deviation shift in the underlying transition risk score. At higher maturities, the effect is still significant but slowly declines to just <2% at the 30-year maturity. For the Trump effect, we note that the relative increase in the CDS curve is the largest and also statistically highly significant at the 1-year maturity. A one standard deviation increase in the transition risk score leads to a nearly 6% decrease in the CDS spread due to the Trump election. This effect becomes less pronounced at longer maturities, but remains highly significant.

4.5. Using Alternative Measures for Climate Risk Disclosure

A major contribution of our paper is a novel way to measure climate risk based on regulatory disclosure. Therefore, we also benchmark our approach against other recent approaches. First, we use the firm-level climate scores from Sautner et al. (2022) and redo some of the analysis, which we have done in the previous section. In Appendix C, we present these results, showing that we cannot replicate our findings, nor do we find some significant results that would give us a convincing story on the impact of the firm-level climate score constructed in Sautner et al. (2022). We strongly believe that, as argued in Section 2, the reason for this observation lies in the inferior performance of keyword-based approaches for the classification task. Second, we use carbon emissions data to proxy for the companies' transition risk as in Bolton and Kacperczyk (2020) and Ilhan, Sautner, and

Vilkov (2021). Also, here we cannot replicate our findings. We conjecture that the reason might be in the heterogeneous quality of the voluntary emission disclosure by companies. But we leave a closer investigation of this conjecture for future research.

5 Conclusion

The disclosure of climate-related risks is a fundamental concern for companies, investors, and regulators worldwide. This article contributes a novel metric of climate risk based on mandatory disclosure and state-of-the-art NLP methods. Specifically, we use BERT to analyze 10-K reports that firms are required to file with the SEC. This measure's key advantages are that it is based on mandatory filings and allows differentiating between transition and physical risks.

Using this novel measure, we find that CDS spreads respond differently to regulatory climate risk disclosures, depending on whether they are concerned with transition or physical risk. Disclosure of transition risk increases leads to higher CDS spreads because it increases investors' risk perception, particularly after the Paris Agreement of 2015. However, this effect was weakened by Trump's election, which our transition risk score is also able to capture. In contrast, the disclosure of physical risk drives CDS spreads down because it improves the signal about unobservable risks, which leads to a decrease in the uncertainty premium attached to credit spreads.

Our paper is the first study to demonstrate the opposing effects of disclosing transition and physical risks on CDS spreads to the best of our knowledge. In future research, we plan to extend the analysis to other markets. In particular, it would be interesting to explore the risk-perception and information-uncertainty effects in the options markets since CDS spreads are intimately related to out-of-the-money put options. Moreover, we plan to extend our BERT-based algorithm to analyze also voluntary climate-risk reporting by companies.

Supplemental Data

Supplemental data are available at https://www.datahostingsite.com.

Appendix A

A.1. Additional Material for Section 2.3

In this section, we provide additional results on the comparison of the different methods to classify sentences related to physical and transition risk. We can further investigate the models' performance by inspecting the confusion matrices in Figure A.1. It turns out that all the models, except BERT, have some difficulties in separating the "general" class from the "transition" and "physical" classes.

In Figure A.2, we also plot the receiver operating characteristic (ROC) curves for BERT, which nicely show how well BERT is able to discriminate between the three classes. For the results using the dictionary-based approach in Sautner et al. (2022), we only plot the results for the binary classification into "physical" and "transition." The problem is that the list of bigrams is too sparse. Therefore, we drop the "general" class for the dictionary-based approach. However, even if we are willing to restrict ourselves to a binary classification into

