Beyond Climate: The impact of biodiversity, water, and pollution on the CDS term structure

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Abstract

We investigate the impact of three non-climate environmental criteria: biodiversity, water, and pollution prevention, on infrastructure firms' credit risk term structure from the perspective of double materiality. Our findings show that firms that effectively manage these three environmental risks to which they are materially exposed have up to 93bps better long-term refinancing conditions compared to the worst-performing firms. While the results are less significant for the firm's material impact on the environment, investors still reward the management of these criteria beyond climate with improved long-term financing conditions for infrastructure investments. Overall, we find that financial markets respond positively to the prospect of more stringent regulations related to these criteria, which are currently used by the EU Taxonomy to assess the sustainability of investments.

Keywords: Double materiality, EU Taxonomy, infrastructure, term structure.
JEL classification: G12; G18; G32; M14; Q52

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1 Introduction

This study explores the influence of the EU Taxonomy's non-climate environmental criteria, including biodiversity, water, and pollution, on infrastructure companies' credit risk term structure. Our results suggest that improved management of these environmental factors beyond climate change leads to more favorable long-term financing conditions. This is reflected in lower credit default spreads (CDS) on infrastructure investments, indicating that investors consider better environmental management an important factor in determining creditworthiness.

The European Union's Taxonomy on Sustainable Finance is a novel classification system designed to provide clear criteria for sustainable investing, promoting environmentally sound investments (Regulation (EU) 2020/852, 2020). Detailed environmental criteria help to assess whether an investment merits the green label. It further allows investors to better understand their sustainability footprint based on a transparent benchmark. Six environmental goals are at the heart of this legislation. Those are (1) climate change mitigation, (2) climate change adaptation, (3) sustainable use and protection of water and marine resources, (4) transition to a circular economy, (5) pollution prevention and control, and (6) protection and restoration of biodiversity and ecosystems. An investment is considered green when it significantly contributes to one of these categories without harming any of the others.

Despite the EUTSF's importance in combating environmental issues and its potential consequences for companies and investors, a research gap exists on the relative importance of individual technical indicators in the taxonomy beyond climate change. This study is the first to identify the impact of key benchmark indicators beyond climate change, i.e., biodiversity, water, and pollution prevention, on the credit risk term structure of firms in the infrastructure sector.

The importance of pollution prevention, biodiversity, and water scarcity on the economy is becoming a prominent topic in both practical and public policy circles. In the United States, the Environmental Protection Agency (EPA) has been working to promote pollution prevention measures and reduce the environmental impact of businesses. Meanwhile, in the European Union, the EU Taxonomy has been developed to identify activities that contribute to environmental sustainability, including those related to biodiversity, water scarcity, and pollution. On March 22, 2023, the UN Secretary-General, Antonio Guterres, emphasized the significance of water as a vital resource for economic development and prosperity in all nations. Experts have also warned that water supplies are dwindling, and competition from sectors that are heavy users of water, such as agriculture, energy, industry, and urban areas, will only increase. As a result, water scarcity is likely to become the biggest scarcity ever faced by humanity.[1]

While the focus on these issues is growing, it is surprising that there is little academic research on how biodiversity and other factors beyond climate impact financial markets. This lack of knowledge has been noted in recent academic literature, including calls for research on biodiversity finance. Recently, Karolyi and Tobin-de la Puente (2023) called for research on biodiversity finance. According to the authors, there is a noticeable dearth of studies on the risks related to biodiversity loss, how these risks can be priced, and how private financing flows need to be intermediated, particularly in top-tier finance journals. This research gap has also been highlighted in the 2023 Presidential Address by Laura Starks at the American Finance Association Meetings. The factors contributing to this knowledge gap include, among others, the scarcity of data on biodiversity and other environmental factors beyond emission data.[2]

Only recently, two contemporaneous papers deal with biodiversity finance. Flammer et al.

[1]This sentiment echoes the concerns of scientists from the European Commission's Joint Research Centre. They warned already in 2005 of the increasing competition for water resources from agriculture, energy, industry, and urban areas. See the Financial Times, https://www.ft.com/content/982ff714-9976-11d9-ae69-00000e2511c8.

[2]For this reason, we exclude the climate change theme since it has been extensively discussed in studies such as Alekseev et al. (2022), Bolton and Kacperczyk (2021), and Engle et al. (2020), among others.

(2023) provide evidence of the use of private capital to finance biodiversity conservation and restoration. On the other hand, Garel et al. (2023) conducted an event study that showed that following the UN Biodiversity Conference (COP15) in October 2021 (Kunming) and December 2022 (Montreal), firms with larger corporate biodiversity footprints experienced a decline in their value. This response is consistent with investors revising their valuation of these firms downwards upon the prospect that regulations to preserve biodiversity will become more stringent. However, further research is still needed to measure better and understand the impacts of firms on biodiversity, water scarcity, and pollution prevention and the associated financial risks for a broad range of companies.

Our study focuses on the infrastructure sector for several reasons. First, as highlighted by a report published by the United Nations Environment Programme in 2021,[3] infrastructure is responsible for 79 percent of all greenhouse gas emissions and 88 percent of all adaptation costs. Hence, the infrastructure sector plays a key role in fostering taxonomy-compatible developments. Second, infrastructure projects often involve significant investments in assets designed to operate over the long term.[4] Historically, the design of these facilities has been based on the assumption of a regulatory environment and a future climate similar to current conditions. However, risks associated with biodiversity, pollution prevention, and water directly threaten the infrastructure sector due to potentially costly environmental regulations, activists trying to prevent projects to preserve nature, and reputation costs to firms operating in this sector. As a consequence, the negative implications also impact those who rely on the services provided by these assets. Third, the EUTSF primarily aims to increase private funding to 'shift the trillions' and foster green infrastructure investments.

The main goal of this study is to shed light on the market's view concerning the timing of the

[3] The report "Infrastructure for Climate Action" is the product of a collaboration between UNOPS, UNEP, and the University of Oxford. See https://www.unep.org/resources/report/infrastructure-climate-action.

[4] For example, coal-fired power plants are designed for a lifetime of 40 to 50 years, hydropower dams, and large geotechnical structures with a lifetime of up to 100 years.

three EUTSF environmental risks beyond climate change and whether they are perceived as long- or short-term issues. Very little research has been done on these topics, although the urgency is no less due to increasing droughts and the destruction of the natural habitat of countless species. While challenges related to the preservation of water and biodiversity have received limited attention in financial research, our results suggest that they are important factors in firms' financing conditions, substantiating our rationale to explore environmental issues beyond climate change. Our findings show that firms managing any of these three risks best have up to 94bps better relative long-term refinancing conditions than the worst ones. Concerning the second part of double materiality (i.e., the firm's impact on the environment), we find statistically significant results only for pollution prevention of up to 73bps. The flattening of the CDS curve indicates that investors perceive those risks as long-term issues. In contrast, we do not observe a statistically significant relationship between a firm's impact on biodiversity and CDS slopes. However, this result does not reflect investors' indifference to infrastructure firms' impact on biodiversity but rather that investors exhibit more pressing concerns. Our results for disclosure quality within pollution prevention and water risk categories confirm the long-termism view.

Finally, we corroborate the causal relationship between taxonomy performance and corporate credit risk by looking at regulatory shocks. We leverage the global shift towards more right-wing politics with the Brexit referendum in Europe and the election of Donald Trump in 2016. For most of the environmental themes outlined in the EU taxonomy, we find that these shocks led to a reversal in the effects of taxonomy performance on the credit spread curve. However, the reversal is primarily on the short end of the CDS term structure, while the long end remains unaffected by these potentially short-lived political changes. Our evidence indicates that financial markets do react to current political events necessitating a revision in short-term expectations without losing sight of the long-term perspective.

Our study differs from previous work in that we explore the impact of three key KPIs from the EUTSF on the CDS term structure in the infrastructure sector beyond the climate risks typically examined in the literature. The three categories of interest comprise a) pollution prevention, b) water, and c) biodiversity. When establishing a relationship between firms' financing conditions and environmental performance measures, we take into account the concept of double materiality, which highlights the importance of considering the environmental impacts of investments (i.e., the impact of the firm's activities on the environment) and the potential risks of the environment for the firm (i.e., conventional materiality). Hence, we are the first to explore potential cash-flow risks to firms when legislators attempt to internalize the social costs of business operations with negative externalities in one of the three categories. Also, companies with high exposure to those risks might be adversely impacted by extreme weather events, natural disasters, or reputation loss when they fail to adhere to best practices. Second, we investigate how the firm's business operations influence environmental sustainability. This channel focuses on the consequences of firms' negative externalities on their CDS curve. Lastly, we investigate how reporting mediates the results.

We contribute to the growing body of research on the relationship between Environmental, Social, and Governance (ESG) factors and various financial outcomes such as stock returns, risk exposure, and firm financial performance.[5] In previous research, much attention has been paid to greenhouse gas emissions. For instance, Bolton and Kacperczyk (2021) find that higher emissions correlate with higher returns. Some investors exclude companies based on their carbon intensity profile. These empirical findings are backed by general equilibrium asset pricing models showing that dirty firms are more exposed to climate risk. Therefore, investors demand compensation which is reflected in higher expected returns (Hsu et al. (2022).[6] From

[5]Fama and French (2007) show that two key assumptions - agreement amongst investors on the expected return of an asset and investment decision purely driven by pecuniary motives - are mostly unrealistic. Indeed, some investors are willing to sacrifice some of their profits to hold stocks aligned with their tastes. Hence, an investor who cares about the environment leaves money on the table to hold greener assets. Hartzmark and Sussman (2019) find that investors have a preference for sustainable assets. Moreover, Krueger et al. (2020) suggest that institutional investors care about climate risk, and their survey reveals that it is expected to materialize in the near future.

[6]Such a view is also supported by studies such as Albuquerque et al. (2019).

the investors' perspective, it becomes increasingly relevant to consider climate risk in their portfolio choice. Engaged ESG shareholders can help reduce downside risk for companies, especially regarding climate-related topics (Hoepner et al., 2018). To lower exposure to climate risks, dynamic strategies using mimicking portfolios to hedge against adverse climate news have been proposed (Engle et al., 2020). As shown by Kölbel et al. (2022), investors are also concerned about climate risk and its potential impact on credit risk. As such, Blasberg et al. (2022) find that lenders demand a higher cost of credit protection for firms with higher exposure to carbon risk. Starks et al. (2017) show that ESG investors tend to exhibit longer investment horizons and hold on to highly rated ESG stocks even if they perform poorly. Other studies such as Gibson et al. (2020) corroborate the view that socially responsible investors are more long-term oriented. This further motivates us to examine the term structure of environmental criteria beyond climate change in this study.

