Dear Professors Flammer and Giglio

With this letter, I would like to express my interest in participating in the *PhD Student Workshop on Climate Finance* and submit my recent work:

"The Materiality of Biodiversity Risk for SMEs in the United Kingdom"

This is an original, unpublished work that is still in progress, which I recently had the pleasure of presenting at the Financial Economics of Climate and Sustainability Workshop at the University of Oxford, organised by Professor Marcin Kacperczyk to bring together PhD students conducting research on climate and sustainable finance in the UK.

Please find below the requested information.

Thank you for organising this workshop. I hope to have the opportunity to contribute to it.

Sincerely,

Guglielmo Visentin

Name: Guglielmo Alessandro Visentin

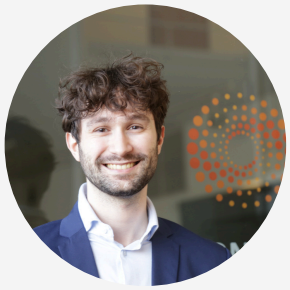
Contact information: g.visentin@pgr.reading.ac.uk (mail), +39 3349169795 (mobile)

University: ICMA Centre, Henley Business School, University of Reading

Current and future research interests: My current research interests focus on the impact of climate change and biodiversity-related risks on firms and financial institutions. I explore these topics using various techniques, including spatial analysis, econometric models, and machine learning. Looking ahead, I am interested in studying the effects of nature-related risks on the macroeconomy and financial contagion. Additionally, my research includes portfolio diversification with alternative assets—particularly sustainable ones—and the interplay between sustainability choices, risk, and return.

Expected completion date of PhD programme: August 2027

Faculty advisers: Simone Varotto (University of Reading, s.varotto@henley.ac.uk) and Lisa Schopohl (University of Reading, l.schopohl@henley.ac.uk).



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Profile

Born 09/05/1998, Age 27
Inquisitive, resilient, self-motivated and used to multicultural environments. My current research interests involve climate finance, biodiversity finance, alternative investments, and systemic risk, but I am eager to expand my interests further.

Skills

- Bloomberg terminal
- EViews, MATLAB, Python, R, Stata
- Latex
- Microsoft Office

Languages

Italian

English (C1)

French (B2)

Publications

Journal articles

- Barro, D., Basso, A., Funari, S. and Visentin, G.A. (2024), "The effects of the introduction of volume-based liquidity constraints in portfolio optimization with alternative investments", Mathematics, 12(15), 2424.

Book articles

- Barro, D., Basso, A., Funari, S. and Visentin, G.A. (2024), "Art as a financial asset in portfolio allocation", p. 37-42, in *Mathematical and Statistical Methods for Actuarial Sciences and Finance. MAF 2024*, Springer.

Work experience

Ph.D. student in Finance — Sept 2024 -
University of Reading

I am carrying out the research project *Measuring how a company's depletion of nature capital affects its financial performance: insights from satellite data and biodiversity indices* at the ICMA Centre.

Research fellow — Feb 2024 - Sept 2024
Ca' Foscari University of Venice

Participated in the research project *Machine learning methods and other new tools for assessing and managing risks associated with the transition to a climate-neutral society*, a Project of Relevant National Interests (PRIN) according to the Ministry of University and Research.

Data analyst — Nov 2023 - Dec 2023
Ca' Foscari University of Venice

I was tasked with providing a statistical analysis and drafting a research report on the responses to a questionnaire for LIFE PollinAction, a project co-funded by the EU.

Research fellow — Nov 2022 - Oct 2023
Ca' Foscari University of Venice

I participated in the research project *The role of art investment in portfolio diversification. Risk, return and resilience to exogenous shocks*. It involved the use of different quantitative techniques, such as clustering, time series analysis and portfolio optimization.

Further experience

Summer School — Jul 2025 - Aug 2025
Ca' Foscari Challenge School

DoCRA - Doctoral Colloquim on Risk Analystics. Session 2: New challenges on long-run risks.

Graduate Teaching assistant — Sept 2024 -
ICMA Centre, University of Reading

GTA for the courses "Corporate finance", and "Alternative investments and structured products".

Teaching assistant — Feb 2024
Ca' Foscari University of Venice

Teaching assistant for the course "Computational tools for economics", bachelor's degree programme in Economics and Business.

Subject expert — Nov 2023 -
Ca' Foscari University of Venice

Subject expert in the academic discipline "Mathematical methods of economics, finance and actuarial sciences", with particular reference to financial applications to the art market.

Working papers

- Barro D., Basso A., Funari S. and Visentin G.A. (2023), "Portfolio Diversification Including Art as an Alternative Asset", Working paper n. 06/2023, Ca' Foscari University of Venice.

- Barro D., Basso A., Funari S. and Visentin G.A. (2023), "A Bibliometric Analysis of Art in Financial Markets", Working paper n. 05/2023, Ca' Foscari University of Venice.

Survey reports

- Basso A., Visentin G.A. and Zolin, B. (2024), "ECOsostenibilMENTE - Prati fioriti per le future generazioni. Statistical analysis of the responses", Department of Economics, Ca' Foscari University of Venice, Unpublished.

Conferences

- Financial Economics of Climate and Sustainability, presentation of "The materiality of biodiversity risk for SMEs in the United Kingdom", University of Oxford, 14 July 2025.

- Workshop on Just Energy Transition – JET: Stochastic and machine learning methods for the evaluation, mitigation and geographical hedging of involved natural risks (with climate in view), presentation of "Is the energy transition impacting the Eurozone sovereign risk? Evidence from Machine Learning", Ca' Foscari University of Venice, 9 January 2025.

- 11th International Conference MAF Mathematical and Statistical Methods for Actuarial Sciences and Finance, presentation of "Art as a financial asset in portfolio allocation", Université Le Havre Normandie, 5 April 2024.

- "Portfolio Diversification Including Art as an Alternative Asset", seminar organized by the Department of Management, Ca' Foscari University of Venice, 11 October 2023.

- XLVII AMASES Annual conference, presentation of "A Bibliometric Analysis of Art in Financial Markets", University of Milan-Bicocca, 22 September 2023.

- "A Bibliometric Analysis of Art in Financial Markets", seminar organized by the Department of Management, Ca' Foscari University of Venice, 27 June 2023.

Young scholar

MacLab Dec 2022 -

Member of MacLab, Management of Art and Culture Laboratory at Ca' Foscari University of Venice.

Erasmus+

University of Burgundy Sep 2021 - Jan 2022

Exams undertaken in English.

Education

Master's degree 2020 - 2022

Economics and Management of Art and Cultural Activities

Ca' Foscari University of Venice

Final degree mark: **110/110 with honours**

Bachelor's degree

Conservation of Cultural heritage 2017 - 2020

Ca' Foscari University of Venice

Final degree mark: **110/110**. Curriculum in Economics and Management

Certificates

Python for data science and ML bootcamp May 2024

Online, issued by Udemy.

IELTS 7.5 (C1) Feb 2024

Issued by the British Council. Academic, computer-delivered exam.

French B2 level June 2023

Issued by the University Language Centre (CLA) of the University of Venice.

MATLAB Fundamentals July 2022

Online, issued by Mathworks.

MATLAB Introduction to statistical analysis March 2022

Online, issued by Mathworks.

The Materiality of Biodiversity Risk for SMEs in the United Kingdom

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Abstract

In this study, we investigate the impact of biodiversity loss on the performance of small and medium-sized enterprises (SMEs) in the United Kingdom and Ireland. Leveraging firms' financial information and postcodes from Moody's Bureau van Dijk and the Biodiversity Intactness Index – a geospatial dataset developed by the Natural History Museum – we geo-locate SMEs, quantify biodiversity loss in the area where firms operate, and assess their exposure to biodiversity-related risks over time. We then employ a fixed effects regression model to estimate the effect of biodiversity loss on firm performance. Our findings indicate that a one-standard-deviation decline in biodiversity leads to a statistically significant reduction in firm operating income by 0.59 percentage points. This impact is economically meaningful when benchmarked against the sample's average operating income. Moreover, SMEs located in more ecologically degraded areas are found to be more exposed to biodiversity-related risks. We also provide evidence of the materiality of dependency risk, while transition risk appears to be non-material within the UK context. The results remain robust across various econometric specifications and when controlling for climate risk factors.

