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## Beyond Climate: The Impact of Biodiversity, Water, and Pollution on the CDS Term Structure

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# 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 the EU Taxonomy currently uses 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 non-climate environmental criteria including biodiversity, water, and pollution on the credit risk term structure of infrastructure companies. Our results suggest that a better management of these three environmental risks predicts more favorable long-term financing conditions for firms. In particular, this is reflected in a flatter term structure of credit default spreads (CDS) for infrastructure investments, indicating that investors consider better environmental management an important factor in determining long-term corporate creditworthiness.

Our study focuses on the infrastructure sector for several reasons. First, as highlighted in a report published by the United Nations Environment Programme in 2021, Infrastructure plays a key role in supporting the achievement of the Sustainable Development Goals (SDGs) and is key to addressing the planetary crisis of biodiversity loss and pollution. Infrastructure is responsible for 88 percent of all adaptation costs, of which 54 percent will need to be spent on the water sector.[1] Hence, the infrastructure sector plays a crucial role in fostering environmentally-compatible developments. Second, infrastructure projects often involve significant investments in assets designed to operate over the long term.[2] Historically, the design of these facilities has been based on the assumption of a regulatory landscape and future environmental conditions similar to the current situation. 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 importance of sustainable infrastructure is highlighted once more in the most recent

[1]The report "Infrastructure for Climate Action" is the product of a collaboration between UNOPS, UNEP, and the University of Oxford. See here.

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

European Union's Taxonomy on Sustainable Finance (EUTSF), primarily aiming to increase private funding to 'shift the trillions' and foster green infrastructure investments.[3]

The importance of pollution prevention, biodiversity, and water scarcity on the economy has been 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 (EU), the 6th Environmental Action Plan (EAP), laying out the foundation for environmental policy actions for the period 2002-2012, identified four priority areas. These are (1) Climate change, (2) Nature and biodiversity, (3) Environment and health, as well as (4) Natural resources and waste (The European Parliament and the Council, 2002). The 7th EAP, the 2020 strategy, and the 8th EAP, the 2030 strategy, together with the EU's Green Deal reiterated those priorities (The European Parliament and the Council, 2013). The current EUTSF expanded and enhanced previous priorities, identifying six environmental goals 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. The EU Taxonomy has been developed to identify activities that contribute to environmental sustainability, including those related to biodiversity, water scarcity, and pollution, but do not significantly harm any of the other categories. 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

[3]'Shifting the trillions' generally denotes the need for the financial sector to mobilize and efficiently allocate the funds necessary to future-proof production methods and business models. Additionally, the need for proper environmental risk management allows us to benefit from the opportunities that sustainable development offers. 'Shifting the trillions' has been used as a catchphrase for many reports and news publications, see, e.g., 31 Recommendations by the Sustainable Finance Committee to the German federal government, Climate Finance Day - How to shift the trillions? and Sierra Club Foundation - Shifting Trillions among others

result, water scarcity is likely to become the biggest threat ever faced by humanity.[4] Despite two decades of regulatory and political advances in combating environmental issues and their potential consequences for companies and investors, a research gap exists on the relative importance of individual technical indicators beyond the well-studied topic of 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.

This lack of research has been noted in the recent academic literature. For example, Karolyi and Tobin-de la Puente (2023) called for more studies on biodiversity finance in his keynote address at the 2022 WFA Meeting in Portland. 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 Meeting in New Orleans. The factors contributing to this knowledge gap include, among others, the scarcity of data on biodiversity and other environmental factors beyond emission data.[5]

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

[4]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.

[5]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.

more stringent. However, further research is still needed to better measure and understand the impact of firms on biodiversity, water scarcity, and pollution prevention as well as the associated financial risks for companies.[6]

The main goal of this study is to shed light on the market's view concerning the timing of three 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 93bps 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 environmental performance and corporate credit risk by investigating regulatory shocks. We leverage the global shift towards more right-wing politics with the Brexit referendum in Europe and the election of Donald

[6]To our knowledge, the most recent research focusing on biodiversity encompasses the work of Coqueret and Giroux (2023), Flammer et al. (2023), Garel et al. (2023), and Giglio et al. (2023). Work related to pollution is Akey and Appel (2021) and Hsu et al. (2022). To the best of our knowledge, there is little available work on water except for the relation between water and electricity generation in Behrens et al. (2017) and Luo et al. (2023).

Trump in 2016. For most of the environmental themes, we find that these shocks led to a reversal in the effects of 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 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. 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.[7] In previous research focusing on climate

[7] Fama and French (2007) show that two key assumptions - agreement among 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

change, 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).[8] From 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. Also, a number of studies investigate the response of credit risk to broader Corporate Social Responsibility (CSR) metrics.[9]

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. Finally, the results in Riedl and Smeets (2017) indicate that socially responsible investors tend to have longer investment horizons, and risk perceptions are unrelated to the holdings of socially responsible investment funds. Whether in our context of credit risk, investors also exhibit longer investment horizons regarding the environmental areas that we consider, still remains an open question. This further motivates us to examine the time horizon for environmental risk assessments beyond climate change particularly through the

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.

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

[9] See e.g, Chava (2014), Goss and Roberts (2011), and Kölbel et al. (2017).

credit term structure.

This study not only offers guidance to companies on those key performance indicators (KPIs), but also provides insight for legislators seeking to refine benchmark criteria. The latter aspect is particularly relevant as the EUTSF is still in the process of development. Consequently, scientific evidence concerning the taxonomy topics' 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.[10] The start of the period coincides either with the availability of CDS data or the respective performance indicator, while the availability of the environmental performance KPIs defines the end of the period.[11] Additionally, 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 the Ethical Investment Research Service (EIRIS). EIRIS started as a non-profit organization based in the United Kingdom in 1983, providing independent research to help investors put their ethical

[10] See Figure B.1 in Appendix B for the country distribution in our sample.

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

principles into practice. EIRIS subsequently merged with Vigeo in 2015 and was ultimately bought by commercial rating provider Moody's in 2019. Li et al. (2022) present evidence that the commercialization of ratings negatively impacts their quality, motivating our choice to end the sample period in 2018.[12]

Following Hoepner et al. (2017), there are several reasons why we opt for EIRIS as our ESG data provider. At the time of our sample, EIRIS was a global leader in the provision of corporate ESG ratings and served as the basis for different FTSE4Good indices until 2013. Since its foundation, EIRIS has accumulated decades of experience assessing and engaging with corporate ESG performance and has developed a global network of analysts and partners. The result is a consistent and robust research process, leveraging numerous information sources, including public company data, a company questionnaire, NGO reports, information from other media sources, and data provided by regulators. The data is analyzed by dedicated sector specialists, and assessments are updated whenever relevant new (ESG) information becomes available. EIRIS has had an excellent track record with academics and NGOs compared to its for-profit competitors, which have been criticized several times.[13] Unlike commercial ESG rating providers, EIRIS does not provide any financial or legal advice to its clients, minimizing any potential conflict of interest in providing their ESG assessments.[14]

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.[15] Unlike competitors, EIRIS

[12]For a more detailed historical context of EIRIS, see e.g., Avetisyan and Hockerts (2017) and Wu and Shen (2013).

[13]See for example Chatterji et al. (2009) for their discussion on KLD scores. Refinitiv ESG (formerly ASSET4) has also received much attention for their changes to historical ESG ratings. Berg et al. (2020) find that these retrospective adjustments to ESG ratings are systematic and related to past financial performance. To the best of our knowledge, EIRIS has never been the subject of such criticism. Berg et al. (2022) present a general discussion on different ESG rating providers and their respective methodological differences.

[14]For a detailed discussion on the advantages and validity of EIRIS as ESG data provider, especially for the time frame of our study, see Hoepner et al. (2017).

[15]Table 1 provides details on the scale and indicator question with regard to our selected KPIs discussed in the next section. Examples of FTSE4Good constituents and non-constituents and their performance assess-

directly provides its raw indicators instead of an aggregate rating. This avoids problems related to ESG rating disagreement present in aggregate scores (Berg et al., 2022), and allows us to focus on only those scores that are of direct relevance to our study. In the next section, we discuss in more detail the selection framework and the individual KPIs we selected for our study.

#### 2.1.1 KPI selection

In selecting the relevant subjects, we use the EU environmental action plans and the most recent EUTSF and their environmental objectives as inspiration. 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 under-researched topics beyond climate change. Due to the availability of the KPIs within the EIRIS scope for the remaining four categories and the lack of attention in the previous EAPs for one of those categories, we cover only three environmental areas. The three main areas within our scope are 'biodiversity', 'water preservation', and 'pollution prevention', while 'circular economy' falls beyond the scope of this paper. The three topics in our scope have already received extensive attention in previous EU environmental action plans since 2002, well before the most recent taxonomy, unlike the 'circular economy' topic.[16] We believe this motivates the potential for these topics to be already considered in the pricing of, especially long-term, CDS spreads during our sample period. We select all relevant EIRIS KPIs that fall within this scope.[17]

Next, in addition to the defined environmental domains, we introduce a second dimension

ment by EIRIS within different topics are presented in Appendix A.1.