Very few studies have started to investigate the impact of the novel EUTSF on firms and financial markets. Hoepner and Schneider (2022) and Lucarelli et al. (2020) outline the key concepts of the taxonomy and provide guidance on the EUTSF definition of sustainable activities. Alessi and Battiston (2022) derive a method to estimate the greenness of a portfolio as measured by the alignment with the criteria in the EU taxonomy. Bassen et al. (2022) show that firms with more taxonomy-aligned revenues experienced higher realized returns after implementing the EUTSF. Dumrose et al. (2022) argue that the taxonomy is a stepping stone to decrease the divergence in ESG ratings, a problem revealed in Berg et al. (2022). Those studies are crucial to enhance our understanding of the impact of the EUTSF on firms and investors. We contribute to this growing literature by investigating the individual criteria beyond climate change and their influence on the term structure of corporate credit risk in the infrastructure sector.

In a study close to ours, Sautner et al. (2022) shed light on the potential impact of the EU taxonomy on (desired) capital allocation. By looking at the relationship between syndicated loan spreads and EU taxonomy-aligned revenues, Sautner et al. (2022) find that financial markets already priced in some of the envisioned effects of the EU taxonomy. The main differences between their study and ours are that we focus on the infrastructure sector and the long-term investment horizon. Additionally, we focus on a firm's (relative) performance on the taxonomy's environmental objectives instead of revenue share from transitional activities. Moreover, we discuss the causal relationship between green KPIs and the financing conditions of companies. In addition, we explore the market's view on the timing of risks associated with environmental taxonomy topics beyond climate change. Finally, to the best of our knowledge, we are the first to shed light on the EU taxonomy of sustainable activities beyond climate change which encompasses the under-researched fields of water, pollution prevention, and biodiversity.

This study not only offers guidance to companies on those key performance indicators (KPIs), but also provides insight for legislators seeking to refine the benchmark criteria. This latter aspect is particularly relevant as the EUTSF is still in the process of development. Consequently, scientific evidence concerning the taxonomy's impact beyond climate change on firms' long-term financing conditions is essential for creating an improved benchmark taxonomy of sustainable investments.

The remaining part of this paper is structured as follows. Section 2 introduces the data. Section 3 discusses our hypotheses and expectations. Section 4 describes our methodology and discusses the results. Section 5 concludes and provides ideas for future research.

2 Data

We use four different data sources for our analysis. The period ranges from December 2007 to January 2018, and the data consists of an international panel of companies classified within the infrastructure SASB sector.[7] The start of the period coincides either with the availability of CDS data or the respective Eiris indicator, while the end of the period is defined by the time that Eiris stopped providing their ESG assessment KPIs.[8] In addition to the Eiris ESG indicators and firm CDS spreads, we collect firm-level and macroeconomic control variables for our regressions.

2.1 Eiris indicators

We exploit a unique and rich dataset of firm-specific ESG indicators provided by Eiris. Eiris qualitatively rates firms on various ESG indicators. Indicators follow a stepwise scale and are described by an accompanying 'question'. Eiris provides their evaluation on the company level as well as an assessment scale for each indicator (see Table 1). We select those Eiris KPIs that relate to the criteria beyond climate change as outlined in the EUTSF. In the next section, we discuss the selection framework and the individual KPIs we use for our study.

2.1.1 KPI selection

The guiding framework for this study is the EUTSF. Therefore, we follow the taxonomy's environmental objectives in selecting the relevant KPIs. The taxonomy lays out six environmental objectives, two of which cover topics related to climate change, adaptation, and mitigation. Our focus goes to the remaining three under-researched topics beyond climate change. Due to the availability of the KPIs within the Eiris scope for the remaining four categories, we cover only three of those environmental areas. The three main areas within our scope are 'biodiversity', 'water preservation', and 'pollution prevention'. We select all relevant Eiris KPIs that fall within this scope.[9]

[7]See Figure A.1 in Appendix A for the country distribution in our sample.

[8]The CDS data starts December 2007, while the various KPIs have different starting dates for which the first scoring has been published by Eiris. See Section 2.1 and Table 2 for the detailed dates for the selected KPIs

[9]For this task, we manually classified indicators into their corresponding areas. The authors initially did this individually and independently to avoid any issues from this preliminary step. Afterward, individual

Next, in addition to the defined environmental domains, we introduce a second dimension by focusing on the taxonomy's implementation side (materiality). We first note that, in classifying economic activities, the taxonomy sets out minimum conditions as part of a technical screening. Among these conditions is assessing an activity's positive contribution within a domain and the potential harm towards any of the other domains (European Commission, 2021). This motivates us to focus on the materiality relationship between companies and the environmental areas.

Double-materiality requires us to consider the two directions of the interaction between firms and the environment. On the one hand, we are interested in how firms directly impact the environment and their efforts to curb negative externalities on the environment. On the other hand, understanding the environment's impact on the company and managing such risks is crucial. Physical (natural disasters), technological (disruptive technologies), and transition risks (legislation) associated with the environment potentially depict a serious threat to the company's business and have implications on the cost of capital, as shown in our results.

Legislation cannot always unambiguously be categorized into either materiality direction. On the one hand, firms that perform badly in terms of their impact on the environment are more prone to suffer from more stringent regulations to curb a firm's negative impact. However, for the materiality in the opposite direction, legislation could play a role too. Stricter regulations might limit infrastructure firms' future investment opportunities due to, for example, increased costs that render a project unprofitable. These risks originate from the changing environment and its impact on the firm.

In addition to the taxonomy's minimum conditions discussed above, the taxonomy sets mandatory requirements on disclosure to improve transparency in environmental performance (European Commission, 2021). Therefore, we focus additionally on the element of disclosure. The

classifications were cross-checked, and discrepancies were discussed to end up with the final categorization. For the category 'Circular economy', we found no suitable KPIs within the Eiris scope.

two-way materiality and disclosure depict the three overarching themes that define our scope.

Insert Figure 1 here.

Finally, linking the three environmental areas with the three themes, we display a matrix of nine combinations as shown in Figure 1, showing the twelve possible combinations. For each cell within this matrix, we select a suitable Eiris KPI, serving as the variables of interest for this study. The selected indicators are reported in Table 1. No suitable KPI was identified for two combinations, and they are therefore not considered in this study. These combinations are greyed out in Figure 1 and left blank in Table 1.[10]

Insert Table 1 here.

2.1.2 Variable construction

The Eiris indicators are qualitative assessments. Hence, we need to translate the raw Eiris KPI ratings into variables that can be used in our regression analyses. The raw indicators represent different ranks on a scale with three to five discrete steps. First, we manually transform the (qualitative) values into numerical scores based on the individual indicator's scale. For consistency, we enforce a positive polarity on the numerical scores, i.e., higher scores indicate better performance. Second, for each indicator, we apply a rank transformation to the numerical scores. The rank transformation is applied on the full cross-section at each point in time.[11]

Using a rank transformation has several advantages. For one, it allows for direct comparison between indicators. Whereas the original indicators operated on different scales, the rank

[10] The combinations for which no KPI is found are "water - Materiality: Firm → Environment" and "biodiversity - Disclosure"

[11] This means the rank score is computed using the entire sample's cross-section, not exclusively the infrastructure sector, nor only those for which we were able to collect all other data. This way, we keep the scores as pure as possible, not bias results by missing data from other sources. Nevertheless, results for scores based on a rank transformation only using firms within the infrastructure sector do not change results significantly.

transformation forces values to lie within the $(0, 1)$ interval, making them directly comparable and easing the interpretation. Second, the rank transform allows us to use the natural ordering already present in the original ratings rather than relying on an arbitrary transformation from the qualitative ratings to quantitative scores. This makes it easier to interpret the scores and the resulting regression coefficients, as they can be directly understood as the effect for the top-performing company for a particular indicator.[12] The selection of a value for observations with equal point values is critical in the rank transformation, especially when only a few discrete point values are available/observed. We opt for using the median percentile rather than the lower or upper boundary percentile for equal observations. By doing so, we force the average rank score over the cross section to equal 0.5 at each point in time. This has the additional benefit of incorporating, to some extent, the "difficulty" and "value" for firms to belong to a certain (rank)score group.[13]

2.2 CDS spreads and control variables

We collect CDS spreads from Thomson Reuters. CDS are traded over the counter (OTC) and quoted by the annuity premium the protection buyer pays the protection seller, the CDS

[12] In a hypothetical case where only one firm is the single best (worst) performer amongst many other, the rank transformed score would be close to 1 (0). Hence, the estimated coefficient in any regression would be the differential effect between the best and worst performers for that variable.

[13] To illustrate this, consider the following example. Take two binary indicators, A and B. For indicator A, 50% of the sample has a score of 0, while the remaining 50% scores 1. For indicator B, this is respectively 90% and 10%. Now consider the rank transform for both indicators when opting to take the lower (upper) boundary. For sample A, those scoring 0 would get a transformed score of 0 (0.5), while those scoring 1 would get 0.5 (1). For indicator B, these respective values would be 0 (0.9) and 0.9 (1). Clearly, when considering the lower boundary, those scoring 0 for both indicators would receive the same rank-transformed value (0). In the opposite case of using the upper boundary, those scoring 1 on both indicators, A and B, will receive an equal rank transformed score (1). Either choice is sub-optimal and does not take into account the distribution of high and low performers. Obviously, having a score of 1 for indicator B is much more valuable/difficult than for indicator A, simply because only 10% of the sample has a 1-score for indicator B versus as much as 50% for indicator A. The rank transform does not reflect this when opting for the upper boundary. Similar reasoning holds for those scoring 0 for Indicator B and using the lower boundary. Arguably, it is not as bad for those firms scoring 0 on Indicator B, while 90% of the sample has the same bad score versus a 0 score for indicator A. Using a third alternative of using the median value, our preferred option, the sample distribution is taken into account. In the above illustration, using the median value would result in rank-transformed scores of 0.25 and 0.75 for indicator A and 0.45 and 0.95 for Indicator B, in effect rewarding (punishing) those scoring higher (lower) in samples where few (many) others have a high-performance rating.

spread, expressed in basis points with respect to the insured notional amount denoted in the company's home currency. Our CDS dataset contains daily spreads for single-name CDS contracts for maturities of one, five, and ten years. We further filter out observations that are likely to be data errors.[14]

In the selection of control variables, we choose both firm-specific and macroeconomic variables that have been shown to have an effect on the credit spread term structure in prior literature.[15] As firm-specific controls, we include leverage, return-on-assets, firm size, and asset volatility. We obtain the book value of total liabilities, net income, market value, and total assets from Datastream to construct the leverage ratio (Lev), firm size ($Size$), 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. ROA is the ratio of net income to total assets. Taking the natural logarithm of a firm's total assets results in our variable for firm size. 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. Stock price data are additionally collected from Datastream.