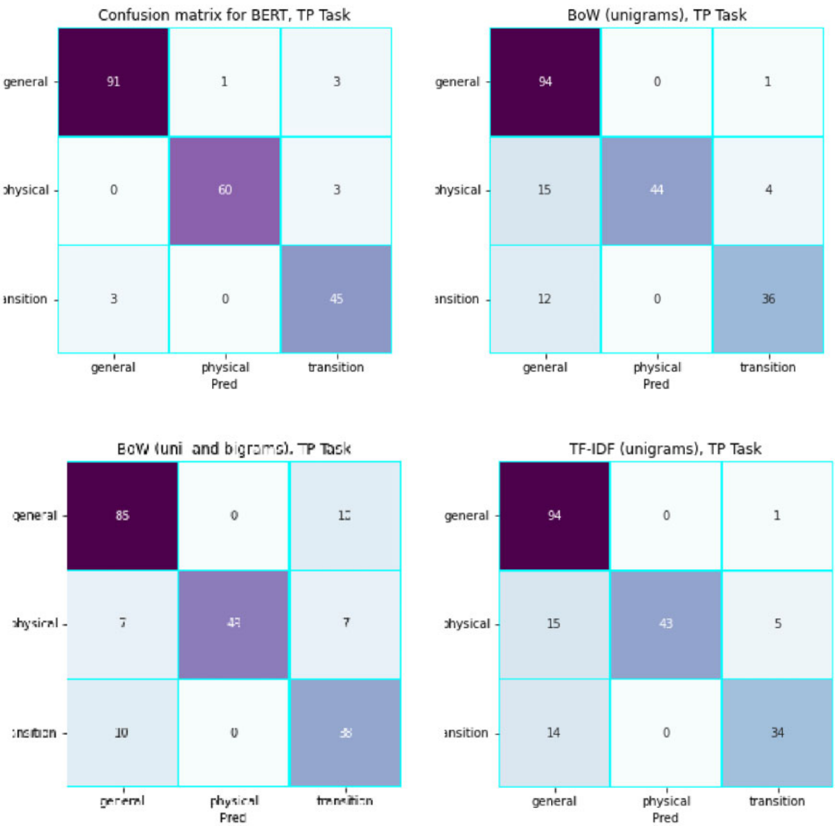

Figure A.1 Confusion matrices. The figures represent the confusion matrices for the different methods that we apply for the transition and physical risk classification task (TP). On the x-axis, we have the predicted classes and on the y-axis the true classes. A perfect model would only have entries on the diagonal of the confusion matrix.

"physical" and "transition," the resulting ROC curve falls basically on the 45-degree line, that is, the usefulness of bigrams for this problem is very limited, basically equal to a random guess (see Figure A.2).

We also tried to use only the bigrams for transition and physical risk from Sautner et al. (2022). However, given that the list of bigrams they provide in their paper is very limited, we did not find reasonable results and, therefore, we do not display them here. We also tested the power of the dictionary-based approach for the simple classification problem "climate" versus "non-climate." Here, using 750 bigrams from Sautner et al. (2022) related to climate, we find that the F1-score is 74.34 and the MCC is 0.512. However, for this task, we achieve with BERT an F1-score of 96.11 and an MCC of 0.923.

Hence, to give some more intuition for the performance of the models, in Figure A.3, we provide examples of where the prediction has failed on the test set. We only show the predictions for the BoW model based on unigrams and BERT.