[16]The The 6th EU environmental action plan set out the framework for environmental policymaking in the European Union for the period 2002-2012, adopted on 22 July 2002, and outlined actions to achieve these. The four priority areas were 'Climate change', 'Nature and biodiversity', 'Environment and health', and 'Natural resources and waste'. (see e.g. here)

[17]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 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.

related to 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 highlights mandatory requirements on disclosure to improve transparency in environmental performance (European Commission, 2021). Therefore, we focus additionally on the element of disclosure. The 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. 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.[18] No suitable KPI was identified for the two combinations, and they are therefore not considered further in this study. These combinations are greyed out in Figure 1 and left blank in Table 1.[19]

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 analyzes. 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 and ease of interpretation, 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.[20] The rank transformation is applied on the full cross-section at each point in time.[21]

Using a rank transformation has several advantages. For one, it allows for direct comparison

[18] Our selected KPIs for pollution prevention have already been the subject of a study by Dam and Scholtens (2013)

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

[20] Concretely, a rank transform replaces the original value in a series with its rank over the whole series. For equal values/ranks, different options exist such as the minimum, maximum or median rank value. We will opt for the median and motivate this choice in more detail.

[21] 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 biasing results by missing data from other sources. Nevertheless, results for scores based on a rank transformation within the infrastructure sector do not significantly change results.

between indicators. Whereas the original indicators operated on different scales, the rank 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 on the top-performing company for a particular indicator.[22] 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.[23] Appendix A.1 presents *RankScore* examples for best- and worst-performers over time for the different environmental areas.[24]

[22]In a hypothetical case where only one firm is the single best (worst) performer among many others, 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.

[23]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 suboptimal 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.

[24]In Appendix A.2 we compare our created *RankScore* variables with scores from MSCI within our environmental scope through a correlation analysis. We find our measures to share significant positive correlations with corresponding MSCI scores, adding to the validity of our selected measures. However, MSCI scores are only available from 2013 onward at the earliest and not for all firms. Utilizing EIRIS KPIs allows us to extend our sample period, starting in 2008, and perform a more representative analysis. Additionally, we

## 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 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.[25]

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.[26] 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

attempted to relate our biodiversity scores to those from Giglio et al. (2023), but after matching our dataset with theirs, we obtain a very small sample, which makes a comparison not sensible. For further details, we refer to Appendix A.2.

[25]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.

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

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 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.[27] 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.

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

## 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 on the EIRIS indicator and represents eleven countries for all indicators.[28] 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.

We also report correlations between scores. The correlation between the different indicators are first computed for each company separately. Figure 2 presents the average correlations across firms. We observe that, on average, the within-firm correlations between the scores

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

are low, even when comparing the two materiality directions for the same environmental area. While most average correlations are positive, the firms' impact on biodiversity depicts, on average, a negative correlation with how companies perform in the pollution prevention space. The results in Figure 2, while some positive correlations exist, indicate that our scores still measure different aspects of environmental performance within firms. This implies that being a good performer in one area does not guarantee the same firm to be a top performer in the other areas. Hence, we cannot generalize the results from one environmental area to another, motivating the study of all three areas.[29] Additionally, aggregating the three areas into one would not be sensible.

Insert Figure 2 here.

# 3 Environmental performance and CDS term structure

We now develop testable hypotheses to study how the alignment with key environmental performance indicators affects the corporate credit default term structure of infrastructure firms. The derivation of predictions for the different environmental themes is challenging since little theoretical work has been done distinguishing how the various environmental categories separately relate to credit default spreads. Ex ante, we have no expectation of differences in the effects between water, biodiversity, and pollution. However, it still remains an empirical question whether markets differentiate between the risks from different environmental areas. Furthermore, there is little empirical evidence on market expectations related to the risk timing and across the materiality directions.

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

[29]This result does not necessarily imply we expect different average effects of better performance in either one of the areas. However, this still needs to be tested for all three areas separately.

and the overspending channel on the other hand. 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). 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). Barth et al. (2022) conclude that it is the risk mitigation channel that causes high ESG scoring firms to exhibit reduced CDS spreads. Similarly, Kölbel et al. (2022) investigate the impact on CDS spreads of increased climate risk through corporate disclosure. By modeling the impact of increased transition risk through a decrease in future asset value, the authors illustrate the positive impact on spreads for firms with higher transition risk exposure using the standard Merton (1974) model. Our $RankScore$ variables effectively measure a firm's environmental performance, mitigating the potential risk exposure within these environmental areas.

Infrastructure firms are key in fostering environment-compatible development, with projects expected to operate over long periods. Considering the existing evidence in Gibson et al. (2020), Riedl and Smeets (2017), and Starks et al. (2017) for ESG investors orienting themselves towards the long-term, we also expect investors to consider the long-term horizon of infrastructure projects and the corresponding timing of environmental risks beyond climate change. Following the risk mitigation argument in combination with the long-term orientation in infrastructure investments, we expect better performance for risks beyond climate change to lower credit spreads, but even more importantly, it will emphasize the long-term goals, effectively flattening the credit spread curve. These combined expectations lead to the following performance-related long-termism hypothesis ($\mathrm{H}_{LT-P}$):

**Hypothesis 1 ($\mathbf{H}_{LT-P}$)** *Infrastructure firms with higher RankScore values have, on average, a flatter CDS term structure, indicating a long-term outlook of investors considering the three environmental criteria.*

Previous studies 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. Similarly, infrastructure firms managing the physical risks of the changing environment better are expected to benefit from better management in the long run. The risk of legislation, as previously discussed, could enter both materiality directions. All with investors still emphasizing the long-term benefits of environmental performance. Hence, we hypothesize that the effects for both materiality aspects are directionally akin across environmental areas. This leads us to the following materiality-related hypothesis ($\mathrm{H}_{LT-M}$):

**Hypothesis 2 ($\mathbf{H}_{LT-M}$)** *Infrastructure firms with higher RankScore values for either materiality direction have, on average, a flatter CDS term structure, indicating long-termism of investors for both the environmental impact of the firm on the environment and vice versa.*

Lastly, considering corporate risk disclosure and its effect on credit risk, the literature presents us with two opposing effects; a risk perception effect and an information uncertainty effect.[30] 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 CDS spreads.

Our disclosure-themed indicators assess firms' reporting quality across environmental areas. Given the focus on the quality of reporting, we argue that only the information uncertainty channel is relevant here. The disclosure indicators do not measure individual firms' exposure,

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

nor do they incorporate how much firms disclose concerning each environmental theme. In the spirit of Campbell et al. (2014) and Yu (2005), we conjecture that more qualitative disclosure reduces firms' opaqueness resulting in a decrease in credit risk premia. Those results would corroborate the motivation of our hypotheses that investors are long-term oriented with regard to the three considered environmental areas.[31] This leads to the final disclosure related long-termism hypothesis ($H_{LT-D}$):

**Hypothesis 3 ($\mathbf{H}_{LT-D}$)** *Infrastructure firms with more qualitative disclosure, i.e., higher RankScore values in the disclosure theme, have, on average, a flatter CDS term structure, indicating long-termism.*

# 4 Empirical Results

As argued in the previous section, we are particularly interested in the time 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 themes and environmental areas. Instead of considering individual CDS maturities, we look for more direct evidence of the impact of environmental performance by investigating the effect on the slope of the CDS curve.

## 4.1 Long-Termism and Term Structure Slopes

As there exists little theoretical guidance on the effects of environmental performance or sustainability, in general, the question of timing and materiality across the CDS term structure

[31]Note that we would only expect disclosure quality to have a significant impact on the CDS term structure when the environmental topic itself is considered risk relevant. Provided that the environmental topic is term structure relevant in at least one direction, we expect a similarly negative effect of disclosure quality within that environmental area. Credit risk relevance in this sense would mean we observe an effect on the term structure of CDS, i.e. in our main CDS slope results. Appendix C presents results on the CDS levels to corroborate the risk-relevance.

remains an empirical question.[32] 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 macroeconomic control vectors, respectively. Our regressions additionally include industry and time-fixed effects in the form of $\mu_i$ and $\tau_t$, 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.[33] Since the time series is very slow-moving (updates occur on a monthly to annual basis), we abstain from a first-difference analysis of the EIRIS KPIs.[34] By focusing on CDS slopes, i.e., differences between levels, we consider a more direct measure for the relative comparison between levels, and we hope to alleviate to some extent the problem with heterogeneous firm effects that we would have in CDS level regressions. 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

[32] For instance, in the classical credit risk literature, Han and Zhou (2015) derive predictions from structural models for both firm-specific and macroeconomic 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.

[33] 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.

[34] Figure A.1 in Appendix A highlights the issue of little within-firm variation, making a model including firm fixed effects or a first-difference analysis not feasible. We acknowledge that this allows for unobserved firm heterogeneity not captured by the firm-specific controls to still be present.