We include the general business climate and risk-free rate for macroeconomic controls. We quantify a firm's business climate (BC) by the return on the S&P500 index for US firms and the return on the market portfolio for a firm's respective country for non-US firms. A firm's country is defined by the country code in its respective ISIN. International market portfolio returns are taken from Kenneth French's data library. We proxy the risk-free rate (IR) by the yield on a 10-year government bond. Similarly to the business climate, we take the yield that is adjusted for a firm's country. We allow for the possibility of non-linear dependency on the interest rate by including IR^2 in the model (Collin-Dufresne et al., 2001). Additionally, we

[14] Specifically, we filter out negative CDS spreads and observations with values of 0 for all maturities except for the five-year maturity. Following Zhang et al. (2009), we also drop CDS observations with spreads above 2,000 basis points. Given the international setting, we also dropped non-weekdays from the sample and days for which a large part of the full sample has no data due to, e.g., regional holidays.

[15] See Collin-Dufresne et al. (2001), Ericsson et al. (2009), and Zhang et al. (2009).

capture the slope of the interest rate term structure (*Term*) following Han and Zhou (2015) by the difference between the 10-year and 2-year government bond yield. Government bond yield data is collected from *Investing.com*.

Because data is available at different frequencies, we make a compromise to the frequency trade-off between these different frequencies and decide on performing monthly regressions. Hence, we re-sample higher frequency data by taking the average for each month, and we repeat and forward fill lower frequency data by taking the last observation for each month.

2.3 Industry classification

To select companies within the infrastructure sector, we opt to use the Sustainability Accounting Standards Board's (SASB) Sustainable Industry Classification System (SICS) as industry classification. In the first step, we use the sector classification to select companies within the infrastructure sector. Second, we use the more granular industry classification within the infrastructure sector.[16] We motivate the choice for using SICS over many traditional classifications because SICS does not focus solely on the common market and financial characteristics, but it also emphasizes a company's sustainability profile, such as sustainability-related risks and opportunities. Given our focus on sustainability themes, such a sustainability-oriented industry classification is better suited for our purpose.

2.4 Summary statistics

Insert Table 2 here.

Table 2 provides an overview of our rank-transformed Eiris KPIs, where higher values reflect better performance. The indicators are categorized in their respective environmental area and theme. The infrastructure sector sample comprises 51 to 68 companies depending

[16] See Figure A.2 in Appendix A for the sample composition in terms of SASB industries within the infrastructure sector

on the Eiris indicator and represents eleven countries for all indicators.[17] The reason for indicator-dependent samples is that the respective indicators are unavailable for all companies. Similarly, some indicators only become available on a later date because Eiris did not rate them up to that date. So do indicators in the "water" area have only been in use starting December 2011. All indicators last until the end of the Eiris data, being January 2018. Overall, the statistics make us confident that each sample has enough cross-sectional variability to draw meaningful conclusions. This observation is motivated by the observed standard deviation, close to 0.25 across indicators, as well as by the low minimum and high maximum rank score for all indicators. Firms in our sample are, on average, ranked among the top half performers except for indicators measuring a firm's impact on the environment. This is especially true within the "biodiversity" area, where our sample's average and maximum rank score is considerably lower than for the other indicators. Table 3 displays the summary statistics for the five-year CDS spreads and the control variables. In particular, the mean spread is a good reference point to interpret the economic significance of the results in the regression analysis.

Insert Table 3 here.

3 Taxonomy performance and CDS term structure

We now develop testable hypotheses to study how the alignment with key environmental performance indicators from the EU taxonomy affects the corporate credit default term structure. The derivation of predictions for the different taxonomy-inspired environmental themes is a major challenge since little theoretical work has been done to distinguish how the various environmental categories relate to credit default spreads. Hence, we do not derive our hypotheses for each individual theme from an existing model, and we abstain from a distinction between the environmental categories in this section. Instead, we discuss potential channels through

[17] The country and industry composition in Appendix A is based on the full sample of 68 companies.

which the relationship with credit spreads and the credit term structure can be explained.

Barth et al. (2022) investigate two opposite views on how aggregated ESG performance has an effect on corporate credit risk spreads, namely the risk mitigation channel on the one hand and the overspending channel on the other hand. The risk mitigation channel suggests that firms with higher ESG ratings are firms whose future cash flows are more resilient to sustainability-related shocks, leading to higher and/or less volatile future cash flows, which consequently results in lower credit spreads in the spirit of Merton (1974). The overspending argument contends that investments made in favor of ESG are a waste of scarce resources, which can lead to an increase in default risk (Goss & Roberts, 2011). Barth et al. (2022) conclude that it is the risk mitigation channel that causes high ESG scoring firms to have reduced CDS spreads. With our taxonomy-inspired $RankScore$ variable in the double-materiality categories, we effectively measure a firm's performance within each taxonomy area. Following the risk mitigation argument, we hypothesize that infrastructure firms with higher values in the $RankScore$ variable exhibit on average lower CDS spreads and that the effect is more pronounced in the long term. The predictions are identical for both directions of materiality. Our hypotheses are corroborated by previous studies that have shown that investors and lenders with pro-environmental preferences are more willing to provide funding to firms that inflict less damage on nature due to an idiosyncratic reduction in environmental risk exposure.[18] Infrastructure firms are key in fostering climate-compatible development, with projects often operating over the long term. Ideally, investors align their investments, considering the timing of projects. Hence, we not only expect better taxonomy performance to lower credit spreads, but even more importantly, it will emphasize the long-term goals, effectively flattening the credit spread curve.

With regard to corporate risk disclosure and its effect on credit risk, the literature presents

[18]For example, Pástor et al. (2021) show that firms with better ESG ratings have lower expected returns due to less risk exposure. However, temporarily it is possible that green stocks have higher average returns due to unexpected increases in climate concerns (Pástor et al., 2022).

us with two opposing effects; a risk perception effect and an information uncertainty effect.[19] When corporate environmental disclosure leads to the discovery of additional risk factors, it should lead to an increase in credit spreads. This is the risk perception effect. In contrast, the information uncertainty channel states that risk disclosure increases transparency and reduces the information asymmetry between firms and investors, resulting in a decrease in credit spreads (Campbell et al., 2014). For transition and physical climate risks disclosed in the 10-K filings, Kölbel et al. (2022) show that both forces are at work and influence credit spreads.

Considering our specific setup, our disclosure-themed indicators mainly assess firms' reporting quality across the environmental areas. Given the focus on the quality of reporting, we argue that only the information uncertainty channel is relevant to our case. The disclosure indicators do not measure individual firms' exposure, nor do they incorporate how much firms disclose concerning each environmental theme. In a similar spirit as Campbell et al. (2014) and Yu (2005), we conjecture that more qualitative disclosure reduces firms' opaqueness resulting in a decrease in credit risk premia, again focused on the long- vs. short-term impact.

Note that we would only expect disclosure quality to have an impact when the environmental topic itself is considered risk relevant. Hence, testing this hypothesis should be in conjunction with the previously developed hypotheses on area-specific environmental performance and the concept of double-materiality. Provided that the environmental topic is credit risk relevant in at least one direction, we expect a negative effect of disclosure quality within that environmental area.

[19] Duffie and Lando (2001) present the theoretical framework for the role of incomplete information on credit risk.

4 Empirical Results

As argued in the previous section, we are particularly interested in the horizon of infrastructure investing. To test the long-termism hypotheses empirically, we establish a causal relationship between the shape of the credit term structure and infrastructure firms' performance on the various taxonomy themes and environmental areas. Instead of considering individual CDS maturities, we investigate the slope of the CDS curve.

4.1 Long-Termism and Term Structure Slopes

As there exists little theoretical guidance on the effects of taxonomy performance or sustainability, in general, the question of timing and materiality across the CDS term structure remains an empirical question.[20] We perform the following one-month predictive regression

$$CDS_{i;t+1}^{LT-ST} = \alpha + \beta RankScore_{i;t} + \Gamma X_{i;t} + \Theta Y_t + \mu_i + \tau_t + \epsilon_{i;t+1}, \tag{1}$$

where $CDS_{i;t+1}^{LT-ST}$ is the difference between the long- and short-term maturity. $X_{i;t}$ and Y_t are firm-specific and macro-economic control vectors respectively. Our regressions additionally include industry and time-fixed effects in the form of μ_i and τ_t, respectively. $RankScore_{i;t}$, represents the rank transformed variable for the various Eiris indicators as discussed in Section 2.1. We double cluster standard errors on the entity and time level.[21] Since the time series is very slow-moving (updates occur on a monthly to annual basis), we abstain from a

[20]For instance, in the classical credit risk literature, Han and Zhou (2015) derive predictions of structural models for both firm-specific and macro-economic variables and their effect on the slope of the CDS term structure and test these predictions empirically. For example, higher leverage is associated with increased CDS spreads on short- and long-term maturity contracts. However, Han and Zhou (2015) predict this effect to be larger in the long run and empirically corroborate that, indeed, leverage has a significantly positive association with their CDS slope defined by the difference between the five-year and the one-year spread. For our analysis, however, we do not have such a structural model at hand but we acknowledge that it would be an interesting avenue for future research.

[21]Note that we cannot cluster on an industry level, which would be the more conservative level. Following Petersen (2009), the number of different industries would not result in enough clusters to have consistent standard errors, hence our choice for clustering on the firm level.

first-difference analysis of the Eiris KPIs. We perform the regression from Equation (1) for each of the selected KPIs. In our case, we consider both the ten- and five-year spread for the long end while taking the five- and one-year spread for the short end to capture distinct parts of the CDS term structure and directly compare the trade-offs between long-, medium- and short-run maturities. We present the results for both materiality directions and disclosure in Tables 4 to 6

Insert Table 4 here.

For the materiality environment on firm, Table 4 provides clear evidence for water and biodiversity risk management to have a significantly negative effect on CDS slopes. Intuitively we would perceive this flattening effect on the CDS term structure as evidence for the market's long-term views.[22] To corroborate this view and aid in interpreting the slope regression results, we plot the effects of taxonomy performance on the CDS levels in Figure 2. For each taxonomy theme and environmental area, we present the average credit spread for the one-, five- and ten-year maturity and the respective effects of *RankScore* on them. To demonstrate the (economic) relevance of taxonomy performance we present the effect of different levels in the *RankScore* variable. We compute the effects by multiplying the respective *RankScore* value with a regression coefficient from a regression similar to our base setup for the CDS slopes.[23]

[22]Technically, a flattening of the CDS term structure curve, which is ordinarily upward-sloping, could be observed in two scenarios. One is when the negative effects are larger on the long-run spreads over the short-run ones. Alternatively, a flattening occurs when the shorter-term maturity spreads increase more than the longer-term spreads do. We provide evidence for the former scenario justifying the interpretation of our results in favor of long-termism.