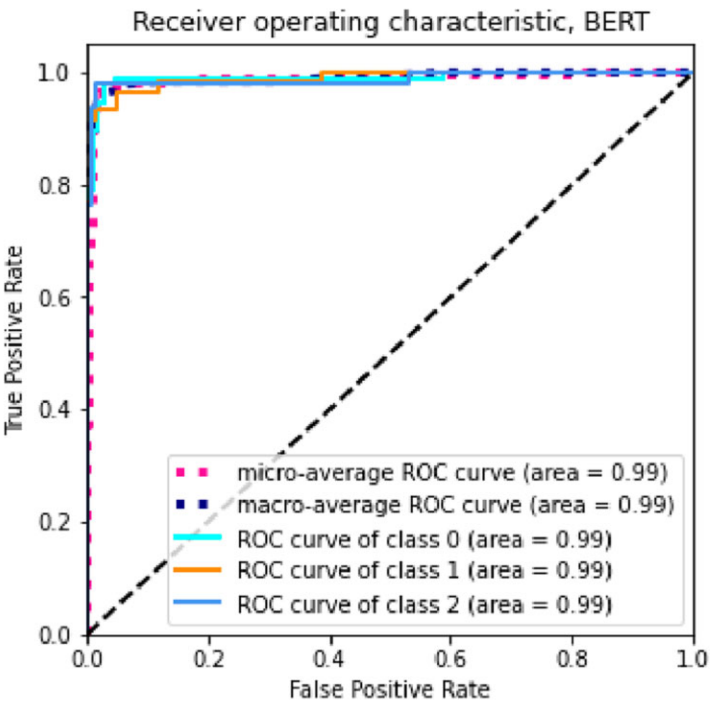

Figure A.2 ROC curves. The figures illustrate the ROC curves for the transition and physical risk classification task (TP). We plot the micro- and macro-averages together with the ROCs for the different classes.

Label: General BoW: General BERT: Transition

Sentence:
Many factors affect prices for oil and gas, including macroeconomic conditions, currency values, and the ability of some industry entities to influence prices.

Label: Transition BoW: Physical BERT: Transition

Sentence:
The Company reviews the carbon-intensity of reserves in the future as part of its overall reserves evaluation process, including its modeling of the energy intensity of production, transport, and refining as well as consideration of pricing for different types of hydrocarbon assets (i.e., potential discounts of such reserves relative to benchmark crudes due to increased downstream processing costs resulting from climate impacts).

Label: Physical BoW: General BERT: Physical

Sentence:
In Brazil, the shifting precipitation patterns may result in increased coca tree mortality in Bahia, and may result in competition for arable land with coffee.

Figure A.3 Example sentences from the test set. We present three examples where the prediction deviates from the true label. For comparison, we use the BoW model based on unigrams and BERT.

Appendix B

B.1. Industry Classification

In Table B.1, we present the distribution of our sample across industries. SICS identifies a total of 77 different industries, of which 66 are represented in our sample.

Table B.1 Industry constituents

Industry	# F	# F–m	Industry	# F	# F–m
Real Estate[a]	30	3809	Electric Utilities and Power Generators[b]	27	3291
Insurance[a]	22	2995	Industrial Machinery and Goods	20	2561
Multiline and Specialty Retailers and Distributors	19	2324	Chemicals[b]	16	1836
Oil and Gas—Exploration and Production[b]	15	1901	Telecommunication Services	12	1129
Medical Equipment and Supplies	11	1349	Software and IT Services	11	1435
Home Builders	11	1375	Containers and Packaging[b]	10	1115
Health Care Delivery[a]	9	1001	Iron and Steel Producers[b]	9	1238
Apparel, Accessories and Footwear	9	1084	Professional and Commercial Services	8	1127
Aerospace and Defense	8	948	Biotechnology and Pharmaceuticals	8	654
Semiconductors[b]	8	959	Media and Entertainment	8	910
Hardware	8	912	Household and Personal Products	7	949
Processed Foods	7	900	Managed Care[a]	6	640
Oil and Gas—Services[b]	6	457	Electrical and Electronic Equipment	6	707
Casinos and Gaming	5	540	Commercial Banks	5	666
Auto Parts	5	621	Airlines	5	656
Tobacco	4	420	Metals and Mining[b]	4	526
Food Retailers and Distributors	4	445	Building Products and Furnishings	4	529
Alcoholic Beverages	3	333	Agricultural Products	3	225
Oil and Gas—Midstream	3	304	Hotels and Lodging[a,b]	3	270
Consumer Finance	3	357	Air Freight and Logistics	3	423
Health Care Distributors	3	350	Waste Management	3	422
Drug Retailers	3	306	Restaurants	3	404
Advertising and Marketing	3	315	Non-Alcoholic Beverages	3	376
Construction Materials[b]	3	392	Investment Banking and Brokerage	3	380
Rail Transportation	3	423	E-Commerce	2	282
Asset Management and Custody Activities	2	267	EMS and ODM	2	172
Toys and Sporting Goods	2	282	Oil and Gas—Refining and Marketing[b]	2	113
Appliance Manufacturing	2	282	Mortgage Finance[a]	2	241
Pulp and Paper Products[b]	2	180	Meat, Poultry and Dairy[b]	1	141
Leisure Facilities	1	141	Car Rental and Leasing	1	124
Forestry Management[a]	1	141	Automobiles	1	141
Coal Operations[b]	1	15	Gas Utilities and Distributors	1	141
Engineering and Construction Services	1	128	Internet Media and Services	1	141