Keywords: Biodiversity finance; Biodiversity risk; SMEs; United Kingdom; Biodiversity Intactness Index

JEL classifications: G32; Q57

1 Introduction

Biodiversity loss is increasingly recognised as a significant risk for firms and financial institutions. Among those potentially affected are also small businesses, which may face declines in performance and creditworthiness due to the degradation of natural capital. In this paper, we focus on the United Kingdom (UK) and Ireland and employ biodiversity indices and spatial data to measure biodiversity loss in the areas where small and medium-sized enterprises operate and assess the materiality of biodiversity risk for these firms.

Economic activities are deeply reliant on natural capital. First, the primary sector depends extensively on natural resources for activities such as agriculture, livestock farming, and fishing. Second, industrial sectors require surface and groundwater for manufacturing processes (Van Toor et al., 2020; Hadji-Lazaro et al., 2024). Third, pharmaceutical companies develop drugs and medicines by extracting chemical compounds from plant species, while the tourism and hospitality sectors frequently depend on the aesthetic value of the landscape. Indeed, plant and animal species offer numerous benefits, including nutrition, pest control, climate regulation, flood protection, recreational opportunities, and aesthetic value, and preserving *biodiversity* is essential to ensuring the sustained provision of these benefits over the long term. Moreover, research has demonstrated that high levels of biodiversity significantly enhance ecosystems and the services they provide (Balvanera et al., 2006; Isbell et al., 2011; Gamfeldt et al., 2013). Biodiversity and nature are so closely intertwined that some define biodiversity as "nature by another name" (The Nature Conservancy, 2025).

The whole Earth is undergoing massive biodiversity destruction (IPBES, 2019). The well-known MEA (2005), a research project financed by the United Nations, shows the degeneration of ecosystems caused by human activities over the past 50 years, threatening the provision of natural resources and their benefits in the long-run. Similarly, the OECD (2021) estimates that the value of natural capital stocks per individual dropped by 40% between 1992 and 2014, and the WWF (2025) quantifies a global biodiversity loss of around 70% from 1970 to 2020. These figures are deeply concerning for the human well-being, as exceeding the tipping point of biodiversity loss could lead to irreversible economic consequences. For instance, the extinction of pollinator species may disrupt a large share of food crop, massive deforestation could lead to increased global warming and catastrophes, and the loss of plant species would lead to a shortage of medicines, such as cancer drugs (MSCI, 2023). In other words, several industries are so dependent on nature that the disruption of *ecosystem services* can lead to lower levels of well-being, on the one hand, and to consequent economic and financial crises, on the other hand.

Biodiversity has been seriously compromised in the UK. State of Nature Partnership (2023) reveals that the average abundance of over 700 terrestrial and freshwater species in the UK has decreased by 19% between 1970 and 2021, and Lusardi et al. (2024) report

that marine, coastal margins, freshwaters and wetlands, mountains moorlands and heaths, and woodlands assets are at high risk, urging for investment in nature capital before the occurrence of further degradation. Given the serious depletion of natural resources and the consequent economic damages, the UK has implemented strategies to halt and reverse biodiversity loss (see Department for Environment, Food & Rural Affairs, 2011). This appears extremely urgent due to the high reliance that businesses – and, indirectly, the financial system – have on ecosystem services (Van Toor et al., 2020; Schrapffer et al., 2022; Boldrini et al., 2023; Hadji-Lazaro et al., 2024).

Since biodiversity loss is an urgent matter, scholars have begun to study the influence of biodiversity-related risks for companies. Giglio et al. (2023), Garel et al. (2024), and Coqueret et al. (2025) explore the pricing of biodiversity loss in the equity market and show that investors are factoring biodiversity risk into company evaluations, requiring higher premiums for stocks more exposed to such a risk. Hoepner et al. (2023) report that a successful management of biodiversity risk results in lower credit risk, while Cosma et al. (2024) and Bach et al. (2025) find that firm performance negatively correlates with biodiversity risk exposure. Battiston et al. (2024) conduct a stress test to assess the stability of the UK banking system to shocks in nature capital, showing that domestic holdings of the banks considered could see significant adjustments. Finally, Becker et al. (2025) demonstrate that transition risk exposure entails higher loan prices in the European Union (EU) and the UK. All in all, studies show that biodiversity physical and transition risks are becoming material.

Research has focused on the impact that biodiversity risk has on large companies, yet biodiversity risk may become even more relevant for small and medium enterprises (SMEs). Nguyen et al. (2025) report that small businesses may be even more impacted by the degradation of nature capital compared to large companies, given that they are less diversified and more geographically concentrated. Due to their more localised operations, the link between biodiversity loss, firm performance and risk is often more direct for SMEs than for large firms, whose widespread activities and biodiversity-related impacts or dependencies typically arise along complex supply chains. However, apart from Nguyen et al. (2025), who focus on credit risk in the US, no studies have explored biodiversity risk for SMEs. We argue that biodiversity risk is a relevant topic for SMEs, especially in the UK, for several reasons: first, SMEs play a vital role in the UK economy, accounting for 43% of total turnover and 46% of national employment (ONS, 2023); second, the literature has shown that listed firms are highly exposed to biodiversity physical risk through their supply chains (Wilting and van Oorschot, 2017; Wolff et al., 2017), which include SMEs. Therefore, evaluating the materiality of biodiversity risks for SMEs is crucial also for understanding potential chain reactions; third, sustainability reporting is increasingly growing in importance. In the EU, the Corporate Sustainability Reporting Directive (European Commission, 2022), will require all listed firms, including those

categorised as SMEs, to disclose environmental and social risks to which they are exposed and how their activities impact the environmental and social spheres. In the UK, it is not mandatory for SMEs to disclose about sustainability, but the UK government supports and may consider future mandates aligned with the Taskforce on Nature-related Financial Disclosures (TNFD), a voluntary framework released in 2023. Hence, in the future, SMEs may need to assess both impact and dependencies on nature capital, not differently from very large and large enterprises.

Biodiversity entails a geographic component. Different locations host different ecosystems, which, in turn, support different species. Moreover, some species are endemic, that is, they are native to and exclusive to specific territories. Therefore, the measurement of biodiversity is inherently tied to its strong geographic and local component. For this reason, spatial data can be useful for tracking biodiversity loss and constructing an index measuring the intactness of ecosystems at the local level, at a high resolution. Spatial analysis can also be relevant in financial studies, as Caldecott et al. (2023) argue. For instance, spatial data can be used to link environmental degradation to company activities, detect areas for restoration investment, and implement commodity trading strategies. In other words, spatial data can be successfully integrated into the study of financial decisions, especially in the context of biodiversity (J.P. Morgan, 2023).

To our knowledge, no prior studies have examined the impact of biodiversity risk on the profitability of SMEs in the UK. This paper aims to fill that gap. Specifically, we use the *Biodiversity Intactness Index* (BII), developed by the Natural History Museum, which tracks global biodiversity loss over time at a spatial resolution of 10 km^2 – allowing for high granularity and location-specific analysis. By matching SME postcodes to the BII grid, we geo-locate firms and extract the corresponding index values at each location over time, thereby measuring their exposure to biodiversity-related physical risks. To evaluate the materiality of this risk, we conduct a regression analysis in which SME performance is modelled as a function of local biodiversity loss, while controlling for standard accounting and financial variables. Additionally, drawing on the methodologies of Addoum et al. (2020) and Cathcart et al. (2022), we construct firm-level global warming indices to account for climate-related risk.