[23]Concretely, we estimate the following regression

$$CDS^{5Y}_{i;t+1} = \alpha + \beta RankScore_{i;t} + \Gamma X_{i;t} + \Theta Y_t + \mu_i + \tau_t + \epsilon_{i;t+1} \tag{2}$$

where controls and the regression setup are identical to the one in Equation (1), except for the interest rate term structure variable omitted here. We compute the *RankScore* effects in Figure 2 by multiplying the respective values with the estimated coefficient, $\hat{\beta}$ and adding the effect to the average CDS. For example, the "Mean Rank effect" is the result of multiplying the sample mean *RankScore* with the estimated $\hat{\beta}$ added to the sample mean CDS. Similarly, the max, min, and median effects are computed similarly using the respective sample *Rankscore* value. Only the standard deviation increase effect is computed as a one standard deviation

Insert Figure 2 here.

The results in Figure 2 validate our interpretation of the slope results as evidence for the long-term view in the CDS market for Infrastructure firms. Effects of increased performance on CDS spreads are primarily negative and more outspoken in the long-term over the short maturity across taxonomy themes and environmental areas.

In light of the results from Figure 2, our results in Table 4 show a clear signal from markets that the risks associated with water and biodiversity are perceived as long-term issues rather than medium- to short-run challenges. For biodiversity, governments but also environmental activists may pose a long-term threat to the revenues of infrastructure firms. To protect endangered species or preserve natural habitats, laws that, e.g., forbid building roads or rails in protected areas, could lead to high additional costs for firms operating in this business. Interestingly, while we do not find a significant result on the short end of the curve for pollution prevention, we do observe a significantly negative impact on the long end of the curve. One potential explanation is legislation that already internalizes clean-up costs for companies when they pollute on- or off-site (e.g. the United States Environmental Protection Agency (EPA) implemented several laws such as the Clean Air Act in 2015, amongst others).

Insert Table 5 here.

Table 5 shows the results for the other materiality direction. Here, we find strong evidence in favor of the firm's impact on the environmental pollution on the CDS slope. The results in Table 5 provide clear evidence that, indeed, an infrastructure firm's commitment towards pollution prevention has stronger long-term implications on their credit spread compared to the impact in the short run. For the biodiversity theme, we highlight the importance to

increase in *RankScore* relative to the mean. The min (max) *RankScore* represent the worst (best) performing firms within the sample, respectively. We note that the resulting CDS range is theoretical and comparison to the mean CDS is one possible choice. However, presenting it this way eases interpretation. It also provides an accurate sense of the size differential of the difference between the best and worst performing firms in the sample relative to the average CDS size.

distinguish between the two directions of materiality. Regarding infrastructure firms' impact on the environment, earlier results already suggested it to be a more pressing matter, which is further substantiated by our slope results. We find no significant relationship between *RankScore* and CDS slopes. Hence, there is no evidence that the market expects different effects across maturities. We do want to stress that these results specifically emphasize the differential effect between the short-, medium- and long-run, unlike the effects presented in Figure 2.

From Table 6 we conclude that in a similar fashion as for water risk management, qualitative disclosure within the water area is regarded as more effective and rewarded in the long run. We observe a similar effect for the quality of disclosure concerning pollution prevention, though the estimated coefficients are smaller than for water and only weakly significant at the 10% level.

Insert Table 6 here.

4.2 Right-wing shocks

In the past decade, we have observed a trend toward more right-wing politics. On a global scale, the election of President Trump can be seen as one of the most incisive elections. Most polls predicted a triumph for the Democratic Party. Therefore, the outcome of the election can be considered an unpredictable shock toward more conservative-leaning politics. Also, President Trump promoted a resurrection of the coal industry during his campaign, which entails that the outcome was not only a political earthquake but also a major setback to environmental efforts on a global scale. In Europe, Brexit was similarly surprising and encompassed the withdrawal from several climate agreements with negative consequences for Europe and the goal of the European Union to become carbon neutral. Given the unexpected nature of both events and their similarly detrimental effects on the push for environmental policies, we consider both shocks in conjunction. They serve as an ideal testing ground to highlight the causal nature of environmental performance on credit risk. We expect markets to react to the shock of an expected slowdown, or even reversal, of pro-environmental regulation with a similar reversal in the effect of taxonomy performance on credit spreads.

To this end, we introduce a right-wing dummy variable (RW) in our regressions to capture both the Trump election and Brexit together. This dummy equals one for months after the Trump election on November 8, 2016, and for all European-based firms after the Brexit election on June 23, 2016, and equals zero otherwise. Equation (3) presents the resulting regression setup when including the dummy for our slope regressions. To capture the effect of a shift towards more right-wing politics on taxonomy performance, we interact our $RankScore$ variable with the newly created dummy, i.e., we specify the regression as

$$\begin{aligned} CDS_{i,t+1}^{LT-ST} = \alpha + \beta_1 RankScore_{i,t} + \beta_2 RW_{i,t} + \beta_3 (RankScore \times RW)_{i,t} \\ + \Gamma X_{i,t} + \Theta Y_t + \mu_i + \tau_t + \epsilon_{i,t+1}. \end{aligned} \tag{3}$$

where the firm-specific (X) and macro-economic (Y) controls are the same as in (1).

Table 4 presents the results for better management of the impact of the environment on firms with regard to the CDS slopes. We observe a clear difference between the different taxonomy topics.

In the area of biodiversity (columns III, VI, and IX), we confirm the initial negative effect on the CDS term structure measured by different slope definitions as well as the emphasis on the long-term effect over the short run. However, after the global right-wing shift, we observe a reversal of the initial negative effect, especially for the short end of the term structure. The threat of new regulation is the primal source of external risk that affects firms' CDS spreads for biodiversity. Transition risk poses less of a threat to companies after the election of governments that are less likely to implement laws that would render negative environmental externalities costly to firms. We note that there is no reversal effect for the long end of the term structure, taken by the slope between the ten- and five-year spread. Considering the estimated coefficients on the interaction terms, they are almost identical for both slope definitions using the one-year spread as short maturity. Both observations suggest that investors indeed acknowledge the immediate effect that more right-wing governments have, but they do not expect this to be a long-lasting consequence and therefore still perceive insufficient management of environmental issues beyond climate change as a risk factor for the long haul.

Insert Table 7 here.

It should not be surprising that we do not find such a reversal effect when considering water risks (columns II, V, and VIII). These risks, in essence, have little direct connection to the regulatory environment. Hence, only the initial effect of water risk management is confirmed. Interestingly, in the area of pollution prevention (columns I, IV, and VII), we reveal that CDS slopes increase after the right-wing shift for well-performing firms. We argue that before the election, there was still a lot of uncertainty around the approach to pollution prevention, while after the election, the political climate clearly shifted away from pro-environmental regulations, hence leading to a more pronounced and significant effect. In a similar way to our reasoning for biodiversity, the market anticipates this evolution to be transient rather than a long-term trend, evidenced by the significant effect only being present in the mid-term to short-term maturity slope. One reason could be that the Trump election is expected to last only for a one-period term after which a potentially more environmentally friendly government follows.

Considering the other side of the materiality coin again, we present the results in Table 8. We observe no such reversal effect for infrastructure firms' impact on biodiversity. This suggests that even after electorally gains for right-wing politicians, investors still perceive negative externalities on biodiversity as a source of risk despite an environment of lower regulatory risk. For example, a firm that intends to build a factory in a protected area is still equally exposed to a strong loss in reputation as well as legal repercussions, which again emphasizes the need to distinguish between the two materiality directions. For pollution, however, the effects of a firm's commitment toward pollution prevention show a similar pattern as in the case when considering the impact of the environment on the firm.

Insert Table 8 here.

Finally, Table 9 presents the results for Disclosure (quality). They confirm our earlier results for water, i.e., more qualitative disclosure negatively impacts CDS slopes, indicating an emphasis on a long-term vision by investors. As for water risk management, not unsurprisingly, we do not observe any reversal effect in the quality of disclosure.

Insert Table 9 here.

In a similar fashion to Figure 2, we report results for the effect on the CDS levels in the right-wing period in Figure 3 with the extension that we present the aggregate effect split into a main and a right-wing effect.[24] The results in Figure 3 corroborate our interpretation of the market's long-termism view and the short-term reversals due to the global electoral right-wing shift.

Insert Figure 3 here.

[24]In accordance to our base results, we perform the following regression for the CDS levels:

$$\begin{aligned} CDS^{5Y}_{i,t+1} &= \alpha + \beta_1 RankScore_{i,t} + \beta_2 RW_{i,t} + \beta_3 (RankScore \times RW)_{i,t} \\ &\quad + \Gamma X_{i,t} + \Theta Y_t + \mu_i + \tau_t + \epsilon_{i,t+1}, \end{aligned} \tag{4}$$

We compute the aggregate $RankScore$ effects in the right-wing period in Figure 3 by multiplying the respective values with the estimated coefficients, $\hat{\beta}_1$ and $\hat{\beta}_3$ and adding the effects to the average CDS. The main (right-wing) effect is computed by solely multiplying with the respective coefficient, $\hat{\beta}_1$ ($\hat{\beta}_3$), added to the average CDS.

5 Conclusion

This study examines how firms' financing conditions, as measured by CDS spreads, in the infrastructure sector are influenced by the impact of the environment on firms and the impact of firms on the environment. Inspired by the EUTSF, we study three environmental topics beyond climate change: biodiversity, water risks, and pollution prevention.

Our analysis strongly suggests that the risks associated with water and biodiversity impacting a firm are perceived to be long-term issues, as evidenced by significantly negative effects on CDS slopes. The negative effects are weaker but still significant for pollution prevention, also suggesting a long-term vision. The financing benefits due to a firm's commitment to pollution prevention, however, have stronger long-term implications rather than short-term advantages. In contrast, a firm's impact on biodiversity has no such timing differential, revealing a more imminent awareness. The results on qualitative disclosure regarding water and pollution prevention corroborate the infrastructure sector's long-termism, especially for water risks. These findings demonstrate the importance of following the principle of double materiality and analyzing the timing of these interactions.

Moreover, we find that the political climate (specifically, a shift towards right-wing governments) had reversing effects on biodiversity and pollution prevention but not on water risks. The reversing effect was more pronounced for the short end of the term structure but negligible on the long end of the curve. We attribute this effect to the limited time that a government is elected. Therefore, investors expect this right-wing shock to be temporary.

Overall, our findings identify the long-term focus on infrastructure firms' financing conditions with regard to the environmental topics covered in the latest EU taxonomy beyond climate change. Moreover, they highlight the importance of considering both materiality sides, i.e., the impact of the environment on firms and the impact of firms on the environment.

References

Albuquerque, R., Koskinen, Y., & Zhang, C. (2019). Corporate social responsibility and firm risk: Theory and empirical evidence. *Management Science*, *65*(10), 4451–4469.