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. These effects are not only statistically significant but also economically when compared to established influencers like leverage (Han & Zhou, 2015). Considering the ten-minus-one-year slope, a one standard deviation increase in the *RankScore* for biodiversity (water), results in a slope flattening of 21.6bps (13.3bps), while a one standard deviation increase in leverage equals a slope steepening of 26.3bps and 24.3bps in the respective regressions.

Intuitively we perceive this flattening effect on the CDS term structure as evidence for the market's long-term views.[35] To corroborate this intuition and aid in interpreting the slope regression results, we plot the performance effects on the CDS levels in Figure 3. For each environmental area and implementation theme, 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, 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.[36]

Insert Figure 3 here.

[35]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.

[36]Our focus is on the time-horizon if infrastructure investing, hence we abstain from presenting full results here. Regression table results for the CDS levels are presented in full in Appendix C. We compute the *RankScore* effects in Figure 3 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 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.

The results in Figure 3 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 environmental areas and themes.

In light of the results from Figure 3, 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, among others).

Insert Table 5 here.

Table 5 shows the results for the alternative materiality direction and provides clear evidence that an infrastructure firm's commitment towards pollution prevention has an impact on the CDS slope. The evidence points in favor of long-termism with a one standard deviation increase in *RankScore*, reducing the difference between the ten- and one-year spread with 17.4bps. Compared to a 27bps increase from a one standard deviation increase in leverage, this is also economically significant. Looking at the firm's impact on biodiversity (columns II, IV and VI in Table 5), results highlight the importance to distinguish between the two directions of materiality when compared to earlier results in Table 4. Here, we find no significant relationship between *RankScore* and CDS slopes and hence 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. Both results presented in Figure 3 and Table C.2 suggest that infrastructure firms' biodiversity impact is credit risk relevant, but without the long-termism view this is considered a more pressing matter for investors.

From Table 6 we conclude that similarly 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 emphasized the shift towards more right-wing politics, away from pro-environmental efforts. Brexit 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 (2) 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

$$\begin{aligned} CDS_{i,t+1}^{LT-ST} = \alpha + \beta_1 RankScore_{i,t} + \beta_2 RW_{i,t} + \beta_3 (RankScore \times RW)_{i,t} \\ + \Gamma X_{i,t} + \Theta Y_t + \mu_i + \tau_t + \epsilon_{i,t+1}. \end{aligned} \tag{2}$$

where the firm-specific ($X$) and macroeconomic ($Y$) controls are the same as in Equation (1).

Table 7 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 environmental 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 such 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.

Interestingly, we do not find such a reversal effect when considering water risks (columns II, V, and VIII). The results indicate that investors do not believe a change in the current regulatory climate will affect firms' exposure to water risks and therefore continue to perceive better water risk management as a risk mitigation tool. In the area of pollution prevention (columns I, IV, and VII), we again confirm our earlier negative effects on slopes from Table 4, however, this time also the short end of the curve is statistically significantly impacted. Results reveal that, especially on the short end of the curve, the initially negative impact reversed because of more right-wing politics in the near future. We argue that before the election, there was still lots 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. Similarly 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 short- to mid-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, we do not observe any reversal effect in the quality of disclosure. In Table 6 we only observed weakly significant results for disclosure on the medium to long end of the CDS curve, we find similar results in Table 9 without the reversal, which is not surprising given the initial effect is mostly on the long end of the curve beyond the time horizon of potentially short-lived political shifts.

Insert Table 9 here.

Similarly to Figure 3, we report results for the effect on the CDS levels in the right-wing period in Figure 4 with the extension that we present the aggregate effect split into a main and a right-wing effect.[37] The results in Figure 4 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 4 here.

[37] In accordance to our base results, the regression results for the levels are presented in full in Appendix C. We compute the aggregate $RankScore$ effects in the right-wing period in Figure 4 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.

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# 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) 5Y-1Y | (II) 5Y-1Y | (III) 10Y-1Y | (IV) 10Y-1Y | (V) 10Y-5Y | (VI) 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: $CDS^{LT-ST}_{i,t+1} = \alpha + \beta RankScore_{i,t} + \Gamma X_{i,t} + \Theta Y_t + \mu_i + \tau_t + \epsilon_{i,t+1}$, where $RankScore_{i,t}$ is the respective rank transformed Eiris KPI for the Taxonomy theme: "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) 5Y-1Y | (II) 5Y-1Y | (III) 10Y-1Y | (IV) 10Y-1Y | (V) 10Y-5Y | (VI) 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: $CDS_{i,t+1}^{LT-ST} = \alpha + \beta_1 RankScore_{i,t} + \beta_2 RW_{i,t} + \beta_3 (RankScore \times RW)_{i,t} + \Gamma X_{i,t} + \Theta Y_t + \mu_i + \tau_t + \epsilon_{i,t+1}$, 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) | (II) | (III) | (IV) | (V) | (VI) |
|---|---|---|---|---|---|---|
| | 5Y-1Y | 5Y-1Y | 10Y-1Y | 10Y-1Y | 10Y-5Y | 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.

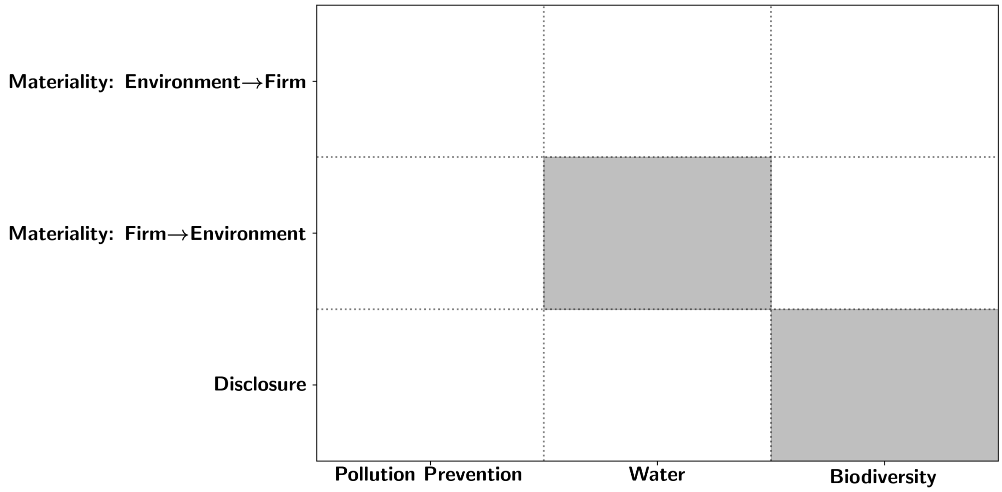


**Figure 2:** Average within firm correlation between scores

Figure presents the average within-firm correlation of the EIRIS-based *RankScore* variables. Correlations between different indicator series are computed per firm and then averaged across firms. The resulting average is presented here.

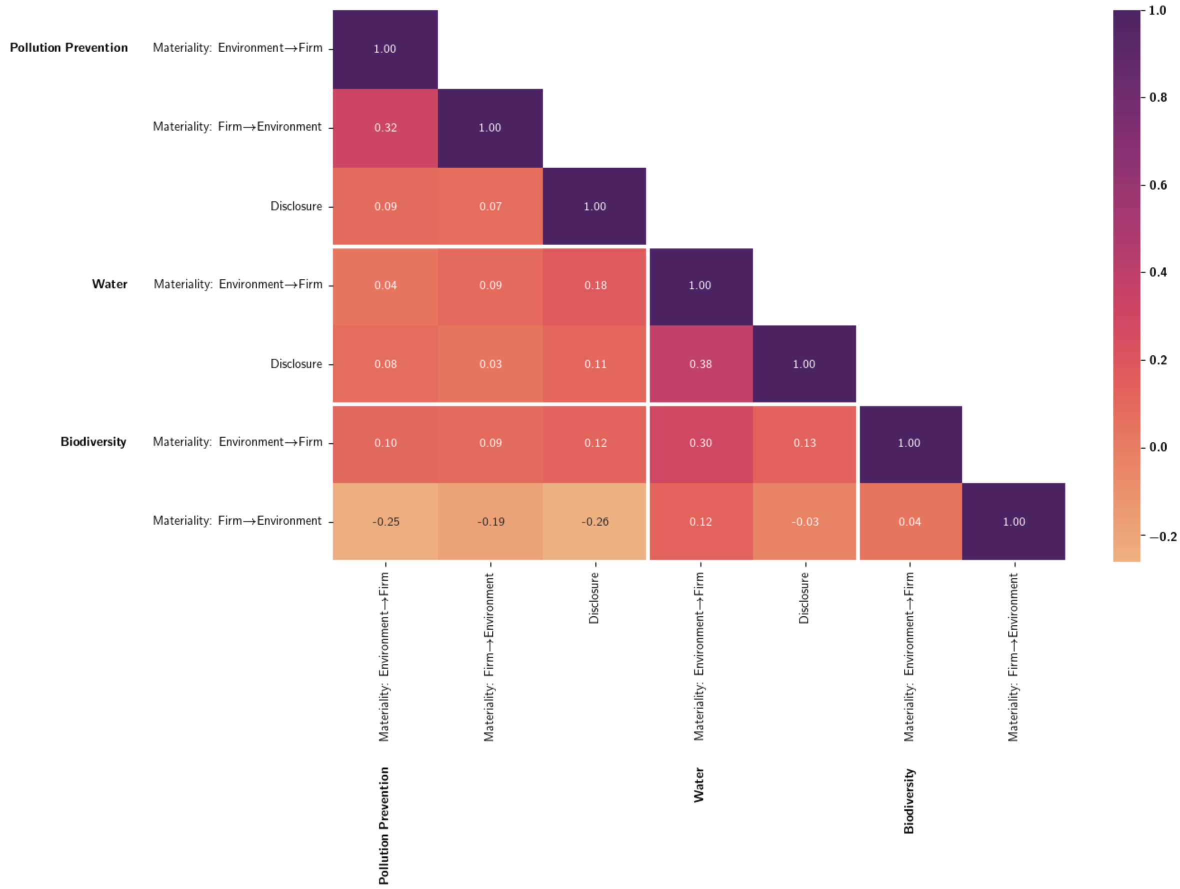


**Figure 3:** RankScore effects on CDS levels

This figure presents 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.