We contribute to the literature in several key ways. First, as said, we are the first to assess the materiality of biodiversity risk for SMEs in the UK, a country where small businesses play a critical role in employment and supply chains. By employing fixed effects regression models and controlling for climate-related risks, we provide new insights into how biodiversity loss affects smaller firms, which often receive less attention than large corporations but are nonetheless critical to the economy and financial markets, particularly through their role in supply chains. Our findings align with those from studies on large firms and other countries (Giglio et al., 2023; Garel et al., 2024; Coqueret et al., 2025), indicating that SMEs in the UK are likewise significantly affected by biodiversity

risk.

Second, instead of relying on corporate-level metrics designed by data providers (Cosma et al., 2024; Garel et al., 2024; Coqueret et al., 2025) or textual analysis of financial and sustainability reports (Giglio et al., 2023; He et al., 2024; Ma et al., 2024), we leverage the potential of biodiversity indices and spatial data to develop a methodology that enables us to measure corporate exposure to biodiversity risk, applicable to firms of all sizes, including those with limited financial disclosures, such as small businesses. Given that SMEs typically operate at a local scale, our approach enables a robust linkage between firm-level financial risk and location-specific biodiversity physical risk.

Third, we construct firm-specific biodiversity risk indices that are both interpretable and suitable for integration into ESG metrics and sustainability reporting frameworks. This is particularly relevant as investors increasingly seek effective ways to assess and manage their exposure to nature-related risks, while aligning with the recommendations of the TNFD. According to Zhu and Carrasco (2025), current ESG assessments often fail to adequately capture or reflect biodiversity-related risks. As a result, there is ongoing research aimed at improving how biodiversity considerations are integrated into E ratings (see, for instance, Rossi et al, 2024).

Our paper is structured as follows: section 2 surveys the literature on biodiversity finance and on SMEs sustainability and develops the hypotheses further tested; section 3 describes the data and the methodology used; section 4 reports the results of our empirical investigation; section 5 concludes with some financial implications and recommendation.

2 Literature review and hypotheses development

Perhaps, the birth of *biodiversity finance* can be traced back to Karolyi and Tobin-de la Puente (2023)'s article, where the researchers call on finance scholars to conduct research on the financing of nature, given the urgency of the nature-positive transition that the economy, including the financial sector, must undertake. In fact, in the last few years, a number of scholars have devoted their time to studying biodiversity-related issues in finance, such as impact and dependencies of firms on nature (Kulionis et al., 2024) and preferences for investment in biodiversity projects (Flammer et al., 2025). Still, it is important to acknowledge that the financial implications of biodiversity have not been entirely overlooked in prior research, though only a few papers have tackled the topic.

Van Toor et al. (2020) conducted a seminal study assessing the reliance of Dutch financial institutions' portfolios, totalling EUR 1,400 billion, on ecosystem services. In their analysis, they investigate the link between financial assets and ecosystem services through firm business processes. The findings reveal that 36% of the portfolio (EUR 510 billion) is highly or very highly dependent on one or more ecosystem services, underscoring the Dutch financial system's exposure to biodiversity physical risks. Other studies also

find figures similar or higher than that found in Van Toor et al. (2020) for domestic financial institution portfolios across different emerging and developed countries, such as Brazil, Malaysia, and EU member states (Calice et al., 2021; World Bank and BNM, 2022; Boldrini et al., 2023; Calice et al., 2023; Laurinaityte and Borges, 2023; Hadji-Lazaro et al., 2024). These findings highlight the evident exposure of businesses to biodiversity physical risk. However, as Ranger et al. (2024) argue, such studies do not investigate the materiality of physical risk, thus providing only limited understanding of the significance of financial risks for businesses and financial firms.

Other papers offer more insights into the materiality of biodiversity risk for firms and financial institutions. Becker et al. (2025) show that creditors in the EU and the UK impose higher interest rates on borrowers with greater exposure to biodiversity risks, indicating an increasing integration of nature-related considerations into financing decisions. Similarly, Nguyen et al. (2025) report that physical risk is associated with higher interest rates for small businesses. Moreover, several studies show that investors are pricing biodiversity risk exposure and demanding a biodiversity premium in the international stock markets (Creti et al., 2024; Garel et al., 2024; Coqueret et al., 2025), the US stock market (Giglio et al., 2023), and the Chinese stock market (Ma et al., 2024). In particular, Garel et al. (2024) find evidence that the premium appears following the Kunming Declaration (2021), in October 2021, after which firms with a large environmental footprint lost value. Consistently, scholars show that exposition to biodiversity risk increases the likelihood of stock price crashes (Bassen et al., 2024; Liang et al., 2024) and corporate bond spreads (Cherief et al., 2025). Overall, although a few studies do not report evidence of a relationship between biodiversity risk and stock returns (Xin et al., 2023) or loan values (Arlt et al., 2024), the literature seems to confirm that biodiversity loss is considered a source of material risk by economic agents.

Barro et al. (2025) note that SMEs have received considerable attention in the credit risk literature (Altman and Sabato, 2007; Czarnitzki and Hottenrott, 2011; Cathcart et al., 2020; D'Amato, 2020), as access to credit represents a key transmission channel for economic shocks affecting these firms. More recently, SMEs have also begun to attract growing interest in the field of sustainability reporting, particularly in light of upcoming regulatory changes: from 2027, the EU will require listed SMEs to disclose potential environmental risks (European Commission, 2022). In this context, biodiversity risk may affect the creditworthiness and financial performance of SMEs, much like it does for large and very large firms (see Hoepner et al., 2023). A limited number of studies have examined sustainability reporting (Rodríguez-Gutiérrez et al., 2021; Ortiz-Martinez and Marín-Hernández, 2022) and ESG assessments (Barro et al., 2025) in the context of SMEs, highlighting the urgent need to develop robust disclosure frameworks to enhance environmental and social accountability. In parallel, small and micro enterprises have increasingly been studied within the climate finance literature. For instance, Cathcart et

al. (2022) and Cathcart et al. (2023) demonstrate that global warming adversely affects firms' operating income and probability of default. By extension, biodiversity loss is also likely to impact small and micro enterprises, particularly in sectors highly dependent on natural capital—such as agriculture, livestock, and food, beverage, and tobacco.

Based on the review of the literature, we hypothesise that biodiversity loss negatively affects firm operations. Firms rely on ecosystem services – such as pollination, water purification, and soil fertility – to support their economic activities. Consequently, an index capturing biodiversity loss should reflect the degradation or improvement of these services over time and across locations, and depletion of nature capital should coincide with lower profitability. Based on this premise, our main hypothesis is as follows:

H1. There is a negative and significant relationship between biodiversity loss, as proxied by the BII, and income.

In addition, following from hypothesis H1, we posit that firms operating in areas which are more impacted by biodiversity loss have a lower income due to the inferior quality of the ecosystem services in the area. Biodiversity underpins a wide range of ecosystem services that are critical to business operations. When biodiversity is lost, these services degrade, leading to higher input costs, increased operational inefficiencies, and greater vulnerability to environmental shocks. Formally, our second hypothesis is:

H2. Firms that conduct their operations in highly degraded areas have lower income than firms operating in areas that display higher biodiversity, as proxied by the BII.

Finally, to explore the mechanism linking biodiversity loss to firm performance in greater detail, we hypothesise that firms with high dependence on ecosystem services are more adversely affected by biodiversity loss than those with lower direct dependence. In other words, physical risk is more material for firms with a higher direct dependence. On the other hand, firms with a high impact on natural capital do not necessarily incur losses in the event of biodiversity loss, as they are subject to transition risk only in case of stricter regulation or worse reputation. Thus, we hypothesise:

H3. Firms with a high dependence on biodiversity have lower income than firms with less dependence on biodiversity, as proxied by the BII.

H4. Firms with a high impact on biodiversity do not have lower income than firms that have a smaller impact on biodiversity, as proxied by the BII.

We explain how we test these hypothesis in Section 3.3, where we outline the econometric methodology employed in this paper.