Alekseev, G., Giglio, S., Maingi, Q., Selgrad, J., & Stroebel, J. (2022). *A quantity-based approach to constructing climate risk hedge portfolios* (tech. rep.). National Bureau of Economic Research.

Alessi, L., & Battiston, S. (2022). Two sides of the same coin: Green taxonomy alignment versus transition risk in financial portfolios. *International Review of Financial Analysis*, *84*, 102319.

Barth, F., Hübel, B., & Scholz, H. (2022). ESG and corporate credit spreads. *The Journal of Risk Finance*.

Bassen, A., Kordsachia, O., Tan, W., Tan, W., & Lopatta, K. (2022). Revenue alignment with the EU Taxonomy regulation. *Working Paper*.

Berg, F., Koelbel, J. F., & Rigobon, R. (2022). Aggregate confusion: The divergence of ESG ratings. *Review of Finance*, *26*(6), 1315–1344.

Blasberg, A., Kiesel, R., & Taschini, L. (2022). Carbon default swap – disentangling the exposure to carbon risk through CDS. *Working Paper*.

Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, *142*(2), 517–549.

Campbell, J. L., Chen, H., Dhaliwal, D. S., Lu, H.-m., & Steele, L. B. (2014). The information content of mandatory risk factor disclosures in corporate filings. *Review of Accounting Studies*, *19*(1), 396–455.

Campbell, J. Y., & Taksler, G. B. (2003). Equity volatility and corporate bond yields. *The Journal of Finance*, *58*(6), 2321–2350.

Collin-Dufresne, P., Goldstein, R. S., & Spencer, M. J. (2001). The determinants of credit spread changes. *The Journal of Finance*, *56*(6), 2177–2207.

Duffie, D., & Lando, D. (2001). Term structures of credit spreads with incomplete accounting information. *Econometrica*, *69*(3), 633–664.

Dumrose, M., Rink, S., & Eckert, J. (2022). Disaggregating confusion? the EU Taxonomy and its relation to ESG rating. *Finance Research Letters*, *48*, 102928.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging climate change news. *The Review of Financial Studies*, *33*(3), 1184–1216.

Ericsson, J., Jacobs, K., & Oviedo, R. (2009). The determinants of credit default swap premia. *Journal of Financial and Quantitative Analysis*, *44*(1), 109–132.

European Commission. (2021). FAQ: What is the EU Taxonomy and how will it work in practice? https://ec.europa.eu/info/files/sustainable-finance-taxonomy-faq_en

Fama, E. F., & French, K. R. (2007). Disagreement, tastes, and asset prices. *Journal of Financial Economics*, *83*(3), 667–689.

Flammer, C., Giroux, T., & Heal, G. (2023). Biodiversity finance.

Garel, A., Romec, A., Sautner, Z., & Wagner, A. F. (2023). Do investors care about biodiversity?

Gibson, R., Krueger, P., & Mitali, S. F. (2020). The sustainability footprint of institutional investors: ESG driven price pressure and performance. *Swiss Finance Institute Research Paper*, (17-05).

Goss, A., & Roberts, G. S. (2011). The impact of corporate social responsibility on the cost of bank loans. *Journal of Banking & Finance*, *35*(7), 1794–1810.

Han, B., & Zhou, Y. (2015). Understanding the term structure of credit default swap spreads. *Journal of Empirical Finance*, *31*, 18–35.

Hartzmark, S. M., & Sussman, A. B. (2019). Do investors value sustainability? A natural experiment examining ranking and fund flows. *The Journal of Finance*, *74*(6), 2789–2837.

Hoepner, A. G., Oikonomou, I., Sautner, Z., Starks, L. T., & Zhou, X. (2018). ESG shareholder engagement and downside risk. *Working Paper*.

Hoepner, A. G., & Schneider, F. I. (2022). EU green taxonomy data–a first vendor survey. *The Economists' Voice.*

Hsu, P.-H., Li, K., & Tsou, C.-Y. (2022). The pollution premium. *The Journal of Finance, Forthcoming.*

Karolyi, G. A., & Tobin-de la Puente, J. (2023). Biodiversity finance: A call for research into financing nature. *Financial Management.*

Kölbel, J. F., Leippold, M., Rillaerts, J., & Wang, Q. (2022). Ask BERT: How regulatory disclosure of transition and physical climate risks affects the CDS term structure. *Journal of Financial Econometrics.*

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, *33*(3), 1067–1111.

Lucarelli, C., Mazzoli, C., Rancan, M., & Severini, S. (2020). Classification of sustainable activities: EU taxonomy and scientific literature. *Sustainability*, *12*(16), 6460.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, *29*(2), 449–470.

Pástor, L., Stambaugh, R. F., & Taylor, L. A. (2021). Sustainable investing in equilibrium. *Journal of Financial Economics*, *142*(2), 550–571.

Pástor, L., Stambaugh, R. F., & Taylor, L. A. (2022). Dissecting green returns. *Journal of Financial Economics*, *146*(2), 403–424.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, *22*(1), 435–480.

Regulation (EU) 2020/852 on the establishment of a framework to facilitate sustainable investment, and amending Regulation (EU) 2019/2088, REGULATION (EU) 2020/852 (2020). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32020R0852

Sautner, Z., Yu, J., Zhong, R., & Zhou, X. (2022). The EU Taxonomy and the syndicated loan market. *Working Paper.*

Starks, L. T., Venkat, P., & Zhu, Q. (2017). Corporate ESG profiles and investor horizons. *Working Paper*.

Yu, F. (2005). Accounting transparency and the term structure of credit spreads. *Journal of Financial Economics*, *75*(1), 53–84.

Zhang, B. Y., Zhou, H., & Zhu, H. (2009). Explaining credit default swap spreads with the equity volatility and jump risks of individual firms. *The Review of Financial Studies*, *22*(12), 5099–5131.

Tables

Table 1: Selected EIRIS indicators

This table presents the questions behind the indicators we have selected as well as the original scale of the Eiris KPIs for the different environmental themes and ares combinations

Area	Theme	Indicator question	Original scale (#levels)
Pollution prevention	Materiality: Environment→Firm	How does Eiris rate the Company's environmental management system?	Inadequate-Exceptional (5)
	Materiality: Firm→Environment	How does Eiris rate the Company's environmental policy and commitment?	Inadequate-Exceptional (5)
	Disclosure	How does Eiris rate the Company's environmental reporting?	Inadequate-Exceptional (5)
Water	Materiality: Environment→Firm	How is the Company managing water risks?	No evidence-Advanced (5)
	Materiality: Firm→Environment	/	
	Disclosure	How is the Company addressing water management disclosure?	No evidence-Advanced (5)
Biodiversity	Materiality: Environment→Firm	How does Eiris rate the Company's biodiversity policy?	No policy-Good policy (4)
	Materiality: Firm→Environment	What potential impact does the Company have on biodiversity?	Low-High (3)
	Disclosure	/	

Table 2: Summary statistics of selected rank transformed KPIs

This table presents the summary statistics of the rank transformed KPI scores. The table contains information on the starting date for the respective KPIs, the number of firm-month observations for each sample as well as the mean, median, standard deviation, minimum, maximum, skewness and excess kurtosis.

		Start	# Obs.	Mean	Median	Std	Min	Max	Skew	Kurt
Pollution Prevention	Materiality: Environment→Firm	31/12/2007	7225	0.633	0.687	0.249	0.151	0.894	−0.581	−0.905
	Materiality: Firm→Environment	31/12/2007	7225	0.637	0.760	0.245	0.153	0.980	−0.859	−0.527
	Disclosure	31/12/2007	7225	0.636	0.800	0.265	0.308	0.972	−0.238	−1.692
Water	Materiality: Environment→Firm	31/12/2011	3735	0.597	0.583	0.227	0.145	0.997	−0.387	−0.158
	Disclosure	31/12/2011	3735	0.632	0.780	0.253	0.225	0.996	−0.515	−1.156
Biodiversity	Materiality: Environment→Firm	31/12/2007	6376	0.684	0.779	0.227	0.206	0.980	−0.858	−0.289
	Materiality: Firm→Environment	31/12/2010	5233	0.219	0.134	0.178	0.127	0.709	2.023	2.713

Table 3: Summary statistics of the dependent and control variables

This table presents the summary statistics of dependent variable, the 5-year cds spread, and the control variables, leverage, return-on-assets, (log) firm size, volatility, the business climate and the interest rate. The statistics in this table are based on the KPI sample with the most firm-month observations, being the environment on firm materiality in the Pollution prevention area in this case.

	5Y (bp)	Lev (%)	ROA (%)	Vol (%)	BC (%)	IR (%)	Size (Log)
Mean	123.64	59.56	2.76	1.78	0.62	2.16	18.30
Median	89.54	60.27	2.72	1.53	1.01	2.12	17.66
Std	113.85	16.37	3.94	0.96	5.28	1.22	2.04
Min	10.24	14.39	−35.13	0.56	−28.31	−0.23	15.26
Max	1550.34	98.54	39.12	10.20	29.61	7.08	23.47
Skew	3.87	−0.27	−0.13	2.61	−0.53	0.47	0.88
Kurt	25.73	−0.32	26.22	11.30	1.98	0.17	−0.34
Q10	39.33	36.74	−0.04	0.95	−6.04	0.61	16.15
Q25	57.53	49.29	1.43	1.17	−2.03	1.30	16.84
Q75	154.08	71.59	3.91	2.09	3.77	2.92	19.29
Q90	232.29	80.42	6.20	2.87	6.66	3.82	21.82

Table 4: Monthly regression results for the different CDS slopes for the Taxonomy theme: Materiality: Environment→Firm

This table shows the regression results for a panel regression of the form: $CDS^{LT-ST}_{i,t+1} = \alpha + \beta RankScore_{i,t} + \Gamma X_{i,t} + \Theta Y_t + \mu_i + \tau_t + \epsilon_{i,t+1}$, where $RankScore_{i,t}$ is the respective rank transformed Eiris KPI for the Taxonomy theme: "Materiality: Environment→Firm". Different environmental areas are presented as variable names. Coefficients are estimated by performing pooled OLS for each subsample. All regressions include both Industry and time effects. Standard errors are clustered on both a time and entity level. The longest sample period ranges from December 2007 to January 2018, depending on the KPI, the starting date is different. By *, **, and *** we denote p-levels below 10%, 5%, and 1%, respectively.