Notes: Industry constituents based on the SASB's SICS. The table shows per industry the number of companies in our sample (#F) and the number of firm–month observations (# F–m). [a(b)] superscript with an industry shows that the industry belongs to the physical material (material) group. The sample period ranges from February 2010 to October 2021.

Appendix C

C.1. Robustness Checks

For the robustness checks, we consider the firm-specific climate risk measures based on earnings calls transcripts, released as part of a working paper by Sautner et al. (2022). In addition, we consider carbon emissions as a proxy for transition risks since it has been used in several-related papers Bolton and Kacperczyk (2020) and Ilhan, Sautner, and Vilkov (2021).

C.2. Firm-Specific Climate Risk Score of Sautner et al. (2022)

We use the climate scores from Sautner et al. (2022) resulting from an elaborate keyword-based textual analysis of earnings conference calls that should allow for a fine-grained distinction between different aspects of climate-change discussions. Relying on a method introduced by King, Lam, and Roberts (2017), they produce four sets of climate change bigrams: a broadly defined climate-change measure and measures focusing on opportunity, physical, and regulatory shocks. For each of these four sets, they construct "exposure," "risk," and "sentiment" measures. They apply the method by counting the frequency with which certain climate change bigrams occur in each earnings call transcript, scaled by the total number of bigrams in the transcript. Their paper argues that the information extracted from earnings calls should be unbiased and only minimally exposed to greenwashing effects. Therefore, we expect that, in this respect, their data source should be of similar quality as the 10-K filings, allowing us to employ their scores in our analysis for comparison.

For our robustness analysis, we mainly focus on the 5-year CDS spreads.[43] As Table C.1 suggests, in the period after the Paris Agreement, the exposure measure for the broadly defined climate category had a significant negative impact on CDS spreads, irrespective of materiality. Although only significant at the 10% level, the strongest impact of this measure is for the non-material industries. Furthermore, the risk measure has no significant impact on CDS spreads during this period. However, it negatively impacts CDS spreads for the whole period, supporting the information-uncertainty effect. This finding is slightly at odds with their observation that they find an increase in the firms' climate-change exposure since the Paris Agreement in 2015 and the 2016 Trump election. Given that these results are not convincing, we switch to more specific measures that differentiate between regulatory and physical aspects.

In Table C.2, we account for the differences between regulatory and physical exposures, risk, and sentiments. We find that the exposure to regulatory shocks negatively affects the non-material industries after the Paris Agreement. Simultaneously, the effect of the risk of regulatory shocks switches sign and becomes positive, hence supporting a risk-perception effect. The same observation can be made for the risk of physical shocks. It also changes signs, depending on the Paris Agreement, but it does so (statistically significant) for the non-material industries.

Overall, we do not find clear and consistent results to link our theoretical predictions regarding risk-perceptions and information-uncertainty effects, as we did with our BERT-based climate measure. Again, we believe that the regression results' fuzziness stems from

43 All other results can be obtained by the authors.

Table C.1 Monthly FD regression results using the climate scores from Sautner et al. (2022), controlling for materiality and the Paris agreement