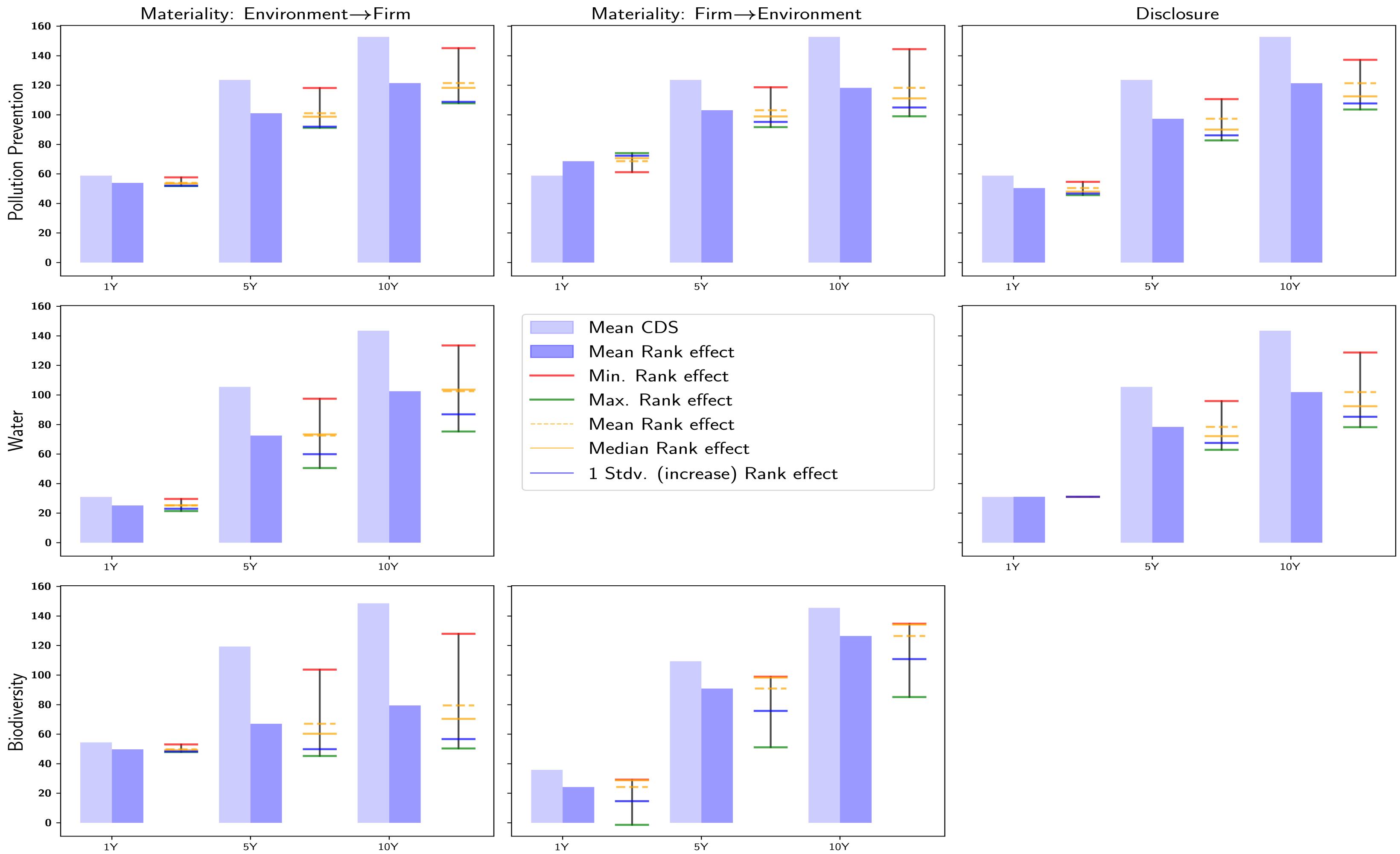
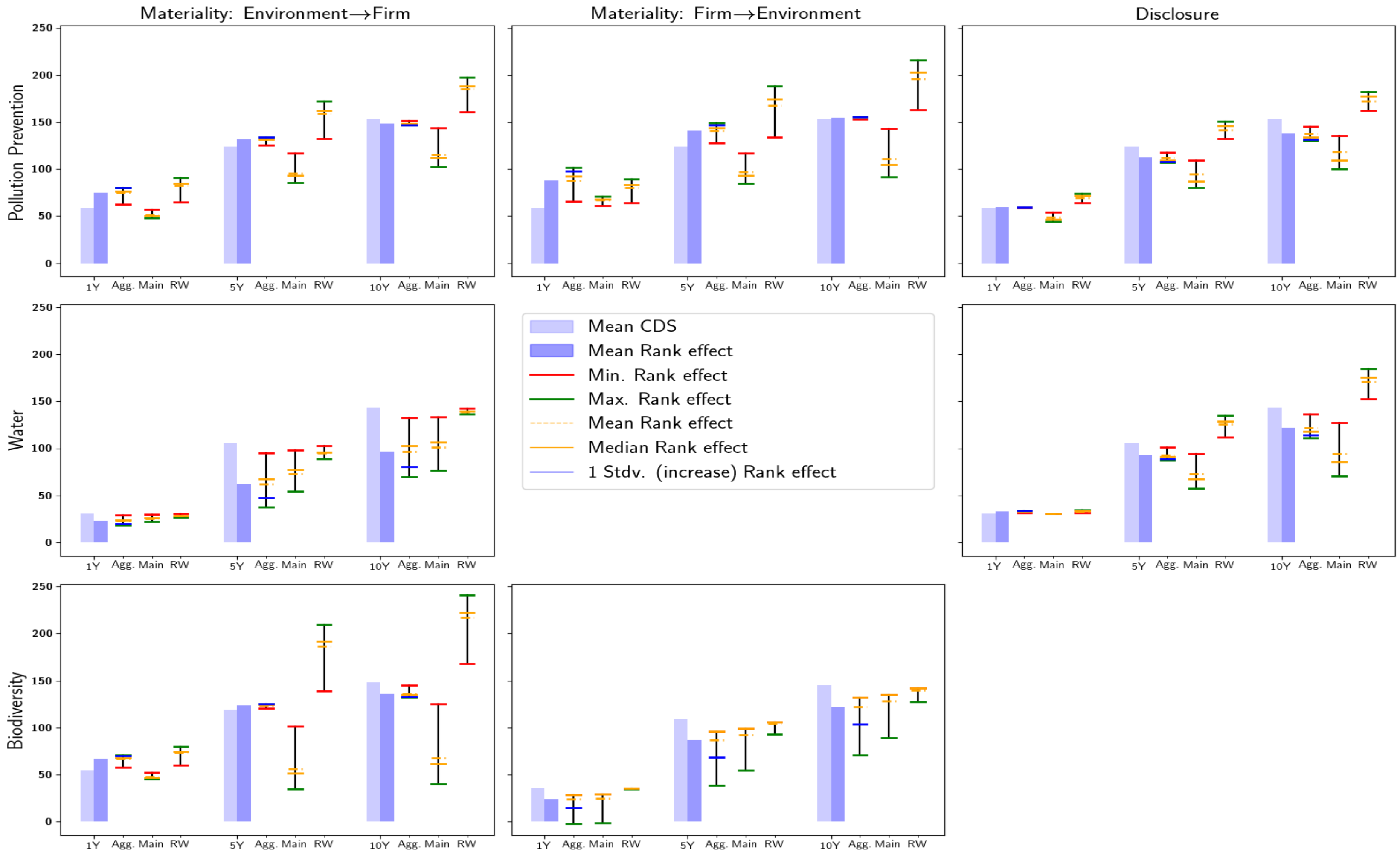


**Figure 4:** RankScore effects on CDS levels after electoral right-wing shock

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 Additional EIRIS material

## A.1 Examples

In this section, we provide examples of best and worst performers in different environmental areas. We believe this helps the understanding of the qualitative assessment by EIRIS and our rank transformation as well as providing validation for the use of EIRIS as ESG data provider. As highlighted in Section 2.1, EIRIS served as the driver for different FTSE4Good indices until 2013. We present best-performers that have consistently been index constituents for the period 2008-2013, while the worst-performers have not been an index constituent at any point during the same period.