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
	5Y-1Y	5Y-1Y	5Y-1Y	10Y-1Y	10Y-1Y	10Y-1Y	10Y-5Y	10Y-5Y	10Y-5Y
$PollutionPrevention$	−29.369			−43.757*			−14.037**		
	(−1.450)			(−1.759)			(−2.236)		
$Water$		−43.683***			−58.029***			−13.950***	
		(−2.624)			(−2.866)			(−2.748)	
$Biodiversity$			−69.187***			−93.806***			−25.533***
			(−2.805)			(−3.289)			(−3.689)
BC	0.010	−0.049	−0.024	0.223	0.213	0.181	0.267	0.242***	0.259
	(0.025)	(−0.131)	(−0.063)	(0.422)	(0.505)	(0.357)	(1.524)	(2.768)	(1.505)
IR	17.146*	18.132**	11.336	20.350	17.463	12.892	3.629	0.222	2.051
	(1.865)	(2.096)	(1.044)	(1.645)	(1.514)	(0.908)	(0.801)	(0.043)	(0.410)
$IR2$	−2.263	−1.192	−1.349	−3.392	−1.541	−2.174	−1.125	−0.421	−0.826
	(−1.512)	(−0.997)	(−0.812)	(−1.643)	(−0.925)	(−0.975)	(−1.538)	(−0.550)	(−1.070)
Lev	1.171***	1.076***	1.327***	1.581***	1.521***	1.805***	0.411***	0.443***	0.482***
	(4.025)	(4.567)	(4.866)	(4.304)	(4.813)	(5.268)	(4.299)	(3.886)	(5.175)
ROA	1.563**	0.511	1.603***	2.604***	0.646	2.534***	1.027***	0.082	0.918***
	(2.403)	(1.011)	(3.147)	(2.773)	(0.862)	(3.176)	(2.940)	(0.214)	(2.739)
$Size$	−6.801**	−11.392***	−8.783***	−9.365**	−16.175***	−12.098***	−2.472**	−4.670***	−3.175**
	(−2.398)	(−3.965)	(−2.977)	(−2.577)	(−4.268)	(−3.179)	(−2.278)	(−3.007)	(−2.554)
$Term$	−10.547	−12.886	−8.093	−8.833	−4.105	−5.123	1.116	8.274**	2.300
	(−1.505)	(−1.330)	(−1.047)	(−1.038)	(−0.376)	(−0.556)	(0.536)	(2.562)	(1.056)
Vol	−1.972	16.550***	−5.282	−11.392	12.571	−15.801	−9.508**	−2.918	−10.717**
	(−0.218)	(2.738)	(−0.527)	(−0.919)	(1.258)	(−1.132)	(−2.417)	(−0.622)	(−2.355)
$const$	129.393**	208.623***	192.830***	201.304**	313.991***	284.162***	69.333**	100.546***	88.698***
	(2.186)	(3.585)	(2.722)	(2.487)	(4.014)	(2.979)	(2.573)	(3.006)	(2.807)
No. Obs.	7189	3725	6360	7107	3687	6278	7108	3687	6279
R-squared	0.134	0.317	0.209	0.172	0.391	0.259	0.236	0.396	0.291

Table 5: Monthly regression results for the different CDS slopes for the Taxonomy theme: Materiality: Firm→Environment

This table shows the regression results for a panel regression of the form: $CDS^{LT-ST}_{i,t+1} = \alpha + \beta RankScore_{i,t} + \Gamma X_{i,t} + \Theta Y_t + \mu_i + \tau_t + \epsilon_{i,t+1}$, where $RankScore_{i,t}$ is the respective rank transformed Eiris KPI for the Taxonomy theme: "Materiality: Firm→Environment". Different environmental areas are presented as variable names. Coefficients are estimated by performing pooled OLS for each subsample. All regressions include both Industry and time effects. Standard errors are clustered on both a time and entity level. The longest sample period ranges from December 2007 to January 2018, depending on the KPI, the starting date is different. By *, **, and *** we denote p-levels below 10%, 5%, and 1%, respectively.

	(I)	(II)	(III)	(IV)	(V)	(VI)
	5Y-1Y	5Y-1Y	10Y-1Y	10Y-1Y	10Y-5Y	10Y-5Y
$PollutionPrevention$	−50.522***		−72.577***		−22.573***	
	(−2.826)		(−3.337)		(−3.433)	
$Biodiversity$		−33.051		−32.519		1.847
		(−1.139)		(−0.824)		(0.130)
BC	−0.008	−0.016	0.200	0.216	0.260	0.327***
	(−0.021)	(−0.043)	(0.375)	(0.507)	(1.485)	(4.408)
IR	15.890*	17.598*	18.701	18.629	3.171	1.209
	(1.684)	(1.808)	(1.493)	(1.437)	(0.707)	(0.254)
$IR2$	−2.104	−1.456	−3.189	−1.967	−1.071	−0.467
	(−1.370)	(−0.944)	(−1.523)	(−0.949)	(−1.473)	(−0.646)
Lev	1.249***	1.141***	1.692***	1.572***	0.446***	0.447***
	(4.262)	(3.246)	(4.645)	(3.516)	(4.907)	(3.652)
ROA	1.780***	0.299	2.917***	0.695	1.125***	0.387
	(2.963)	(0.473)	(3.413)	(0.837)	(3.542)	(1.184)
$Size$	−7.486***	−10.926***	−10.407***	−15.421***	−2.809***	−4.459***
	(−2.803)	(−3.510)	(−3.031)	(−3.770)	(−2.673)	(−3.129)
$Term$	−11.181	−9.284	−9.744	−4.287	0.840	4.281*
	(−1.586)	(−1.189)	(−1.144)	(−0.475)	(0.409)	(1.795)
Vol	−4.390	6.435	−14.821	0.229	−10.546***	−6.756
	(−0.493)	(0.400)	(−1.212)	(0.010)	(−2.715)	(−0.965)
$const$	157.275***	189.376***	241.069***	284.447***	81.548***	93.739***
	(2.593)	(2.862)	(2.948)	(3.124)	(3.035)	(2.747)
No. Obs.	7189	5197	7107	5147	7108	5148
R-squared	0.151	0.208	0.192	0.264	0.254	0.322

Table 6: Monthly regression results for the different CDS slopes for the Taxonomy theme: Disclosure

This table shows the regression results for a panel regression of the form: $CDS_{i,t+1}^{LT-ST} = \alpha + \beta RankScore_{i,t} + \Gamma X_{i,t} + \Theta Y_t + \mu_i + \tau_t + \epsilon_{i,t+1}$, where $RankScore_{i,t}$ is the respective rank transformed Eiris KPI for the Taxonomy theme: "Disclosure". Different environmental areas are presented as variable names. Coefficients are estimated by performing pooled OLS for each subsample. All regressions include both Industry and time effects. Standard errors are clustered on both a time and entity level. The longest sample period ranges from December 2007 to January 2018, depending on the KPI, the starting date is different. By *, **, and *** we denote p-levels below 10%, 5%, and 1%, respectively.

	(I)	(II)	(III)	(IV)	(V)	(VI)
	5Y-1Y	5Y-1Y	10Y-1Y	10Y-1Y	10Y-5Y	10Y-5Y
$PollutionPrevention$	-29.264		-38.068^{*}		-10.322^{*}	
	(-1.489)		(-1.670)		(-1.888)	
$Water$		-40.653^{**}		-64.654^{***}		-23.354^{***}
		(-2.230)		(-2.960)		(-4.041)
BC	0.025	-0.084	0.256	0.122	0.283	0.186^{**}
	(0.064)	(-0.229)	(0.479)	(0.302)	(1.602)	(2.361)
IR	15.254^{*}	18.908^{**}	18.614	17.239	3.397	-0.729
	(1.698)	(2.202)	(1.534)	(1.571)	(0.741)	(-0.156)
$IR2$	-1.955	-1.159	-3.102	-1.252	-1.086	-0.173
	(-1.335)	(-1.033)	(-1.529)	(-0.822)	(-1.465)	(-0.249)
Lev	1.133^{***}	1.051^{***}	1.530^{***}	1.483^{***}	0.398^{***}	0.431^{***}
	(3.821)	(4.481)	(4.000)	(5.027)	(3.797)	(4.507)
ROA	1.543^{**}	0.398	2.579^{***}	0.493	1.022^{***}	0.043
	(2.490)	(0.831)	(2.874)	(0.777)	(3.004)	(0.131)
$Size$	-7.079^{**}	-10.769^{***}	-9.888^{***}	-15.013^{***}	-2.687^{**}	-4.145^{***}
	(-2.487)	(-3.434)	(-2.693)	(-3.966)	(-2.377)	(-3.128)
$Term$	-11.465	-13.332	-10.042	-4.080	0.822	8.716^{***}
	(-1.620)	(-1.247)	(-1.182)	(-0.332)	(0.408)	(2.639)
Vol	-1.506	16.829^{***}	-10.494	12.479	-9.194^{**}	-3.258
	(-0.165)	(2.953)	(-0.832)	(1.357)	(-2.298)	(-0.752)
$const$	139.474^{**}	197.230^{***}	212.432^{***}	300.844^{***}	71.851^{***}	98.782^{***}
	(2.305)	(3.280)	(2.607)	(3.908)	(2.717)	(3.312)
No. Obs.	7189	3725	7107	3687	7108	3687
R-squared	0.138	0.315	0.173	0.403	0.232	0.439

Table 7: Monthly regression results for the different CDS slopes for the Taxonomy theme: Materiality: Environment→Firm

This table shows the regression results for a panel regression of the form: $CDS^{LT-ST}_{i,t+1} = \alpha + \beta_1 RankScore_{i,t} + \beta_2 RW_{i,t} + \beta_3(RankScore \times RW)_{i,t} + \Gamma X_{i,t} + \Theta Y_t + \mu_i + \tau_t + \epsilon_{i,t+1}$, where $RankScore$ is the respective rank transformed Eiris KPI for the Taxonomy theme: "Materiality: Environment→Firm" and RW a dummy capturing the global shift towards more rightwing leadership. Different environmental areas are presented as variable names. Coefficients are estimated by performing pooled OLS for each subsample. All regressions include both Industry and time effects. Standard errors are clustered on both a time and entity level. The longest sample period ranges from December 2007 to January 2018, depending on the KPI, the starting date is different. By *, **, and *** we denote p-levels below 10%, 5%, and 1%, respectively.