	(I) All ΔS^{5Y}	(II) Non-Mat ΔS^{5Y}	(III) Mat ΔS^{5Y}	(IV) All ΔS^{5Y}	(V) Non-Mat ΔS^{5Y}	(VI) Mat ΔS^{5Y}	(VII) All ΔS^{5Y}	(VIII) Non-Mat ΔS^{5Y}	(IX) Mat ΔS^{5Y}
Δcc-expo	1.307	6.673**	0.776						
	(1.187)	(3.139)	(1.245)						
Δcc-risk				–21.745**	–15.335	–23.053**			
				(8.617)	(24.754)	(9.618)			
Δcc-sent							3.223	2.076	4.243
							(3.327)	(3.640)	(4.908)
Δcc-expo × Paris	–1.872	–5.187	–2.627						
	(1.569)	(6.102)	(2.404)						
Δcc-risk × Paris				5.597	7.115	4.357			
				(11.332)	(28.889)	(13.605)			
Δcc-sent × Paris							–2.385	0.115	–4.038
							(3.297)	(5.290)	(4.406)
ΔParis	8.184***	5.876***	16.269	7.963***	5.612***	15.452	7.982***	5.619***	15.623*
	(2.835)	(1.905)	(10.020)	(2.753)	(1.794)	(9.467)	(2.723)	(1.792)	(9.413)
Number of observation	49,363	37,250	12,113	49,568	37,354	12,214	49,467	37,354	12,113
R-squared	0.038	0.031	0.062	0.038	0.031	0.064	0.038	0.031	0.062
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the regression results for a panel first difference regression of the form: $\Delta S^{m}_{i,t+1} = \beta\Delta \mathrm{CC}_{i,t} + \eta\Delta \mathrm{Paris}_{i,t} + \gamma\Delta(\mathrm{Paris} \times \mathrm{CC})_{i,t} + \Phi\Delta X_{i,t} + \Theta\Delta Y_t$, where $\mathrm{CC}_{i,t}$ is one of the general scores constructed by Sautner et al. (2022), X and Y are vectors of firm-specific and macro-economic controls, respectively. Coefficients are estimated by performing pooled OLS using the difference and this for different subsamples. Materiality subsamples are determined on expected climate change materiality on an industry level based on Matsumura, Prakash, and Vera-Muñoz (2018) and the SASB's materiality map. To measure the impact of the Paris agreement, we include "Paris" as a dummy for the subsequent period and interact this dummy with our climate risk exposure variable. Standard errors are clustered on an industry level. The sample period ranges from February 2010 to October 2021. By *, **, and *** we denote p-levels below 10%, 5%, and 1%, respectively.

Table C.2 Monthly FD regression results using the regulatory and physical scores from Sautner et al. (2022), controlling for both materiality and the Paris agreement

	(I) All ΔS^{5Y}	(II) Non-Mat ΔS^{5Y}	(III) Mat ΔS^{5Y}	(IV) All ΔS^{5Y}	(V) Non-Mat ΔS^{5Y}	(VI) Mat ΔS^{5Y}	(VII) All ΔS^{5Y}	(VIII) Non-Mat ΔS^{5Y}	(IX) Mat ΔS^{5Y}
Δrg-expo	3.356	14.674	2.770						
	(5.989)	(21.027)	(5.765)						
Δrg-risk				–52.807***	–76.521	–51.196***			
				(12.126)	(48.350)	(6.445)			
Δrg-sent							13.135	–0.050	20.522
							(15.977)	(11.986)	(22.842)
Δph-expo	64.684**	80.655**	32.985						
	(28.551)	(36.831)	(28.593)						
Δph-risk				–60.617	–160.872*	11.513			
				(63.868)	(86.217)	(25.752)			
Δph-sent							38.140	71.971	–2.333
							(28.391)	(50.548)	(22.963)
Δrg-expo × Paris	–7.260	–53.622*	–13.393						
	(7.731)	(31.008)	(14.366)						
Δrg-expo × Trump	–3.033	48.265	0.285						
	(10.196)	(33.358)	(14.983)						
Δrg-risk × Paris				–75.422	–380.882***	96.543**			
				(163.968)	(38.681)	(42.566)			
Δrg-risk × Trump				53.130	459.646***	–137.599*			
				(138.117)	(32.960)	(71.093)			
Δrg-sent × Paris							3.039	–10.488	–5.963
							(13.324)	(22.027)	(12.773)