Figure A.1 presents the *RankScore* for six firms across three indicators spanning the covered environmental areas.[38] The actual raw score only changes once for one firm throughout the entire sample for these six examples. Changes are limited which is a general observation for all firms and indicators.[39] The majority of (small) changes in the *RankScore* over time are the result of new firms being scored and added to the EIRIS dataset or the re-assessments of the existing firms changing the composition of performance groups. Figure A.1 also highlights the effect of opting for the median value in the rank transform. We observe that in the Water risk management and Pollution area, the group of top performers is smaller than those with low impact on biodiversity. The biodiversity is also the indicator with only three levels in the grading-scale, which explains why relatively more firms are evaluated to be in the highest scale. In contrast, the number of firms in the worst performing group does not seem to be too different between the presented indicators.

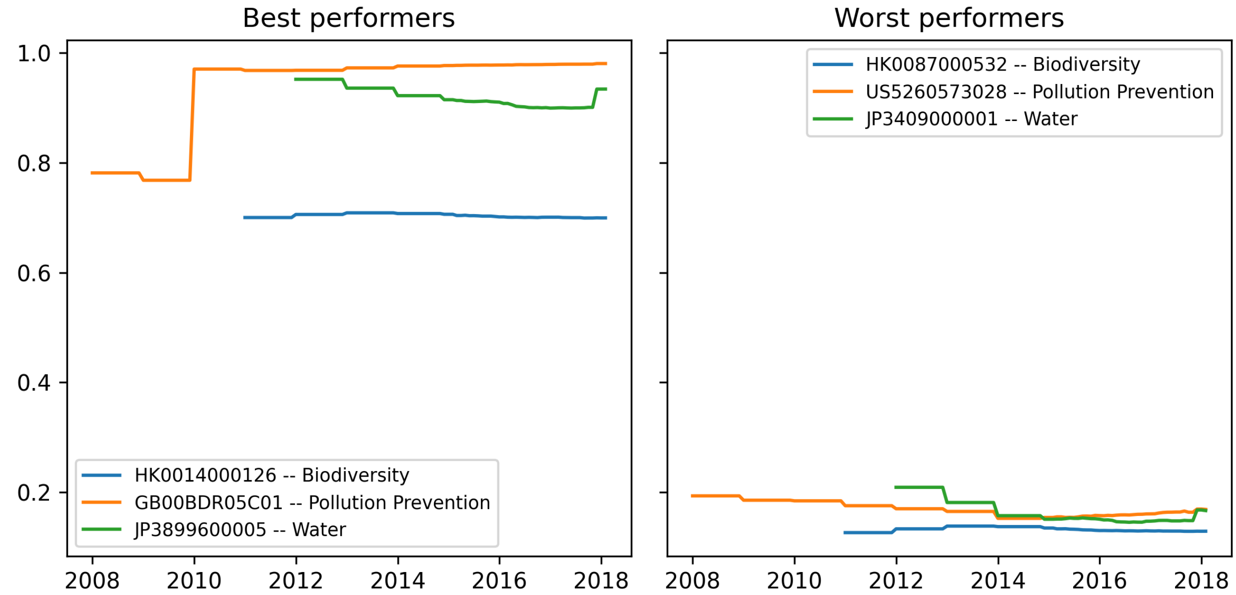
Hysan development (HK0014000126) is a Real estate company operating in Hong Kong and

[38] For water, we present the environmental materiality on the firm, while for biodiversity and pollution prevention we present the assessment of a firm's impact on the environment.

[39] The one changing firm in this example changes from the second level to the highest rating level in a five-step scale.

**Figure A.1:** *RankScore* examples of best and worst performers in three environmental areas

The figure presents the *RankScore* evolution for three firms among the best (left) and three firms among the worst performers (right) across three environmental areas. For water and pollution prevention we present the indicator measuring environmental materiality on the firm, while for biodiversity we present the assessment of a firm's impact on the environment.




has been consistently scoring high in terms of their impact on biodiversity. Their efforts over the years are highlighted by development projects in the Hong Kong area. In 2012, Hysan opened their newly constructed office building and shopping center *Hysan Place*. Hysan place received various accolades and awards for its green and sustainable development, and it was the first building in Hong Kong to receive the highest certification (platinum) under the Leadership in Energy and Environmental Design (LEED) of the United States Green Building Council (USGBC).[40] Moreover, on the rooftop of Hysan place, spanning around 8000 square feet, a new urban farm was placed to help improve the microclimate and biodiversity in the urban area.[41] More recently, *Lee Garden Three*, an office and retail building completed in 2017, was constructed with 'Green walls' to reduce the building's heat island effect and to

[40] USGBC

[41] See Hysan corporate responsibility report 2013 and Hysan environmental efforts and other media coverage on Hysan Place, BBC

improve the area's microclimate. The building also included a garden with specific flora to attract butterflies and to enhance the building's biodiversity.[42]

In contrast, Swire Pacific (HK0087000532) is a Real Estate firm listed on the Hong Kong stock exchange that has been under-performing in terms of their biodiversity impact. Indicative for this bad assessment is our analysis of the annual Sustainable developments report of Swire Pacific's subsidiary, Swire Properties.[43] In the reports from 2010-2012, we read

> "Since our land and properties are predominately situated within urban environments, we do not have an overarching biodiversity strategy in place. We do, however, comply with government requirements related to biodiversity..."

In the reports for following years, 2013-2015, there is not even a single mentioning of "Biodiversity". Only starting with the reports from 2016, biodiversity received specific attention with Swire Properties reporting their intent to establish a biodiversity policy and to integrate biodiversity considerations into new developments by 2020.[44] However, in the 2017 and 2018 reports, the topic of biodiversity is considered to be the least important to business continuity and development and the environmental topic least important to external stakeholders.[45] The group's most recent biodiversity policy that we were able to identify is a simple one-page document, mostly containing definitions and vague intentions over concrete actions.[46]

National Grid PLC (GB00BDR05C01) is a British electricity and gas company, and since 2010 among the best-performers in the scope of firm's environmental pollution management. Generally, over the past decade, National grid has been a top performer in environmental commitments and is currently highly rated by several instances.[47]

[42]HKGBC - Lee Garden Three and Hysan corporate responsibility report 2017
[43]All annual report are available for download here.
[44]See table on p.68 in the 2016 report.
[45]See the materiality matrix on p.27 of the 2018 report.
[46]Swire Pacific biodiversity policy
[47]As of 2022, National grid received an A-list rating from the Carbon Disclosure project, an ESG risk rating of 17 from Sustainalytics, an AAA ESG rating from MSCI, Prime status by Institutional Shareholder Services

An example of a bad performer in the pollution area is the American home builder, Lennar corp. (US5260573028). For more than a decade, Lennar has been in the center of controversy and lawsuits related to environmental pollution. In 2009, Lennar settled a violation of the Clean Air Act with the Environmental Protection Agency (EPA).[48] The violation occurred during residential construction in 2003-2005 when Lennar failed to install trackout control devices to remove particulate matter from vehicles and failed to immediately clean up dirt tracked out 50 feet beyond their sites.[49] Lennar was also involved in the redevelopment of the former Navy shipyard at Hunters Point which was followed by years of legal battles (Roberts & Brinklow, 2020). In 1989, the site, a former nuclear research ground, was declared a Superfund site requiring long-term efforts to clean up hazardous material contamination. Lennar has received much opposition from local residents and environmental action groups, who challenge Lennar's Environmental Impact Report (EIR) and accused the company of failing to disclose the health impacts of toxic contamination. Lennar has also been accused of failing to install proper air monitoring systems preventing dust, containing asbestos, from settling over the area when workers started excavating and grading one of the parcels in 2006 (Arrieta, 2011; Harrison, 2022). Recently, a settlement of $6.3 million for a 2018 class action lawsuit was approved after a first deal of $5.4 million was earlier rejected by the judge (Waxmann, 2023). The lawsuit was filed by homeowners claiming they were sold property that was unsafe after inadequate soil mitigation efforts (Kukura, 2022).[50]

Finally, Mitsubishi Estate Group (JP3899600005) and Sumitomo Realty & Development (JP3409000001) are two Japanese real estate firms with the former being assessed with a superior water risk management over the latter. Mitsubishi Estate currently uses a science

and is a longstanding constituent of the FTSE4Good index series.

[48] See EPA's press release

[49] Particle pollution is a severe problem as these particles can reach the deepest regions of the lungs, affecting the respiratory system.