3 Data and methodology

3.1 The Biodiversity Intactness Index

The Biodiversity Intactness Index (BII) is a species-related biodiversity index that measures the extent to which the native biodiversity survives human-induced pressures. It is expressed in percentage terms, where zero indicates the complete loss of the original biodiversity and 100 signifies that there has been no change to biodiversity. The BII has been proposed for the first time by Scholes and Biggs (2005) and has become the designated metric for the Natural History Museum (NHM)'s PREDICTS project (Natural History Museum, 2025b). This initiative aims at measuring and forecasting biodiversity intactness as a function of human-induced pressures, under various scenarios, in order to understand how human activities might impact species and ecosystems. To calculate the BII, the PREDICTS initiative uses data drawn from ecological studies to construct a database of over 50,000 species, including plants, animals, and fungi. Such studies allow for the calculation of biodiversity in near-undisturbed ecosystems, providing a reference site for the local original biodiversity. PREDICTS combines two models: one assessing how human activities – namely, land use, road density, and human population – affect species abundance in an area and another evaluating the compositional similarity of ecological communities to near-undisturbed sites, considering which species remain and dominate. These models are combined with maps of human pressures, such as land use change, population growth, and landscape simplification, to produce maps of abundance and compositional similarity. Using satellite imagery, field data, and algorithmic modelling, PREDICTS generates the BII for landscapes worldwide, representing the percentage of the original ecological community that persists in a given area (Natural History Museum, 2025a).

Mathematically, the PREDICTS project's BII is calculated as follows:

$$BII = \frac{2\sum_{i=1}^{P} min(N_{i,S} N_{i,S_{ref}})}{\sum_{i=1}^{P}(N_{i,S} + N_{i,S_{ref}})} \tag{1}$$

where $N_{i,S}$ and $N_{i,S_{ref}}$ are the abundance of species i in site S and in the reference site S_{ref}, and P is the total number of species, both native and invasive. Following Newbold et al. (2016), the BII is calculated at spatial scale globally, with a 10 km^2 of resolution. The BII for the UK in the period 2006-2021 is represented in Figure 1.

[Insert Figure 1]

The BII is a comprehensive index that allows for an in-depth assessment of biodiversity loss at the local level. However, as Ben Rejeb-Mzah et al. (2024) point out, it still suffers

from a few problems. First, it disregards whether invasive species are neutral or invasive to existing living organisms; second, the BII gives equal importance to all species in the database, as other biodiversity indices, such as the Mean Species Abundance (Alkemade et al., 2009), do. Third, it heavily relies on modelling techniques. Nonetheless, it remains one of the leading indicators of biodiversity loss and a "cutting-edge indicator of ecosystem integrity" (TNFD, 2025).

3.2 Data

We use the Fame database, provided by Moody's Bureau van Dijk, to collect postcode and annual financial data for UK and Ireland SMEs from 2006 to 2023. SMEs are defined according to the European Commission as firms with fewer than 250 employees and either a turnover below €50 million or a balance sheet total below €43 million. We retain only firms for which operating income, our main dependent variable, is available in at least one year. This results in an initial database of 665,381 SMEs. Of these, 644,048 firms have the postcode available. As is common in the literature, we remove firms operating in the public sector or the financial industry. Moreover, we drop SMEs with missing postcode, resulting in an unbalanced panel database of 510,279 SMEs. The financial indicators include Total assets, Cash, Interest coverage, and the FCP index of financial constraints (Schauer et al., 2019). The sample composition by sector and country is reported in Table 1 and 2, respectively.

[Insert Table 1]

[Insert Table 2]

We obtain annual BII data at spatial scale from 2006 to 2021, from the Natural History Museum. To determine the level of biodiversity loss at the firm level, we geolocate SMEs using their postcodes and we superimpose the SMEs over the maps representing the BII over time (in Figure 2 we present the locations of the firms in our database, by sector). Subsequently, we extract the value of the biodiversity index corresponding to the location (longitude and latitude) of firm i at year t, $BII_{i,t}$. Finally, we calculate biodiversity loss for firm i at year t, $BL_{i,t}$, in the following way:

$$BL_{i,t} = 100 - BII_{i,t} \tag{2}$$

This allows us to construct an index of exposure to biodiversity physical risk over time at the firm level. To obtain BII data for the years 2022 and 2023, we use linear extrapolation.

[Insert Figure 2]

Given the close link between biodiversity loss and climate change (Pires et al., 2018), we also build indices of exposure to climate risk in a similar way, following the procedure detailed in Addoum et al. (2020) and Cathcart et al. (2022). Briefly, we collect annual climate data over time from E-OBS[1] to construct a 10 km^2 weather grid, and we extract firm-level values using geographical coordinates. Using biodiversity and global warming indices, we can study the relationship between nature depletion and climate change. In particular, we collect a heat index, the maximum of daily maximum temperature, i.e., the hottest daily maximum temperature recorded, and a rain index, the Simple Daily Intensity Index (SDII), or average rainfall rate. Such variables provide a proxy for global warming and can be used to control for environmental risks not captured by biodiversity loss. Figures 3 and 4 represent the heat index and the rain index, respectively, over time.

[Insert Figure 3]

[Insert Figure 4]

The list of variables, including climate and financial controls, is reported in Table 3. To exclude outliers, all the variables are winsorised at the 5% and 95% levels.

[Insert Table 3]

3.3 Methodology

To test the relationship between biodiversity loss and firm performance for UK and Ireland SMEs, we rely on regression analysis. Specifically, we employ a fixed effects regression model, where the dependent variable is a measure of income and the proxy for biodiversity loss is obtained following the steps outlined in Section 3.2. Following the literature on biodiversity finance (Garel et al., 2024) and climate finance (Bolton and Kacperczyk, 2023), our baseline model also includes several financial controls and sectoral, geographic, and year fixed effects. In detail, we test hypothesis H1 using the following model:

$$Income_{i,t} = \beta_0 + \beta_1 BL_{i,t-1} + \beta_2 \boldsymbol{X}_{i,t-1} + \theta_j + \mu_c + \gamma_t + \epsilon_{i,t} \quad (3)$$

[1]See https://surfobs.climate.copernicus.eu/dataaccess/access_eobs_indices.php.

where $Income_{i,t}$ is operating income to total assets of firm i at year t, $BL_{i,t}$ is biodiversity loss for firm i at year $t-1$, as defined in equation (2), $\boldsymbol{X}_{i,t-1}$ is the vector of control variables, and θ_j, μ_c, and γ_t are sector, county, and year fixed effects. Following Bolton and Kacperczyk (2023), we use double clustered standard errors at the firm and time levels. If empirical evidence validates hypothesis H1, β_1 in model (3) should be negative and significant.

Based on the results of Garel et al. (2024)[2], we also deem plausible that the effect of biodiversity loss on firm operations is independent from that of climate change. Indeed, although the degradation of nature capital can exacerbate climate change, damages provoked by biodiversity loss can also be independent of climate-related events. For this reason, we also include variables representing climate change in model (3), as an additional robustness check. Following Addoum et al. (2020), we employ variables representing changes in heat and rain, described in Section 3.2. Our model is as follows:

$$Income_{i,t} = \beta_0 + \beta_1 BL_{i,t-1} + \beta_2 Heat_{i,t-1} + \beta_3 Rain_{i,t-1} + \beta_4 \boldsymbol{X}_{i,t-1} + \theta_j + \mu_c + \gamma_t + \epsilon_{i,t} \quad (4)$$

where $Heat_{i,t-1}$ and $Rain_{i,t-1}$ are the temperature and the precipitation variables for firm i at year $t-1$, respectively. Similarly to model (3), we retain sector, county and year fixed effects. Standard errors are double clustered at the firm and year levels.