(continued)

Table C.2 Continued

	(I) All ΔS^{5Y}	(II) Non-Mat ΔS^{5Y}	(III) Mat ΔS^{5Y}	(IV) All ΔS^{5Y}	(V) Non-Mat ΔS^{5Y}	(VI) Mat ΔS^{5Y}	(VII) All ΔS^{5Y}	(VIII) Non-Mat ΔS^{5Y}	(IX) Mat ΔS^{5Y}
Δrg-sent × Trump							−10.146	−2.589	−3.036
							(22.813)	(24.165)	(26.480)
Δph-expo × Paris	−40.156**	−43.152*	−52.024						
	(18.142)	(25.047)	(46.847)						
Δph-expo × Trump	−16.851	−43.795	61.495						
	(37.001)	(34.576)	(81.816)						
Δph-risk × Trump				738.325***	731.755**	920.871*			
				(277.491)	(314.996)	(522.080)			
Δph-sent × Paris							−59.278*	−76.382**	−26.104
							(31.270)	(37.629)	(25.680)
Δph-sent × Trump							15.300	−14.770	64.588
							(44.435)	(63.131)	(54.307)
ΔParis	8.120***	5.751***	16.074*	8.016***	5.662***	15.661*	8.048***	5.695***	15.690*
	(2.779)	(1.798)	(9.688)	(2.744)	(1.801)	(9.408)	(2.753)	(1.797)	(9.445)
ΔTrump	−2.987**	−0.920	−9.737***	−3.055**	−0.908	−9.644***	−3.022**	−0.887	−9.683***
	(1.258)	(1.284)	(2.714)	(1.267)	(1.283)	(2.743)	(1.265)	(1.286)	(2.722)
Number of observation	49,568	37,354	12,214	49,664	37,450	12,214	49,568	37,354	12,214
R-squared	0.038	0.031	0.064	0.038	0.031	0.064	0.038	0.031	0.064
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the regression results for a panel first difference regression of the form: $\Delta S^m_{i,t+1} = \beta \Delta CC_{i,t} + \eta \Delta Paris_{i,t} + \gamma \Delta(Paris \times CC)_{i,t} + \zeta \Delta Trump_{i,t} + \psi \Delta(Trump \times CC)_{i,t} + \Phi \Delta X_{i,t} + \Theta \Delta Y_t$, where $CC_{i,t}$ is the vector containing both the transition and regulatory scores from Sautner et al. (2022). Coefficients are estimated by performing pooled OLS using the difference and this for different subsamples. Materiality subsamples are determined on expected climate change materiality on an industry level based on Matsumura, Prakash, and Vera-Muñoz (2018) and the SASB's materiality map. To measure the impact of the Paris agreement and the Trump election, we include "Paris" and "Trump" as dummies for the respective subsequent periods and interact these dummies with our climate risk exposure variable. Standard errors are clustered on an industry level. The sample period ranges from February 2010 to October 2021. By *, **, and *** we denote *p*-levels below 10%, 5%, and 1%, respectively.

the lack of Prec of keyword-based approaches. Hence, our findings suggest that BERT's improved Prec is necessary to establish a consistent link between climate risk disclosure and CDS spreads.

C.3. Carbon Emissions

Instead of relying on textual analysis, other recent studies like, for example, Bolton and Kacperczyk (2020), study climate risks in equity markets based on carbon emissions data.[44] Indeed, carbon emissions may be a reasonable proxy for transition risk, given that companies with high carbon emissions are expected to be affected most by regulation that is designed to reduce CO_2 emissions. This raises the question of whether our novel measure based on 10-K reports really improves upon risk measures already available. Therefore, we repeat our analysis using carbon emissions data as proxies for (transition) climate risk. We collect carbon emissions data from Asset4, via Datastream. To conduct this test as rigorously as possible, we obtain seven different carbon emission measures, namely direct CO_2 emissions (Scope1), indirect CO_2 emissions (Scope2), scope three indirect CO_2 emissions (Scope3), the total over all three scopes (Scope123), the total over all three scopes scaled by total revenues (Scope123-Rev), estimated CO_2 emissions (EstEm), and an emissions score (EmScore) provided by Asset4. Emission values are measured in million tons of CO_2 equivalent and the emission score is a percentile rank based on emissions data.