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)
	5Y-1Y	5Y-1Y	5Y-1Y	10Y-1Y	10Y-1Y	10Y-1Y	10Y-5Y	10Y-5Y	10Y-5Y
$PollutionPrevention$	−34.434*			−48.126*			−13.630**		
	(−1.690)			(−1.912)			(−2.141)		
$RWXPollutionPrevention$	36.600**			28.773			−5.915		
	(2.320)			(1.587)			(−0.974)		
$Water$		−42.984**			−57.971***			−14.805***	
		(−2.533)			(−2.816)			(−2.969)	
$RWXWater$		−3.509			−0.526			4.041	
		(−0.129)			(−0.019)			(0.717)	
$Biodiversity$			−78.661***			−103.220***			−25.784***
			(−3.081)			(−3.512)			(−3.711)
$RWXBiodiversity$			78.539***			75.756***			0.034
			(3.418)			(2.824)			(0.004)
BC	0.012	−0.050	−0.027	0.236	0.220	0.191	0.279	0.251***	0.274
	(0.032)	(−0.135)	(−0.074)	(0.446)	(0.528)	(0.378)	(1.589)	(3.082)	(1.604)
IR	20.861**	17.885**	16.628	23.819*	17.602	18.628	3.597	0.698	2.682
	(2.232)	(2.119)	(1.515)	(1.912)	(1.524)	(1.294)	(0.826)	(0.135)	(0.539)
$IR2$	−2.685*	−1.172	−1.936	−3.789*	−1.559	−2.813	−1.124	−0.467	−0.901
	(−1.766)	(−0.970)	(−1.161)	(−1.826)	(−0.928)	(−1.258)	(−1.584)	(−0.611)	(−1.181)
Lev	1.178***	1.076***	1.351***	1.584***	1.520***	1.826***	0.409***	0.443***	0.481***
	(4.023)	(4.529)	(4.938)	(4.295)	(4.786)	(5.324)	(4.293)	(3.887)	(5.158)
ROA	1.530**	0.506	1.560***	2.573***	0.646	2.488***	1.028***	0.088	0.913***
	(2.338)	(1.012)	(3.056)	(2.727)	(0.865)	(3.118)	(2.945)	(0.228)	(2.727)
RW	−23.834	1.577	−57.840***	−11.389	2.286	−47.600**	11.801**	0.378	8.960
	(−1.475)	(0.076)	(−3.138)	(−0.617)	(0.105)	(−2.319)	(2.308)	(0.079)	(1.239)
$Size$	−6.428**	−11.405***	−8.340***	−8.964**	−16.145***	−11.554***	−2.420**	−4.621***	−3.062**
	(−2.254)	(−3.873)	(−2.776)	(−2.444)	(−4.166)	(−2.964)	(−2.208)	(−2.942)	(−2.415)
$Term$	−12.992*	−12.625	−10.880	−10.936	−4.143	−8.017	1.332	7.889**	2.111
	(−1.754)	(−1.438)	(−1.386)	(−1.228)	(−0.402)	(−0.857)	(0.652)	(2.334)	(0.985)
Vol	−2.315	16.575***	−6.205	−11.685	12.555	−16.710	−9.493**	−2.966	−10.776**
	(−0.257)	(2.734)	(−0.622)	(−0.942)	(1.254)	(−1.199)	(−2.407)	(−0.632)	(−2.364)
$const$	124.073**	208.603***	187.744***	194.015**	312.879***	275.676***	66.950**	99.368***	85.089***
	(2.061)	(3.466)	(2.607)	(2.361)	(3.881)	(2.842)	(2.466)	(2.915)	(2.659)
No. Obs.	7189	3725	6360	7107	3687	6278	7108	3687	6279
R-squared	0.137	0.317	0.220	0.174	0.391	0.266	0.238	0.397	0.293

Table 8: Monthly regression results for the different CDS slopes for the Taxonomy theme: Materiality: Firm→Environment

This table shows the regression results for a panel regression of the form: $CDS^{LT-ST}_{i,t+1} = \alpha + \beta_1 RankScore_{i,t} + \beta_2 RW_{i,t} + \beta_3(RankScore \times RW)_{i,t} + \Gamma X_{i,t} + \Theta Y_t + \mu_i + \tau_t + \epsilon_{i,t+1}$, where $RankScore$ is the respective rank transformed Eiris KPI for the Taxonomy theme: "Materiality: Firm→Environment" and RW a dummy capturing the global shift towards more rightwing leadership. Different environmental areas are presented as variable names. Coefficients are estimated by performing pooled OLS for each subsample. All regressions include both Industry and time effects. Standard errors are clustered on both a time and entity level. The longest sample period ranges from December 2007 to January 2018, depending on the KPI, the starting date is different. By *, **, and *** we denote p-levels below 10%, 5%, and 1%, respectively.

	(I) 5Y-1Y	(II) 5Y-1Y	(III) 10Y-1Y	(IV) 10Y-1Y	(V) 10Y-5Y	(VI) 10Y-5Y
$PollutionPrevention$	-56.502^{***}		-78.148^{***}		-22.521^{***}	
	(-3.041)		(-3.414)		(-3.360)	
$RWXPollutionPrevention$	50.081^{**}		45.291^{*}		-1.970	
	(2.124)		(1.721)		(-0.272)	
$Biodiversity$		-28.108		-27.794		2.081
		(-0.927)		(-0.678)		(0.145)
$RWXBiodiversity$		-26.910		-25.424		-0.756
		(-1.179)		(-0.988)		(-0.115)
BC	-0.009	-0.024	0.209	0.210	0.271	0.333^{***}
	(-0.023)	(-0.066)	(0.393)	(0.497)	(1.552)	(4.753)
IR	19.855^{**}	17.313^{*}	22.779^{*}	18.464	3.532	1.410
	(1.966)	(1.772)	(1.744)	(1.425)	(0.797)	(0.298)
$IR2$	-2.549	-1.399	-3.651^{*}	-1.925	-1.117	-0.491
	(-1.608)	(-0.914)	(-1.716)	(-0.936)	(-1.556)	(-0.683)
Lev	1.256^{***}	1.155^{***}	1.697^{***}	1.585^{***}	0.445^{***}	0.447^{***}
	(4.269)	(3.289)	(4.638)	(3.543)	(4.892)	(3.628)
ROA	1.751^{***}	0.322	2.887^{***}	0.716	1.123^{***}	0.386
	(2.860)	(0.515)	(3.333)	(0.869)	(3.531)	(1.178)
RW	-35.512^{*}	-0.336	-25.997	0.769	8.281	2.302
	(-1.925)	(-0.037)	(-1.224)	(0.073)	(1.282)	(0.781)
$Size$	-7.056^{***}	-11.030^{***}	-9.934^{***}	-15.501^{***}	-2.739^{**}	-4.425^{***}
	(-2.581)	(-3.449)	(-2.834)	(-3.695)	(-2.576)	(-3.056)
$Term$	-13.256^{*}	-9.519	-11.781	-4.549	0.766	4.202^{*}
	(-1.792)	(-1.203)	(-1.341)	(-0.500)	(0.383)	(1.766)
Vol	-4.938	6.437	-15.325	0.229	-10.558^{***}	-6.775
	(-0.554)	(0.400)	(-1.251)	(0.010)	(-2.709)	(-0.967)
$const$	151.169^{**}	191.054^{***}	232.924^{***}	285.417^{***}	79.010^{***}	92.534^{***}
	(2.432)	(2.791)	(2.794)	(3.045)	(2.912)	(2.666)
No. Obs.	7189	5197	7107	5147	7108	5148
R-squared	0.155	0.209	0.195	0.264	0.255	0.322

Table 9: Monthly regression results for the different CDS slopes for the Taxonomy theme: Disclosure

This table shows the regression results for a panel regression of the form: $CDS^{LT-ST}_{i,t+1} = \alpha + \beta_1 RankScore_{i,t} + \beta_2 RW_{i,t} + \beta_3 (RankScore \times RW)_{i,t} + \Gamma X_{i,t} + \Theta Y_t + \mu_i + \tau_t + \epsilon_{i,t+1}$, where $RankScore$ is the respective rank transformed Eiris KPI for the Taxonomy theme: "Disclosure" and RW a dummy capturing the global shift towards more rightwing leadership. Different environmental areas are presented as variable names. Coefficients are estimated by performing pooled OLS for each subsample. All regressions include both Industry and time effects. Standard errors are clustered on both a time and entity level. The longest sample period ranges from December 2007 to January 2018, depending on the KPI, the starting date is different. By *, **, and *** we denote p-levels below 10%, 5%, and 1%, respectively.

	(I)	(II)	(III)	(IV)	(V)	(VI)
	5Y-1Y	5Y-1Y	10Y-1Y	10Y-1Y	10Y-5Y	10Y-5Y
$PollutionPrevention$	−32.454		−41.624*		−11.031*	
	(−1.612)		(−1.756)		(−1.893)	
$RWXPollutionPrevention$	25.391		27.038		4.526	
	(0.876)		(0.865)		(0.631)	
$Water$		−47.839**		−72.782***		−24.363***
		(−2.523)		(−3.171)		(−4.101)
$RWXWater$		38.359		43.092		5.086
		(1.289)		(1.331)		(0.624)
BC	0.024	−0.108	0.263	0.105	0.292*	0.196***
	(0.061)	(−0.295)	(0.490)	(0.267)	(1.662)	(2.747)
IR	18.288**	20.784**	22.251*	19.623*	4.394	−0.176
	(2.128)	(2.524)	(1.849)	(1.791)	(0.969)	(−0.037)
$IR2$	−2.318	−1.236	−3.536*	−1.370	−1.205	−0.219
	(−1.588)	(−1.105)	(−1.729)	(−0.906)	(−1.642)	(−0.316)
Lev	1.131***	1.070***	1.527***	1.504***	0.397***	0.433***
	(3.817)	(4.521)	(3.991)	(5.051)	(3.778)	(4.481)
ROA	1.524**	0.437	2.555***	0.537	1.014***	0.049
	(2.483)	(0.955)	(2.864)	(0.886)	(2.973)	(0.151)
RW	−17.470	−28.620	−13.410	−29.035	3.005	−0.303
	(−0.711)	(−1.124)	(−0.493)	(−1.026)	(0.521)	(−0.042)
$Size$	−6.756**	−10.805***	−9.470***	−15.003***	−2.549**	−4.094***
	(−2.428)	(−3.423)	(−2.606)	(−3.930)	(−2.231)	(−3.049)
$Term$	−12.996*	−16.214	−11.815	−7.437	0.404	8.199**
	(−1.846)	(−1.587)	(−1.382)	(−0.606)	(0.200)	(2.310)
Vol	−1.697	16.475***	−10.695	12.059	−9.244**	−3.336
	(−0.186)	(2.966)	(−0.849)	(1.333)	(−2.311)	(−0.770)
$const$	134.046**	203.104***	204.405**	305.690***	68.349**	97.640***
	(2.211)	(3.247)	(2.491)	(3.859)	(2.562)	(3.217)
No. Obs.	7189	3725	7107	3687	7108	3687
R-squared	0.139	0.320	0.174	0.408	0.233	0.440

Figures

Figure 1: KPI Matrix of Environmental areas and themes

Visual presentation of all potential combinations between the four environmental ares and the three defined themes. Combinations for which no suitable Eris KPI has been identified are grayed out.