To test whether SMEs operating in ecologically degraded areas exhibit lower income levels compared to those situated in regions with higher biodiversity (H2), we first construct firm-level quartile dummies based on the BII. We then include these dummies in the following regression model:

$$Income_{i,t} = \beta_0 + \sum_{n=2}^{4} \beta_n Q_{n,i} + \beta_5 \boldsymbol{X}_{i,t-1} + \theta_j + \mu_c + \gamma_t + \epsilon_{i,t} \quad (5)$$

where $Q_{n,i}$ is the dummy on the n-th quartile of variable Biodiversity loss; second, we estimate model (3) only for firms that operate in areas where the biodiversity loss is higher than average biodiversity loss (83.14). If hypothesis H2 holds, we should obtain a higher coefficient (in absolute terms) than that found with the model covering the whole sample.

Finally, we move on to test whether firms with a high dependence on biodiversity have lower income than firms with less dependence on biodiversity (H3) and if firms that have a high impact on biodiversity do not display lower income than firms with minimal biodiversity impact (H4). To obtain levels of dependencies and impacts for firms, we use

[2]Garel et al. (2024) show that, after the Kunming Declaration, there is a relationship between stock returns and biodiversity risk even when they control for CO_2 emissions.

ENCORE[3] (Exploring Natural Capital Opportunities, Risks and Exposure). ENCORE is a tool developed by the Natural Capital Finance Alliance and UNEP FI to help financial institutions assess how environmental change, including biodiversity loss, may impact the economy. The tool maps dependencies and impacts of economic sectors on natural capital, including key ecosystem services such as pollination, water quality regulation, and soil formation. ENCORE identifies the extent to which different sectors rely on and impact biodiversity-related services and assesses the materiality of these dependencies and impacts. We match economic activities reported in ENCORE with sectors in our sample to obtain the level of dependency on 25 ecosystem services and the severity of impact across 13 impact drivers. To construct a summary measure of dependency and impact, we compute the average of the dependency scores across the 25 ecosystem services and the impact scores across the 13 impact drivers. We then define two dummy variables, which take the value of 1 if the average dependency or impact score is greater than or equal to 2, respectively. Table 4 reports the summary dependency score and impact score computed using ENCORE.

[Insert Table 4]

We proceed by estimating the two following regression specifications:

$$Income_{i,t} = \beta_0 + \beta_1 BL_{i,t-1} + \beta_2 BL_{i,t-1} \times HD_j + \beta_3 \boldsymbol{X}_{i,t-1} + \theta_j + \mu_c + \gamma_t + \epsilon_{i,t} \quad (6)$$

where HD_j is a dummy variable equal to 1 if sector j is highly dependent on biodiversity and 0 otherwise. Model (6) allows us to test hypothesis H3. And:

$$Income_{i,t} = \beta_0 + \beta_1 BL_{i,t-1} + \beta_2 BL_{i,t-1} \times HI_j + \beta_3 \boldsymbol{X}_{i,t-1} + \theta_j + \mu_c + \gamma_t + \epsilon_{i,t} \quad (7)$$

where HI_j is a dummy variable equal to 1 if sector j has a high impact on biodiversity, as defined above, and 0 otherwise. With model (7) we test hypothesis H4.

If hypothesis H3 holds, β_2 in regression (6) should be negative and significant, while if hypothesis H4 is supported by the data, β_2 should be not statistically different from 0 in regression (7).

4 Results

4.1 Descriptive statistics and correlations

In Table 5 we present the descriptive statistics for the variables used in this study. It is worth noting that the average Biodiversity loss is 83.14, indicating that SMEs in the UK

[3]See https://encorenature.org/en.

typically operate in areas where approximately 17% of the original biodiversity is intact. The average Operating income to total assets is 0.071, with a standard deviation equal to 0.543.

[Insert Table 5]

Table 6 reports the correlation matrix for all the variables. Biodiversity loss is negatively correlated with both operating income (-0.058) and net income (-0.062), which supports our initial hypothesis (H1). On the other hand, the climate variables appear more uncorrelated with the measures of income. It is also interesting to observe that biodiversity loss is positively correlated with the temperature variable (0.273) and negatively correlated with the rain variable (-0.346). Finally, the control variables are in general low correlated with each other, avoiding potential multicollinearity.

[Insert Table 6]

4.2 Regression analysis

Table 7, Column 1, reports the results of estimating equation (3) without control variables. The coefficient on Biodiversity loss is negative and significant at the 1% level, hence, on average, a larger biodiversity loss is associated with a lower operating income. In Column 2, we introduce Ln(Total assets) in the regression and the coefficient on Biodiversity loss retains its negative sign and significance, although it is smaller in magnitude (in absolute terms). In Column 3, all the control variables are introduced and, again, the coefficient on Biodiversity loss remains negative and significant, but this time is equal to -0.0007. Thus, a one-standard-deviation increase in Biodiversity loss is associated with a decrease in Operating income to total assets of 0.59 percentage points, which corresponds to a 8.3% drop in the average value of the dependent variable (0.071). This effect is not only statistically significant but also non-negligible in economic terms. Indeed, these results suggest that degradation of ecosystem services can directly impair productivity and cost efficiency, confirming hypothesis H1. However, this effect may be due to either direct dependencies from nature (physical risk) or stricter environmental regulations (transition risk). We will examine this more in detail in Section 4.5.

[Insert Table 7]

In Columns 4-6, we use Biodiversity loss lagged by 5 years. The results remain robust and the coefficient on Biodiversity loss is slightly higher in magnitude, in absolute terms (-0.0008). The fact that biodiversity loss from five periods ago continues to negatively affect profitability today indicates that its economic impact is persistent. The degradation of natural capital can thus have delayed consequences that gradually appear in financial performance.

4.3 Inclusion of climate change variables

Table 8 reports the estimates of the different specifications of model (4). In Column 1 we include the Heat variable and in Column 2 the Rain variable. In both cases, the coefficient associated to Biodiversity loss is negative and significant, while the climate variables are not significant at the 5% level. In Column 3 we include both the Heat and Rain variables and in Column 4 we include also the financial controls. While no significant effect is found for Heat and Rain, Biodiversity loss remains significant at the 1% level. The coefficient is also similar in magnitude to those found in Section 4.2.

The results found confirm that biodiversity risk is independent of climate risk. Hence, this provides further evidence in favour of hypothesis H1.

[Insert Table 8]

The significance of biodiversity loss, contrasted with the non-significance of climate covariates, may indicate that SMEs in the UK and Ireland are more exposed to the materiality of biodiversity risk than to climate risk. This finding is particularly relevant, as biodiversity risk has only recently begun to receive attention, whereas climate risk has been at the forefront of academic and policy discussions for over a decade.

4.4 Analysis in highly degraded areas

In Table 9, Column 1, we present the estimates of model (5). Firms in the second quartile exhibit an operating income that is 0.0048 lower than those in the first quartile, a difference that is statistically significant at the 5% level. This negative effect increases across quartiles: firms in the third and fourth quartiles report operating incomes that are 0.0092 and 0.0165 lower, respectively, compared to firms in the first quartile.

In Column 2, regression (3) is estimated only on firms that operate in areas where biodiversity loss is higher than the mean (83.14). Consistently with the results of Column 1, the coefficient (-0.0018) is higher in absolute terms than that found for the whole sample (-0.0007), revealing that for SMEs that operate in highly degraded areas biodiversity loss has a greater effect on operating income. This may suggest that firms located in more

degraded areas are disproportionately affected by biodiversity loss. These results confirm the validity of hypothesis H2.

[Insert Table 9]

Additionally, in Column 3 and 4 we exclude firms that operate in London and in London, Birmingham, and Manchester – the three largest cities in the UK – respectively. In both cases, the coefficient on Biodiversity loss remains negative, significant and similar in magnitude to that previously found. This analysis provides a further robustness check and indicates that the results are not merely driven by highly urbanised areas, which tend to exhibit substantial biodiversity loss.

4.5 Sectoral analysis

Finally, we conduct a sectoral analysis to further investigate the mechanism through which biodiversity loss affects operating income. As previously hypothesised, firms that are highly dependent on biodiversity are expected to exhibit lower operating income compared to those with lower dependence, suggesting that the degradation of ecosystem services has a negative effect on firm performance. To establish which sectors are more dependent on ecosystem services we use ENCORE. The sectors which are most dependent on ecosystem services are Agriculture, horticulture and livestock, Biotechnology and life sciences, and Mining and extraction.