[50] It has to be noted that Lennar Corp. was not directly responsible for the cleaning up of the site, this was Tetra Tech, Inc. who still deny any misconduct or fraud during the cleaning operations.

based approach to assess water stress and water risk for their properties.[51] It makes use of the open-source Aqueduct Water Risk Atlas, a water risk analyzes tool created by the World Resource Institute. The Group's 2022 portfolio of properties has no properties in the overall water-related risk category above "Low-Medium", based on all risk factors, including physical water volume, water quality, regulations, and reputational risk.[52]

## A.2 Comparison

As robustness, we compared the EIRIS variables with other data. In Figure A.2, we analyze the correlation between EIRIS *RankScores* and MSCI scores that we identified as being most similar for each of the environmental topics covered. Overall, the results in Figure A.2 show that our measures do share significant positive correlation with relevant MSCI scores, indicating that our measures do measure what we want them to measure.

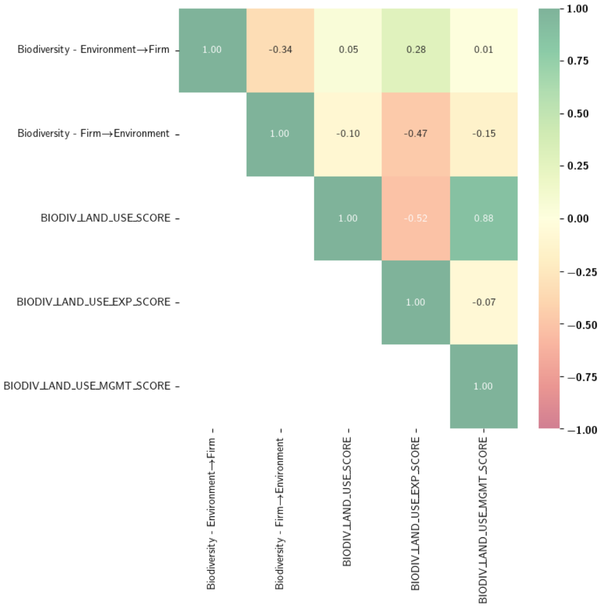
[51] We acknowledge that this is only reported on since 2022 and hence outside our sample time. For this example, we assume that current risk management practices are indicative of past performance.

[52] An assessment overview can be found here as well as the open-source link to the water risk analysis tool.

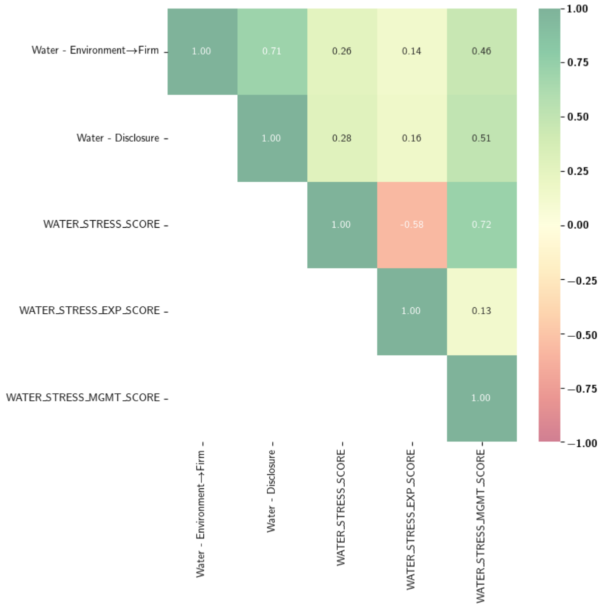
**Figure A.2:** Correlations MSCI scores

These figures present per environmental area the overall correlation between the EIRIS based *RankScore* variables and the most area-relevant ESG scores from MSCI. All but three presented correlations are significant at the 1% level. Correlations with an absolute value below 0.05 are found to be insignificant.

**(Panel a)** Biodiversity




**(Panel b)** Water




**(Panel c)** Pollution Prevention

We wish to stress that MSCI scores are only available from 2013, while our EIRIS data goes back to 2008. The firm overlap for the water and pollution area is close to the full sample available to us. However, this is not the case for the Biodiversity sample where MSCI overlap runs short on only 27 firms. The number of observations in our regression context would be reduced to almost 10% compared to the number of firm-month observations EIRIS would grant us.

To compensate for the lack of usable Biodiversity score data from MSCI, we made an additional attempt to verify our analysis with the biodiversity scores from Giglio et al. (2023). Unfortunately, the overlap is already limited to the US firms only. Moreover, the language-based scores are binary variables with very limited positive hits for our sample. For the 189 firm-year observation matching our US firm subsample, we have 186 (165) of them equaling 0 for the "negative" ("regulation") score from Giglio et al. (2023). Hence, any correlation analysis would already be nonsensical in this case.

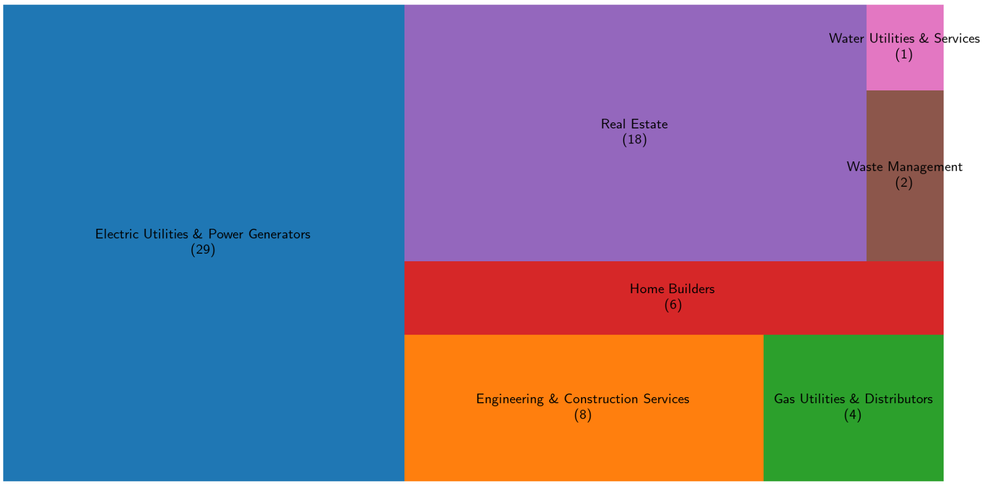
## B Sample composition

**Figure B.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 B.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.



# C Level results

In this section, we present additional results for regressions using the CDS levels to help the interpretation of slope results and to support our long-termism hypotheses.

## C.1 Base Results

In support of our base slope results in Section 4.1, Tables C.1 to C.3 contain the results of the following regression

$$CDS^S_{i;t+1} = \alpha + \beta RankScore_{i;t} + \Gamma X_{i;t} + \Theta Y_t + \mu_i + \tau_t + \epsilon_{i;t+1} \tag{3}$$

where $CDS^S_{i;t+1}$ is the CDS spread for the $S$ maturity. $X_{i;t}$ and $Y_t$ are firm-specific and macroeconomic control vectors respectively. Our regressions additionally include industry and time-fixed effects in the form of $\mu_i$ and $\tau_t$, 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.

**Table C.1:** Monthly regression results for the different CDS levels for the theme: Materiality: Environment→Firm

This table shows the regression results for a panel regression of the form: $CDS^S_{i,t+1} = \alpha + \beta RankScore_{i,t} + \Gamma X_{i,t} + \Theta Y_t + \mu_i + \tau_t + \epsilon_{i,t+1}$, where $RankScore_{i,t}$ is the respective rank transformed Eiris KPI for the 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) |
|---|---|---|---|---|---|---|---|---|---|
| | 1Y | 1Y | 1Y | 5Y | 5Y | 5Y | 10Y | 10Y | 10Y |
| $PollutionPrevention$ | −7.909 | | | −36.246 | | | −50.378 | | |
| | (−0.468) | | | (−1.134) | | | (−1.443) | | |
| $Water$ | | −9.632 | | | −55.068** | | | −68.377** | |
| | | (−0.786) | | | (−2.145) | | | (−2.442) | |
| $Biodiversity$ | | | −6.673 | | | −75.684** | | | −100.245*** |
| | | | (−0.341) | | | (−2.056) | | | (−2.584) |
| $BC$ | −0.376 | −0.547 | −0.252 | −0.661 | −0.752 | −0.562 | −0.352 | −0.376 | −0.257 |
| | (−0.783) | (−1.432) | (−0.533) | (−1.444) | (−1.635) | (−1.071) | (−0.636) | (−0.799) | (−0.413) |
| $IR$ | 9.485 | 11.619 | 16.013 | 23.081 | 25.951* | 24.611 | 26.224* | 28.743** | 27.383 |
| | (0.692) | (0.887) | (1.073) | (1.600) | (1.729) | (1.453) | (1.832) | (2.052) | (1.641) |
| $IR2$ | 0.909 | 0.176 | −0.417 | −0.926 | −0.880 | −1.474 | −2.041 | −1.452 | −2.436 |
| | (0.406) | (0.073) | (−0.177) | (−0.407) | (−0.334) | (−0.581) | (−0.889) | (−0.594) | (−0.963) |
| $Lev$ | 0.459 | 0.003 | 0.028 | 1.523*** | 1.018*** | 1.280*** | 1.984*** | 1.498*** | 1.784*** |
| | (1.258) | (0.014) | (0.078) | (3.893) | (2.914) | (3.178) | (4.851) | (4.016) | (4.315) |
| $ROA$ | −2.593** | −0.052 | −2.286* | −1.179 | 0.271 | −0.731 | −0.080 | 0.551 | 0.226 |
| | (−1.963) | (−0.100) | (−1.781) | (−0.989) | (0.366) | (−0.691) | (−0.072) | (0.741) | (0.244) |
| $Size$ | −4.171 | 0.589 | −2.938 | −9.128** | −9.225** | −10.532** | −12.158*** | −14.832*** | −14.237*** |
| | (−1.254) | (0.234) | (−0.820) | (−2.264) | (−2.323) | (−2.319) | (−2.962) | (−3.702) | (−3.153) |
| $Vol$ | 62.520*** | 35.711** | 68.054*** | 60.758*** | 52.528*** | 65.152*** | 50.498*** | 48.321*** | 53.891*** |
| | (3.639) | (2.157) | (3.358) | (4.399) | (3.922) | (4.439) | (4.300) | (4.637) | (4.482) |
| $const$ | −18.001 | −49.237 | −33.529 | 73.763 | 125.221 | 130.887 | 154.497* | 248.708*** | 231.203** |
| | (−0.203) | (−0.668) | (−0.332) | (0.786) | (1.371) | (1.147) | (1.666) | (2.902) | (2.039) |
| No. Obs. | 7226 | 3752 | 6387 | 7225 | 3735 | 6376 | 7108 | 3687 | 6279 |
| R-squared | 0.291 | 0.281 | 0.325 | 0.319 | 0.340 | 0.364 | 0.303 | 0.398 | 0.354 |