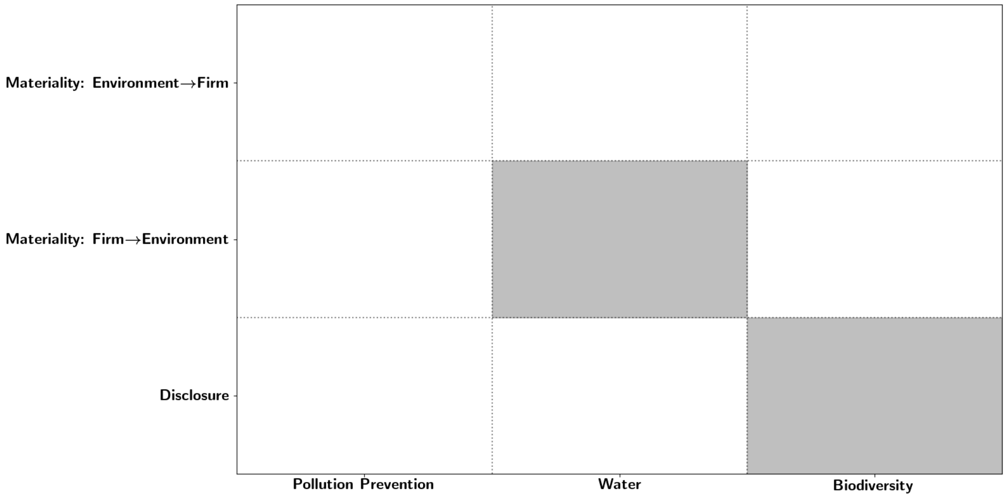


Figure 2: RankScore effects on CDS levels

This figure present the effect of RankScore on the one-, five- and ten-year CDS. We present the average CDS per sample and the average Rankscore effect by bars. The accompanying range depicts the RankScore effect for the maximum, minimum, mean and median RankScore within each respective sample. In addition, we present the effect of a one standard deviation increase in RankScore w.r.t. the average effect and average CDS. Effects are computed in reference to the average CDS and are the result of multiplying the respective RankScore value with the regression coefficient from regressing the CDS level on RankScore and controls. Results per environmental area and theme are presented in separate figures across columns and rows.

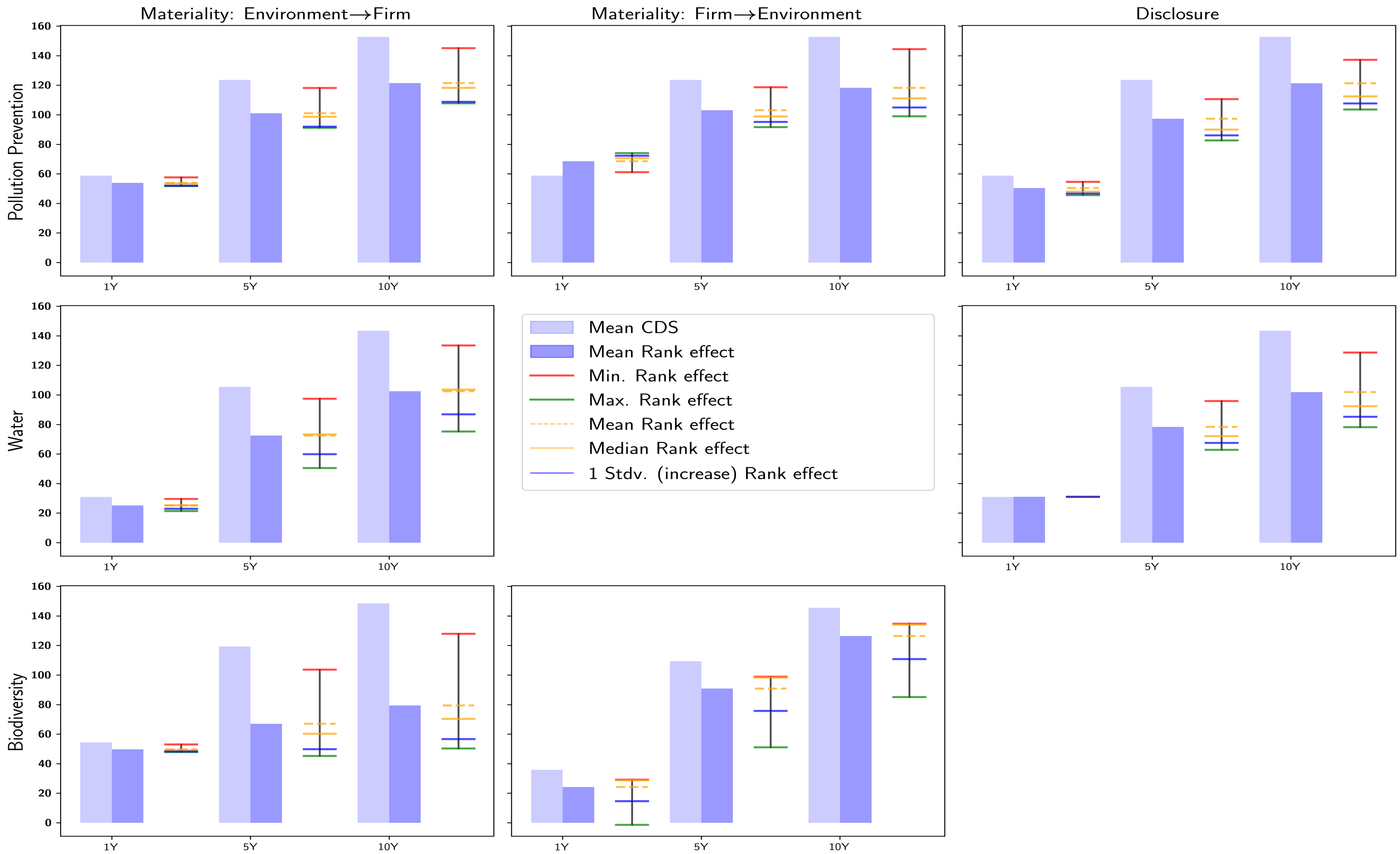
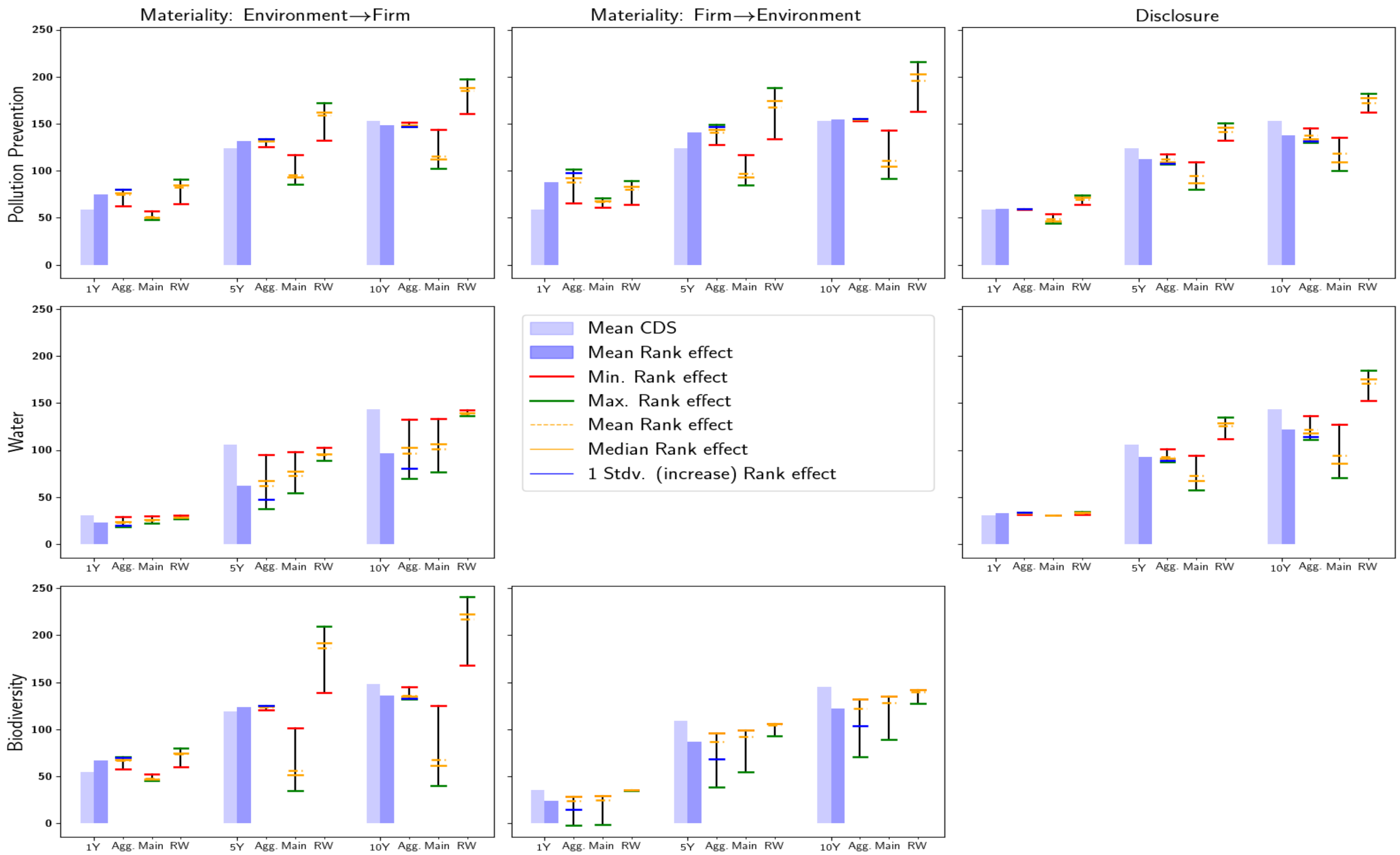


Figure 3: RankScore effects on CDS levels after electoral right-wing shock

This figure present the effect of RankScore on the one-, five- and ten-year CDS after the global electoral right-wing shock. We present the average CDS per sample and the average Rankscore effect by bars. The accompanying ranges depict the aggregate RankScore effect for the maximum, minimum, mean and median RankScore within each respective sample as well as the main and right-wing effect. In addition, we present the effect of a one standard deviation increase in RankScore w.r.t. the average effect and average CDS. Effects are computed in reference to the average CDS and are the result of multiplying the respective RankScore value with the regression coefficients from regressing the CDS level on RankScore, Rankscore interacted with a right-wing dummy and controls. Results per environmental area and theme are presented in separate figures across columns and rows.



A Sample composition

Figure A.1: Country distribution

Visual presentation on the country distribution within our Infrastructure sample. The country distribution presented here is based on the subsample for the KPI(s) for which we have the most firm-month observations, being the environment on firm materiality in the Pollution prevention area in this case.

Figure A.2: Industry distribution

Visual presentation of the SASB Industry distribution within our SASB Infrastructure sector sample. The industry distribution presented here is based on the subsample for the KPI(s) for which we have the most firm-month observations, being the environment on firm materiality in the Pollution prevention area in this case.