Similarly, using ENCORE, we construct a variable for sectors which impact biodiversity the most. These sectors are Agriculture, horticulture and livestock, Construction, Mining and extraction, Transport, freight and storage, Utilities, and Waste management and treatment.

[Insert Table 10]

Table 10, Column 1, reports the estimates of model (6) and Column 2 of model (7). Firms that belong to sectors which are highly dependent on ecosystem services display lower operating income compared to those not considered highly dependent. Conversely, sectors with a high impact on nature do not display lower income. These results confirm hypotheses H3 and H4 and are indicative of the mechanism behind the effect of biodiversity loss on operating income: the degradation of ecosystem services affects the profitability of firms which depend on such ecosystem services to conduct their operations; on the other hand, firms that impact nature are not necessarily impacted by the loss of nature capital, so biodiversity loss should not affect their profitability. In other

words, these results confirm the materiality of physical risk for SMEs in the UK and Ireland, while they suggest that transition risk is not yet material.

4.6 Robustness checks

To corroborate our findings, we conduct a range of robustness tests. The results are presented in Table 11. Column 1 reports the results with the sample period 2006-2021, or, in other words, without extrapolated data. The coefficient on Biodiversity loss retains its magnitude, sign and significance. In Column 2, we control for country fixed effects and for the number of competitors in the county, i.e., the number of firms that belong to the same sector in a county. In Column 3 we replace the FCP Index with the SA index as a financial constraint dummy and in Column 4 we replace operating income with net income. The results remain largely unvaried. Finally, in the unreported results, we also winsorise all the variables at the 1% and 99% percent levels. The results remain largely unchanged.

[Insert Table 11]

Overall, the evidence reported strengthens our findings that, in the UK and Ireland, there is a negative relationship between biodiversity loss and financial performance, measured by operating and net income, for SMEs. These results provide further evidence in support of hypothesis H1.

5 Conclusions

This paper investigates the materiality of biodiversity risk for small and medium enterprises in the United Kingdom and Ireland, using spatial analysis and biodiversity indices. We find that a decline in biodiversity has a statistically significant negative impact on SMEs, reducing firm operating income to total assets by 0.59 percentage points in the event of one-standard-deviation drop in biodiversity. In addition, we find that this effect persists independently of climate change, reinforcing the notion that biodiversity risk is distinct from climate risk. This suggests that public policies aimed at preserving the environment could also have positive effects on SMEs' performance.

Another interesting result concerns the geographic distribution of SMEs. We find that firms operating in areas with a higher biodiversity loss have a lower income than firms that operate in areas that retain more of their original biodiversity. This result is likely due to the inferior quality of the ecosystem services in the area. Stricter regulation in these areas may thus not only sustain the environment but also positively affect firms, in the long run.

Finally, we find that physical risk is material, while transition risk is not material yet. These findings suggest that both firms and investors should recognise the environmental dependencies of SMEs and develop strategies to mitigate the associated risks. On the other hand, the fact that transition risk is not yet material, in the UK, suggests that there is still room for further regulation and that SMEs might be less exposed to transition dynamics compared to large firms, due to fewer reporting requirements and less public scrutiny.

Our study is subject to some limitations. First, it assumes a linear relationship between biodiversity loss and income. However, as observed in climate finance (Monasterolo, 2020), this relationship may in fact be non-linear. Moreover, the paper focuses solely on direct dependencies, while firms may also face physical risks indirectly through disruptions in their supply chains, although this limitation should be reduced due to the type of firms, SMEs, that are being studied in this paper. These drawbacks pave the way for future research. First, scholars may consider non-linear models, such as Artificial Neural Networks, to investigate the relationship between profitability and biodiversity loss; second, using data on flow of goods and services, it may be possible to analyse networks of firms and investigate how biodiversity loss affects firm profitability, including also indirect dependencies.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT for proofreading and to improve the flow of the text. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the manuscript.

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Tables and figures

Tables

Table 1: Sample composition by sector

Sector	Freq.	Percent	Cum.
Agriculture, Horticulture & Livestock	71,190	0.83	0.83
Biotechnology and Life Sciences	37,458	0.44	1.27
Business Services	3,014,964	35.32	36.59
Chemicals, Petroleum, Rubber & Plastic	47,754	0.56	37.15
Communications	60,660	0.71	37.86
Computer Hardware	3,798	0.04	37.9
Computer Software	475,884	5.57	43.48
Construction	862,092	10.1	53.58
Food & Tobacco Manufacturing	62,964	0.74	54.32
Industrial, Electric & Electronic Mac..	89,244	1.05	55.36
Information Services	6,516	0.08	55.44
Leather, Stone, Clay & Glass products	10,116	0.12	55.56
Media & Broadcasting	234,090	2.74	58.3
Metals & Metal Products	64,710	0.76	59.06
Mining & Extraction	40,320	0.47	59.53
Miscellaneous Manufacturing	66,600	0.78	60.31
Printing & Publishing	95,922	1.12	61.43
Property Services	687,438	8.05	69.48
Retail	348,984	4.09	73.57
Textiles & Clothing Manufacturing	33,894	0.4	73.97
Transport Manufacturing	23,868	0.28	74.25
Transport, Freight & Storage	299,448	3.51	77.76
Travel, Personal & Leisure	1,220,580	14.3	92.05
Utilities	83,628	0.98	93.03
Waste Management & Treatment	29,610	0.35	93.38
Wholesale	524,178	6.14	99.52
Wood, Furniture & Paper Manufacturing	40,842	0.48	100
Total	8,536,752	100	

Note: This table reports the sample composition by sector. Column 2 reports the number of firms by sector, Column 3 the percentage, and Column 4 the cumulative percentage.

Table 2: Sample composition by country

country	Freq.	Percent	Cum.
British Crown dependencies	18	0	0
England	8,371,062	91.14	91.14
Northern Ireland	43,038	0.47	91.61
Republic of Ireland	87,228	0.95	92.56
Scotland	453,690	4.94	97.5
Wales	229,986	2.5	100
Total	9,185,022	100	

Note: This table reports the sample composition by country. Column 2 reports the number of firms by sector, Column 3 the percentage, and Column 4 the cumulative percentage.

Table 3: Regression variables description

Variable	Type	Description	Source
Operating income	Dependent	Operating income to total assets	Fame
Net income	Dependent	Net income to total assets	Fame
Biodiversity loss	Interest	Biodiversity loss, as defined in equation (2), in a year at each location on the biodiversity grid	NHM
Heat	Control	Median of the maximum of daily maximum temperature in a year at each location on the weather grid	E-OBS
Rain	Control	Median of the Simple Daily Intensity Index in a year at each location on the weather grid	E-OBS
Ln(Total assets)	Control	Natural log of total assets	Fame
Age	Control	Number of years since incorporation	Fame
Cash	Control	Cash and cash equivalent to total assets	Fame
Interest coverage	Control	EBIT to interest expenses	Fame
FCP index	Control	Schauer et al. (2019)'s Index of financial constraint	Fame
SA index	Control	Hadlock and Pierce (2010)'s index of financial constraint	Fame

Note: This table reports the variables employed in our study. The table reports the variable name, the type of variable in the regression analysis, the description and the source of the data.