In replicating our analysis with carbon emissions data, we faced two additional challenges. First, the disclosure of emissions is non-mandatory, resulting in numerous missing observations when companies did not report. Second, those companies volunteering to disclose emissions data do so in various formats and irregular reporting cycles, making it hard to pinpoint when this information became available to the market. In contrast, 10-K filings are available for all companies and have clearly defined reporting periods and filing dates, which can easily be retrieved *ex post*.[45] To be as consistent as possible, we shift the firms' emission data 6 months after the end of the reporting period to compensate for not knowing the firms' reporting data and to be as consistent as possible for our climate risk proxies based on the 10-K filings and their filing dates.

We replicated our previous analyses with all seven carbon emissions proxies. None of the carbon emissions proxies fully replicate our results.[46] The only measure that partly replicates our results is the scaled total emissions measure *Scope123-Rev*. Therefore, in what follows, we focus on this emission proxy. In Table C.3, we provide the regression analysis results that account for materiality and the Paris accord. We do not narrow down on physical materiality since arguably CO_2-emissions are predominantly related to transitory risks. The results for the materiality subsets, Columns (I) and (II), suggest that only material industries are positively affected by higher direct carbon emissions, but only at a 10% significance level. Moreover, there seems to be no specific Paris effect, in contrast to our

44 Some previous studies observe a premium on stock returns for firms exposed to climate risk. While equity prices could, in parallel, be driven by investors' taste thanks to divestments (see, e.g., Hong and Kacperczyk (2009) and Pastor, Stambaugh, and Taylor (2020)), this alternative hypothesis is highly unlikely in the CDS market.

45 Depending on a firm's size and corresponding filing category, 10-K reports must be filed within 60–90 days of the end of any financial year.

46 The results with different kind of scope 1–3 combinations are available upon request.

Table C.3 Monthly FD regression results, controlling for both materiality and both the Paris agreement and the Trump election

	(I) All ΔS^{5Y}	(II) All ΔS^{5Y}	(III) All ΔS^{5Y}	(IV) Non-Mat ΔS^{5Y}	(V) Non-Mat ΔS^{5Y}	(VI) Non-Mat ΔS^{5Y}	(VII) Mat ΔS^{5Y}	(VIII) Mat ΔS^{5Y}	(IX) Mat ΔS^{5Y}
ΔScope123-Rev	−0.006	−0.005	−0.004	−0.002	−0.001	−0.001	−0.007	−0.005	−0.004
	(0.006)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.008)	(0.007)	(0.006)
ΔScope123-Rev × Paris		−0.001	−0.001		−0.001	−0.001		−0.003	−0.003
		(0.001)	(0.001)		(0.001)	(0.001)		(0.004)	(0.004)
ΔScope123-Rev × Trump			−0.003*			−0.000			−0.003
			(0.001)			(0.001)			(0.002)
ΔParis		9.531**	9.491**		6.446***	6.477***		22.309	22.116
		(4.538)	(4.513)		(2.345)	(2.350)		(18.399)	(18.327)
ΔTrump			−1.839*			−1.437*			−3.518
			(1.080)			(0.856)			(3.626)
ΔLev	2.294***	2.286***	2.295***	1.809***	1.800***	1.803***	3.079***	3.074***	3.095***
	(0.415)	(0.414)	(0.414)	(0.375)	(0.375)	(0.375)	(0.705)	(0.702)	(0.703)
ΔROA	0.221	0.219	0.221	0.416***	0.414***	0.415***	−0.113	−0.117	−0.111
	(0.225)	(0.226)	(0.226)	(0.148)	(0.148)	(0.148)	(0.444)	(0.446)	(0.448)
ΔVol	0.294	0.106	0.101	3.137	3.017	3.016	−5.388**	−5.833**	−5.855**
	(2.171)	(2.199)	(2.201)	(2.827)	(2.843)	(2.844)	(2.407)	(2.452)	(2.482)
ΔBC	−0.106*	−0.098*	−0.092	−0.060	−0.054	−0.052	−0.252	−0.234	−0.220
	(0.061)	(0.058)	(0.058)	(0.040)	(0.040)	(0.040)	(0.185)	(0.170)	(0.172)
ΔIR	−19.099**	−19.800**	−19.490**	−20.248*	−20.721*	−20.583*	−15.493	−17.030	−16.362
	(9.186)	(9.191)	(9.199)	(11.471)	(11.418)	(11.427)	(13.630)	(14.291)	(14.267)
ΔIR2	5.059**	5.326**	5.345**	5.348**	5.529**	5.538**	4.099	4.652	4.708
	(2.084)	(2.080)	(2.083)	(2.657)	(2.637)	(2.636)	(2.805)	(2.990)	(3.031)
Number of observation	22,088	22,088	22,088	15,763	15,763	15,763	6325	6325	6325
R-squared	0.037	0.038	0.038	0.027	0.028	0.028	0.061	0.063	0.064