**Table C.2:** Monthly regression results for the different CDS levels for the theme: Materiality: Firm→Environment

This table shows the regression results for a panel regression of the form: $CDS^S_{i,t+1} = \alpha + \beta RankScore_{i,t} + \Gamma X_{i,t} + \Theta Y_t + \mu_i + \tau_t + \epsilon_{i,t+1}$, where $RankScore_{i,t}$ is the respective rank transformed Eiris KPI for the 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) |
|---|---|---|---|---|---|---|
| | 1Y | 1Y | 5Y | 5Y | 10Y | 10Y |
| $PollutionPrevention$ | 15.482 | | −32.576 | | −54.888** | |
| | (0.829) | | (−1.245) | | (−2.009) | |
| $Biodiversity$ | | −52.581** | | −82.190** | | −85.294** |
| | | (−2.070) | | (−2.421) | | (−2.216) |
| $BC$ | −0.317 | −0.174 | −0.625 | −0.606 | −0.325 | −0.188 |
| | (−0.645) | (−0.292) | (−1.386) | (−1.157) | (−0.598) | (−0.341) |
| $IR$ | 12.060 | 17.661 | 24.152* | 34.556** | 26.688* | 36.501*** |
| | (0.876) | (1.052) | (1.675) | (2.368) | (1.874) | (2.804) |
| $IR2$ | 0.508 | −0.730 | −1.139 | −2.275 | −2.182 | −2.822 |
| | (0.229) | (−0.251) | (−0.498) | (−0.922) | (−0.940) | (−1.287) |
| $Lev$ | 0.442 | −0.354 | 1.576*** | 0.654* | 2.071*** | 1.161*** |
| | (1.235) | (−0.893) | (3.842) | (1.700) | (4.786) | (2.857) |
| $ROA$ | −2.647** | −0.957 | −1.029 | −0.887 | 0.165 | −0.350 |
| | (−2.006) | (−1.015) | (−0.824) | (−1.021) | (0.142) | (−0.437) |
| $Size$ | −4.557 | −0.244 | −10.127** | −9.458** | −13.475*** | −14.834*** |
| | (−1.336) | (−0.092) | (−2.484) | (−2.500) | (−3.281) | (−3.700) |
| $Vol$ | 63.833*** | 66.364** | 59.808*** | 76.758*** | 48.518*** | 69.273*** |
| | (3.624) | (2.101) | (4.225) | (4.109) | (4.047) | (5.347) |
| $const$ | −29.929 | −54.347 | 87.101 | 95.691 | 179.348* | 209.133** |
| | (−0.315) | (−0.647) | (0.896) | (1.044) | (1.916) | (2.312) |
| No. Obs. | 7226 | 5224 | 7225 | 5233 | 7108 | 5148 |
| R-squared | 0.291 | 0.323 | 0.318 | 0.384 | 0.303 | 0.394 |

**Table C.3:** Monthly regression results for the different CDS levels for the theme: Disclosure

This table shows the regression results for a panel regression of the form: $CDS^{S}_{i,t+1} = \alpha + \beta RankScore_{i,t} + \Gamma X_{i,t} + \Theta Y_t + \mu_i + \tau_t + \epsilon_{i,t+1}$, where $RankScore_{i,t}$ is the respective rank transformed Eiris KPI for the 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) |
|---|---|---|---|---|---|---|
| | 1Y | 1Y | 5Y | 5Y | 10Y | 10Y |
| $PollutionPrevention$ | $-13.579$ | | $-42.181$ | | $-50.617$ | |
| | $(-1.002)$ | | $(-1.431)$ | | $(-1.613)$ | |
| $Water$ | | $0.132$ | | $-42.743$ | | $-65.535^{**}$ |
| | | $(0.011)$ | | $(-1.608)$ | | $(-2.266)$ |
| $BC$ | $-0.391$ | $-0.523$ | $-0.668$ | $-0.770^{*}$ | $-0.344$ | $-0.445$ |
| | $(-0.829)$ | $(-1.356)$ | $(-1.418)$ | $(-1.655)$ | $(-0.607)$ | $(-0.955)$ |
| $IR$ | $7.604$ | $12.632$ | $18.943$ | $27.631^{*}$ | $22.133$ | $29.489^{**}$ |
| | $(0.562)$ | $(0.939)$ | $(1.319)$ | $(1.814)$ | $(1.552)$ | $(2.119)$ |
| $IR2$ | $1.204$ | $-0.016$ | $-0.277$ | $-1.029$ | $-1.397$ | $-1.342$ |
| | $(0.543)$ | $(-0.006)$ | $(-0.122)$ | $(-0.385)$ | $(-0.605)$ | $(-0.555)$ |
| $Lev$ | $0.438$ | $-0.001$ | $1.462^{***}$ | $0.986^{***}$ | $1.908^{***}$ | $1.456^{***}$ |
| | $(1.204)$ | $(-0.007)$ | $(3.799)$ | $(2.859)$ | $(4.692)$ | $(4.080)$ |
| $ROA$ | $-2.609^{*}$ | $-0.082$ | $-1.215$ | $0.127$ | $-0.128$ | $0.366$ |
| | $(-1.956)$ | $(-0.156)$ | $(-1.004)$ | $(0.163)$ | $(-0.116)$ | $(0.508)$ |
| $Size$ | $-4.076$ | $0.504$ | $-9.173^{**}$ | $-8.593^{**}$ | $-12.409^{***}$ | $-13.746^{***}$ |
| | $(-1.189)$ | $(0.205)$ | $(-2.222)$ | $(-1.990)$ | $(-2.969)$ | $(-3.258)$ |
| $Vol$ | $62.530^{***}$ | $36.153^{**}$ | $61.182^{***}$ | $53.312^{***}$ | $51.359^{***}$ | $48.664^{***}$ |
| | $(3.683)$ | $(2.173)$ | $(4.485)$ | $(3.830)$ | $(4.402)$ | $(4.422)$ |
| $const$ | $-12.621$ | $-54.812$ | $86.218$ | $106.542$ | $167.163^{*}$ | $230.115^{***}$ |
| | $(-0.142)$ | $(-0.735)$ | $(0.904)$ | $(1.127)$ | $(1.771)$ | $(2.617)$ |
| No. Obs. | 7226 | 3752 | 7225 | 3735 | 7108 | 3687 |
| R-squared | 0.292 | 0.279 | 0.322 | 0.331 | 0.305 | 0.397 |

## C.2 Right-wing Results

In support of the slope effect after right-wing political shocks presented in Section 4.2, Tables C.4 to C.5 contain the results of the following regression

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

where $CDS^{S}_{i;t+1}$ is the CDS spread for the $S$ maturity. $X_{i;t}$ and $Y_t$ are firm-specific and macroeconomic control vectors respectively. Our regressions additionally include industry and time-fixed effects in the form of $\mu_i$ and $\tau_t$, 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.