Table 4: ENCORE dependency score and impact score

Sector	Dependency	Impact
Agriculture, Horticulture & Livestock	3	3
Biotechnology and Life Sciences	2	1
Business Services	1	1
Chemicals, Petroleum, Rubber & Plastic	1	1
Communications	1	1
Computer Hardware	1	1
Computer Software	1	1
Construction	1	2
Food & Tobacco Manufacturing	1	1
Industrial, Electric & Electronic Machinery	1	1
Information Services	1	1
Leather, Stone, Clay & Glass products	1	1
Media & Broadcasting	1	1
Metals & Metal Products	1	1
Mining & Extraction	2	3
Miscellaneous Manufacturing	1	1
Printing & Publishing	1	1
Property Services	1	1
Retail	1	1
Textiles & Clothing Manufacturing	1	1
Transport Manufacturing	1	1
Transport, Freight & Storage	1	2
Travel, Personal & Leisure	1	1
Utilities	1	2
Waste Management & Treatment	1	2
Wholesale	1	1
Wood, Furniture & Paper Manufacturing	1	1

Note: This table reports the ENCORE dependency score and impact score associated to each sector. The dependency score is an average of the single 25 ecosystem services dependency scores. The impact score is an average of the single 13 impact drivers scores. Values are rounded to the nearest integer number.

Table 5: Descriptive statistics

Variable	Obs.	Mean	Std. dev.	Min	Max
Operating income	2,129,722	0.071	0.543	-1.356	1.375
Net income	2,507,677	0.122	0.450	-0.817	1.321
Biodiversity loss	9,183,366	83.139	7.336	67.390	92.200
Heat	8,943,930	30.580	3.091	25.570	37.100
Rain	8,943,948	5.590	0.619	4.591	6.900
Cash	3,007,584	0.361	0.359	0.001	1.000
Interest coverage	854,735	0.292	0.655	-0.176	2.539
Ln(Total assets)	4,246,847	11.889	3.331	5.263	17.287
Age	6,059,609	11.150	9.751	0.000	33.000
SA index	4,246,643	-2.649	1.036	-4.154	-0.202
FCP index	652,065	-25.236	65.905	-182.137	120.808

Note: This table reports the descriptive statistics for the variables used in this study. Operating income, net income and cash are given as ratios to total assets. Interest coverage is the ratio of EBIT to interest expenses. Ln(Total assets) is the natural log of total assets. Age is the number of years since incorporation. SA index is the financial constraint measure from Hadlock and Pierce (2010). FCP index is the financial constraint measure from Schauer et al. (2019). Biodiversity loss is equal to 100 minus the BII. Heat is the median of the maximum of daily maximum temperature. Rain is the median of the Simple Daily Intensity Index. The sample period is 2006-2023.

Table 6: Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11
1	Operating income	1										
2	Biodiversity loss	-0.058	1									
3	Heat	-0.021	0.273	1								
4	Rain	0.008	-0.346	-0.211	1							
5	Cash	0.152	0.014	0.066	0.013	1						
6	Interest coverage	0.343	-0.030	0.012	0.005	0.250	1					
7	Ln(Total assets)	-0.150	0.074	0.081	0.007	-0.278	-0.062	1				
8	Age	-0.015	-0.087	-0.053	0.014	-0.058	0.067	0.168	1			
9	SA index	-0.088	0.124	0.118	-0.006	-0.163	-0.090	0.685	-0.472	1		
10	FCP index	-0.794	0.068	0.028	-0.007	-0.215	-0.512	0.145	-0.029	0.120	1	
11	Net income	0.909	-0.062	-0.026	0.007	0.178	0.408	-0.164	0.009	-0.114	-0.896	1

Note: This table reports the correlation matrix for the variables used in this study. Operating income, net income and cash are given as ratios to total assets. Interest coverage is the ratio of EBIT to interest expenses. Ln(Total assets) is the natural log of total assets. Age is the number of years since incorporation. SA index is the financial constraint measure from Hadlock and Pierce (2010). FCP index is the financial constraint measure from Schauer et al. (2019). Biodiversity loss is equal to 100 minus the BII. Heat is the median of the maximum of daily maximum temperature. Rain is the median of the Simple Daily Intensity Index. The sample period is 2006-2023.

Table 7: Baseline regression model results

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Biodiversity loss	-0.0022**	-0.0016**	-0.0007**			
	(0.000)	(0.000)	(0.000)			
Biodiversity loss (t-5)				-0.0022**	-0.0016**	-0.0008**
				(0.000)	(0.000)	(0.000)
Ln(Total assets)		-0.0041	-0.01350**		-0.0059*	-0.0157**
		(0.002)	(0.002)		(0.002)	(0.002)
Cash			-0.0242			-0.0030
			(0.013)			(0.007)
Interest coverage			0.0005**			0.0005**
			(0.000)			(0.000)
Age			-0.0005**			-0.0004**
			(0.000)			(0.000)
FCP index dummy			-0.1575**			-0.1632**
			(0.005)			(0.004)
Intercept	0.2500**	0.2470**	0.3412**	0.2694**	0.2819**	0.3827**
	(0.017)	(0.031)	(0.029)	(0.020)	(0.033)	(0.029)
Obs.	1,900,346	1,738,358	515,598	1,612,148	1,471,460	415,390
Adj. R square	0.031	0.029	0.107	0.026	0.023	0.116
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table reports the results for the baseline regression (3) estimated by OLS. The dependent variable is operating income. Operating income, net income and cash are given as ratios to total assets. Interest coverage is the ratio of EBIT to interest expenses. Ln(Total assets) is the natural log of total assets. Age is the number oif years since incorporation. FCP index is the financial constraint measure from Schauer et al. (2019). Biodiversity loss is equal to 100 minus the BII. The observations are annual. The sample period is 2006-2023. Standard errors are double clustered at the firms and year levels and are reported in parentheses. ** and * denote statistical significance at the 1% and 5% levels, respectively.

Table 8: Regression model including climate variables results

Variable	(1)	(2)	(3)	(4)
Biodiversity loss	-0.0025**	-0.0026**	-0.0026**	-0.0008**
	(0.000)	(0.000)	(0.000)	(0.000)
Heat	0.0003		-0.0003	0.0002
	(0.004)		(0.004)	(0.000)
Rain		-0.0114	-0.0117	-0.0001
		(0.007)	(0.008)	(0.002)
Cash				-0.0227
				(0.012)
Interest coverage				0.0005**
				(0.000)
Ln(Total assets)				-0.0136**
				(0.002)
Age				-0.0005**
				(0.000)
FCP index dummy				-0.1579**
				(0.004)
Intercept	0.2647	0.3507**	0.3630*	0.3400**
	(0.126)	(0.045)	(0.150)	(0.030)
Obs.	1,850,932	1,850,933	1,850,932	504,225
Adj. R square	0.031	0.031	0.031	0.107
Sector FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note: This table reports the results for regression (4) estimated by OLS. The dependent variable is operating income. Operating income, net income and cash are given as ratios to total assets. Interest coverage is the ratio of EBIT to interest expenses. Ln(Total assets) is the natural log of total assets. Age is the number of years since incorporation. FCP index is the financial constraint measure from Schauer et al. (2019). Biodiversity loss is equal to 100 minus the BII. Heat is the median of the maximum of daily maximum temperature. Rain is the median of the Simple Daily Intensity Index. The observations are annual. The sample period is 2006-2023. Standard errors are double clustered at the firms and year levels and are reported in parentheses. ** and * denote statistical significance at the 1% and 5% levels, respectively.