Notes: This table shows the regression results for a panel first difference regression of the general form: $\Delta S^m_{i,t+1} = \beta \Delta \mathrm{CR}_{i,t} + \eta \Delta \mathrm{Paris}_{i,t} + \gamma \Delta(\mathrm{Paris} \times \mathrm{CR})_{i,t} + \zeta \Delta \mathrm{Trump}_{i,t} + \psi \Delta(\mathrm{Trump} \times \mathrm{CR})_{i,t} + \Phi \Delta X_{i,t} + \Theta \Delta Y_t$, where $\mathrm{CR}_{i,t}$ is Scope123-Rev, the revenue-scaled Scope 1–3 C02 equivalent emissions. X and Y are vectors of firm-specific and macro-economic controls, respectively. Coefficients are estimated by performing pooled OLS using the difference and this for different subsamples. Materiality subsamples are determined on expected climate change materiality on an industry level based on Matsumura, Prakash, and Vera-Muñoz (2018) and the SASB's materiality map. To measure the impact of the Paris agreement and the Trump election, we include "Paris" and "Trump" as dummies for the respective subsequent periods and interact these dummies with our climate risk exposure variable. Standard errors are clustered on an industry level. The sample period ranges from February 2010 to October 2021. By *, **, and ***, we denote p-levels below 10%, 5%, and 1%, respectively.

findings for Transition. After the Paris Agreement, the effect of Scope123-Rev as a climate risk measure does not increase, which is inconsistent with the reasonable expectation that climate risks became much more relevant after Paris.

Thus, while we find some evidence that Scope123-Rev gives some indication of climate risk exposure and influences CDS spreads, our BERT-based measure shows an increased relevance of transition risk after Paris, which is intuitive and has been documented in other studies as well (Delis, de Greiff, and Ongena 2019). We note that by using emissions-based proxies, the sample size is substantially reduced. These missing observations may be driving our results for CR-Transition, which would highlight the importance of mandatory disclosure. CR-Transition offers the benefit of measuring climate risk for all 10-K reporting firms, instead of only those voluntarily disclosing carbon emission data. We also note that while carbon emissions are undoubtedly a relevant driver of climate risk, there is uncertainty about when regulation will come, which industries will be affected most, and to what extent companies will pass on the cost of regulation. Climate risk disclosure in 10-K reports potentially captures these nuances better than emissions figures.

Lastly, if we use carbon emissions as a proxy for transition risk and recalling the economic significance of our transition risk measure giving rise to an increase of 2.88 bps in the average 5-year CDS spread, we can ask whether the significant impact of Scope123-Rev is of similar magnitude. However, we find that a one standard deviation shift in the Scope123-Rev measure leads to a decrease of 1.11 bps in the 5-year CDS spread for the full period.

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