**Table C.4:** Monthly regression results for the different CDS levels for the theme: Materiality: Environment→Firm

This table shows the regression results for a panel regression of the form: $CDS^{S}_{i,t+1} = \alpha + \beta_1 RankScore_{i,t} + \beta_2 RW_{i,t} + \beta_3 (RankScore \times RW)_{i,t} + \Gamma X_{i,t} + \Theta Y_t + \mu_i + \tau_t + \epsilon_{i,t+1}$, where $RankScore$ is the respective rank transformed Eiris KPI for the 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) |
|---|---|---|---|---|---|---|---|---|---|
| | 1Y | 1Y | 1Y | 5Y | 5Y | 5Y | 10Y | 10Y | 10Y |
| $PollutionPrevention$ | −11.932 | | | −42.688 | | | −56.594 | | |
| | (−0.682) | | | (−1.309) | | | (−1.584) | | |
| $RWXPollutionPrevention$ | $36.216^{**}$ | | | $54.400^{**}$ | | | $50.137^{**}$ | | |
| | (1.969) | | | (2.383) | | | (2.187) | | |
| $Water$ | | −8.650 | | | $-51.419^{**}$ | | | $-66.807^{**}$ | |
| | | (−0.720) | | | (−2.148) | | | (−2.506) | |
| $RWXWater$ | | −4.179 | | | −16.849 | | | −7.131 | |
| | | (−0.354) | | | (−0.426) | | | (−0.185) | |
| $Biodiversity$ | | | −9.447 | | | $-86.598^{**}$ | | | $-111.656^{***}$ |
| | | | (−0.455) | | | (−2.259) | | | (−2.771) |
| $RWXBiodiversity$ | | | 26.418 | | | $92.792^{***}$ | | | $94.592^{***}$ |
| | | | (1.138) | | | (3.005) | | | (3.003) |
| $BC$ | −0.414 | −0.555 | −0.288 | −0.713 | $-0.758^{*}$ | −0.630 | −0.393 | −0.379 | −0.315 |
| | (−0.850) | (−1.454) | (−0.600) | (−1.546) | (−1.670) | (−1.196) | (−0.707) | (−0.817) | (−0.504) |
| $IR$ | 10.865 | 11.178 | 16.181 | $25.666^{*}$ | 24.883 | 27.785 | $28.970^{*}$ | $28.260^{*}$ | $31.245^{*}$ |
| | (0.817) | (0.849) | (1.118) | (1.757) | (1.622) | (1.643) | (1.960) | (1.959) | (1.847) |
| $IR2$ | 0.772 | 0.228 | −0.419 | −1.193 | −0.764 | −1.789 | −2.330 | −1.399 | −2.832 |
| | (0.353) | (0.094) | (−0.182) | (−0.524) | (−0.285) | (−0.709) | (−1.003) | (−0.562) | (−1.117) |
| $Lev$ | 0.462 | 0.005 | 0.035 | $1.522^{***}$ | $1.023^{***}$ | $1.296^{***}$ | $1.983^{***}$ | $1.500^{***}$ | $1.798^{***}$ |
| | (1.271) | (0.020) | (0.097) | (3.896) | (2.926) | (3.222) | (4.844) | (4.018) | (4.358) |
| $ROA$ | $-2.629^{**}$ | −0.053 | $-2.297^{*}$ | −1.243 | 0.271 | −0.798 | −0.138 | 0.550 | 0.156 |
| | (−2.001) | (−0.100) | (−1.792) | (−1.045) | (0.368) | (−0.745) | (−0.126) | (0.741) | (0.165) |
| $RW$ | $-39.151^{***}$ | −1.970 | $-36.605^{*}$ | $-53.095^{***}$ | 2.066 | $-88.924^{***}$ | $-43.129^{**}$ | 0.625 | $-81.294^{***}$ |
| | (−2.734) | (−0.250) | (−1.825) | (−2.668) | (0.078) | (−3.330) | (−2.158) | (0.023) | (−3.156) |
| $Size$ | −3.833 | 0.474 | −2.967 | $-8.471^{**}$ | $-9.503^{**}$ | $-9.978^{**}$ | $-11.460^{***}$ | $-14.957^{***}$ | $-13.523^{***}$ |
| | (−1.189) | (0.187) | (−0.847) | (−2.049) | (−2.325) | (−2.177) | (−2.675) | (−3.595) | (−2.914) |
| $Vol$ | $62.208^{***}$ | $35.769^{**}$ | $67.852^{***}$ | $60.265^{***}$ | $52.674^{***}$ | $64.123^{***}$ | $50.029^{***}$ | $48.377^{***}$ | $52.837^{***}$ |
| | (3.584) | (2.161) | (3.317) | (4.298) | (3.939) | (4.291) | (4.196) | (4.642) | (4.312) |
| $const$ | −21.199 | −46.304 | −29.070 | 65.348 | 130.962 | 127.280 | 143.936 | $251.374^{***}$ | $223.009^{*}$ |
| | (−0.243) | (−0.619) | (−0.290) | (0.679) | (1.377) | (1.102) | (1.488) | (2.785) | (1.921) |
| No. Obs. | 7226 | 3752 | 6387 | 7225 | 3735 | 6376 | 7108 | 3687 | 6279 |
| R-squared | 0.292 | 0.281 | 0.326 | 0.321 | 0.341 | 0.369 | 0.304 | 0.398 | 0.359 |

**Table C.5:** Monthly regression results for the different CDS levels for the theme: Materiality: Firm→Environment

This table shows the regression results for a panel regression of the form: $CDS^S_{i,t+1} = \alpha + \beta_1 RankScore_{i,t} + \beta_2 RW_{i,t} + \beta_3 (RankScore \times RW)_{i,t} + \Gamma X_{i,t} + \Theta Y_t + \mu_i + \tau_t + \epsilon_{i,t+1}$, where $RankScore$ is the respective rank transformed Eiris KPI for the 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) | (II) | (III) | (IV) | (V) | (VI) |
|---|---|---|---|---|---|---|
| | 1Y | 1Y | 5Y | 5Y | 10Y | 10Y |
| $PollutionPrevention$ | 12.261 | | $-39.776$ | | $-62.026^{**}$ | |
| | (0.624) | | $(-1.476)$ | | $(-2.180)$ | |
| $RWXPollutionPrevention$ | 31.384 | | $65.821^{**}$ | | $64.743^{**}$ | |
| | (1.496) | | (2.122) | | (2.008) | |
| $Biodiversity$ | | $-52.516^{**}$ | | $-78.082^{**}$ | | $-80.917^{**}$ |
| | | $(-2.134)$ | | $(-2.291)$ | | $(-2.051)$ |
| $RWXBiodiversity$ | | $-1.725$ | | $-22.724$ | | $-25.463$ |
| | | $(-0.101)$ | | $(-0.818)$ | | $(-0.836)$ |
| $BC$ | $-0.350$ | $-0.191$ | $-0.679$ | $-0.642$ | $-0.370$ | $-0.217$ |
| | $(-0.705)$ | $(-0.319)$ | $(-1.507)$ | $(-1.216)$ | $(-0.682)$ | $(-0.393)$ |
| $IR$ | 12.746 | 17.096 | $26.744^{*}$ | $33.480^{**}$ | $29.605^{*}$ | $35.551^{***}$ |
| | (0.956) | (1.014) | (1.792) | (2.266) | (1.960) | (2.681) |
| $IR2$ | 0.451 | $-0.657$ | $-1.399$ | $-2.123$ | $-2.483$ | $-2.684$ |
| | (0.208) | $(-0.224)$ | $(-0.603)$ | $(-0.855)$ | $(-1.043)$ | $(-1.216)$ |
| $Lev$ | 0.446 | $-0.351$ | $1.576^{***}$ | $0.665^{*}$ | $2.073^{***}$ | $1.175^{***}$ |
| | (1.248) | $(-0.882)$ | (3.844) | (1.743) | (4.785) | (2.917) |
| $ROA$ | $-2.664^{**}$ | $-0.949$ | $-1.081$ | $-0.864$ | 0.117 | $-0.324$ |
| | $(-2.024)$ | $(-1.004)$ | $(-0.862)$ | $(-1.001)$ | (0.100) | $(-0.411)$ |
| $RW$ | $-38.415^{**}$ | $-7.011$ | $-66.092^{***}$ | $-10.885$ | $-59.364^{**}$ | $-8.007$ |
| | $(-2.164)$ | $(-0.952)$ | $(-2.638)$ | $(-0.843)$ | $(-2.323)$ | $(-0.593)$ |
| $Size$ | $-4.412$ | $-0.384$ | $-9.541^{**}$ | $-9.705^{**}$ | $-12.823^{***}$ | $-15.054^{***}$ |
| | $(-1.329)$ | $(-0.144)$ | $(-2.259)$ | $(-2.499)$ | $(-2.963)$ | $(-3.631)$ |
| $Vol$ | $63.554^{***}$ | $66.425^{**}$ | $59.142^{***}$ | $76.857^{***}$ | $47.866^{***}$ | $69.348^{***}$ |
| | (3.566) | (2.103) | (4.097) | (4.111) | (3.915) | (5.345) |
| $const$ | $-28.990$ | $-49.972$ | 81.231 | 102.702 | $170.843^{*}$ | $214.879^{**}$ |
| | $(-0.310)$ | $(-0.593)$ | (0.811) | (1.087) | (1.739) | (2.273) |
| No. Obs. | 7226 | 5224 | 7225 | 5233 | 7108 | 5148 |
| R-squared | 0.292 | 0.324 | 0.320 | 0.385 | 0.305 | 0.394 |

## Swiss Finance Institute

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