Table 9: Geographical analysis regression results

Variable	(1)	(2)	(3)	(4)
Biodiversity loss quartiles				
2nd	-0.0048*			
	(0.002)			
3rd	-0.0092**			
	(0.002)			
4th	-0.0165**			
	(0.003)			
Biodiversity loss		-0.0018**	-0.0006**	-0.0004**
		(0.001)	(0.000)	(0.000)
Cash	-0.0242	-0.0211	-0.0217	-0.0208
	(0.013)	(0.011)	(0.017)	(0.017)
Interest coverage	0.0005**	0.0005**	0.0005**	0.0005**
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Total assets)	-0.0135**	-0.0090**	-0.0176**	-0.0181**
	(0.002)	(0.002)	(0.002)	(0.002)
Age	-0.0005**	-0.0003**	-0.0007**	-0.0007**
	(0.000)	(0.000)	(0.000)	(0.000)
FCP index dummy	-0.1575**	-0.1589**	-0.1537**	-0.1532**
	(0.005)	(0.004)	(0.005)	(0.005)
Intercept	0.2879**	0.3598**	0.4005**	0.3958**
	(0.027)	(0.061)	(0.031)	(0.029)
Obs.	515,598	306,028	389,216	367,124
Adj. R square	0.107	0.105	0.110	0.110
Sector FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
London	Yes	Yes	No	No
Birmingham	Yes	Yes	Yes	No
Manchester	Yes	Yes	Yes	No

Note: This table reports the results for the baseline regression (1) and regression (5) estimated by OLS. The dependent variable is operating income. In model (1) the biodiversity loss variable is represented by biodiversity loss quartiles dummies. In model (2) we include only firms operating in areas with a biodiversity loss higher than the average value. In model (3) we exclude London from the sample. In model (4) we exclude London, Birmingham, and Manchester from the sample. Operating income, net income and cash are given as ratios to total assets. Interest coverage is the ratio of EBIT to interest expenses. Ln(Total assets) is the natural log of total assets. Age is the number of years since incorporation. FCP index is the financial constraint measure from Schauer et al. (2019). Biodiversity loss is equal to 100 minus the BII. The observations are annual. The sample period is 2006-2023. Standard errors are double clustered at the firms and year levels and are reported in parentheses. ** and * denote statistical significance at the 1% and 5% levels, respectively.

Table 10: Physical and transition risks regression results

Variable	(1)	(2)
Biodiversity loss	-0.0007**	-0.0007**
	(0.000)	(0.000)
High dependence × Biodiversity loss	-0.0017**	
	(0.000)	
High impact × Biodiversity loss		-0.0003
		(0.000)
Cash	-0.0241	-0.0242
	(0.013)	(0.013)
Interest coverage	0.0005**	0.0005**
	(0.000)	(0.000)
Ln(Total assets)	-0.0135**	-0.0135**
	(0.002)	(0.002)
Age	-0.0005**	-0.0005**
	(0.000)	(0.000)
FCP index dummy	-0.1575**	-0.1575**
	(0.005)	(0.005)
Intercept	0.3410**	0.3412**
	(0.029)	(0.029)
Obs.	515,598	515,598
Adj. R square	0.107	0.107
Sector FE	Yes	Yes
County FE	Yes	Yes
Year FE	Yes	Yes

Note: This table reports the results for regressions (6) and (7) estimated by OLS. The dependent variable is operating income. The variables *High dependence* and *High impact* are constructed using ENCORE. Operating income, net income and cash are given as ratios to total assets. Interest coverage is the ratio of EBIT to interest expenses. Ln(Total assets) is the natural log of total assets. Age is expressed in years. FCP index is the financial constraint measure from Schauer et al. (2019). Biodiversity loss is equal to 100 minus the BII. The observations are annual. The sample period is 2006-2023. Standard errors are double clustered at the firms and year levels and are reported in parentheses. ∗∗ and ∗ denote statistical significance at the 1% and 5% levels, respectively.

Table 11: Robustness checks regression results

Variable	(1)	(2)	(3)	(4)
Biodiversity loss	-0.0007**	-0.0008**	-0.0009**	-0.0005**
	(0.000)	(0.000)	(0.000)	(0.000)
Cash	-0.0251	-0.0257	-0.0260	0.0133**
	(0.015)	(0.013)	(0.012)	(0.004)
Interest coverage	0.0005**	0.0005**	0.0008**	0.0006**
	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Total assets)	-0.0141**	-0.0137**	-0.0124**	-0.0190**
	(0.002)	(0.002)	(0.002)	(0.001)
Age	-0.0006**	-0.0005**	0.0004*	-0.0002
	(0.000)	(0.000)	(0.000)	(0.000)
FCP index dummy	-0.1557**	-0.1581**		-0.1594**
	(0.005)	(0.005)		(0.005)
Number of competitors		-0.0000**		
		(0.000)		
SA index dummy			0.0181**	
			(0.003)	
Intercept	0.3499**	0.3503**	0.2747**	0.3984**
	(0.031)	(0.029)	(0.033)	(0.021)
Obs.	443,554	516,046	515,598	521,657
Adj. R square	0.105	0.105	0.060	0.147
Sector FE	Yes	Yes	Yes	Yes
County FE	Yes	No	Yes	Yes
Country FE	No	Yes	No	No
Year FE	Yes	Yes	Yes	Yes

Note: This table reports the results for the baseline regression (1) estimated by OLS. In model (1) the sample period is 2006-2021. In model (2) we control for country fixed effects and the number of firms per sector in the same county. In model (3) we use the SA index as a measure of financial constraint. In model (4) the dependent variable is net income. In models (1), (2) and (3) The dependent variable is operating income. Operating income, net income and cash are given as ratios to total assets. Interest coverage is the ratio of EBIT to interest expenses. Ln(Total assets) is the natural log of total assets. Age is the number of years since incorporation. SA index is the financial constraint measure from Hadlock and Pierce (2010). FCP index is the financial constraint measure from Schauer et al. (2019). Biodiversity loss is equal to 100 minus the BII. The sample period is 2006-2023. Standard errors are double clustered at the firms and year levels and are reported in parentheses. ** and * denote statistical significance at the 1% and 5% levels, respectively.

Figures

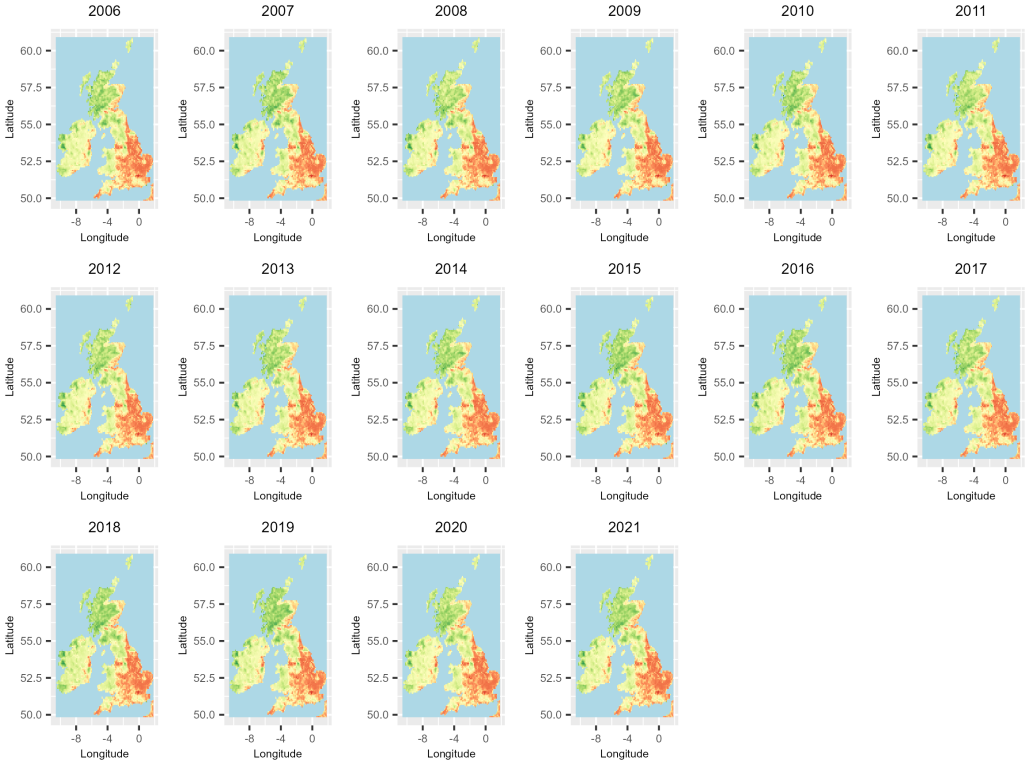


Figure 1: Biodiversity Intactness Index for the UK and Ireland

Note: This figure presents the Biodiversity Intactness Index (BII), developed by the Natural History Museum, for the UK and Ireland. The period spans from 2006 to 2021. Data are at 10 km^2 resolution.

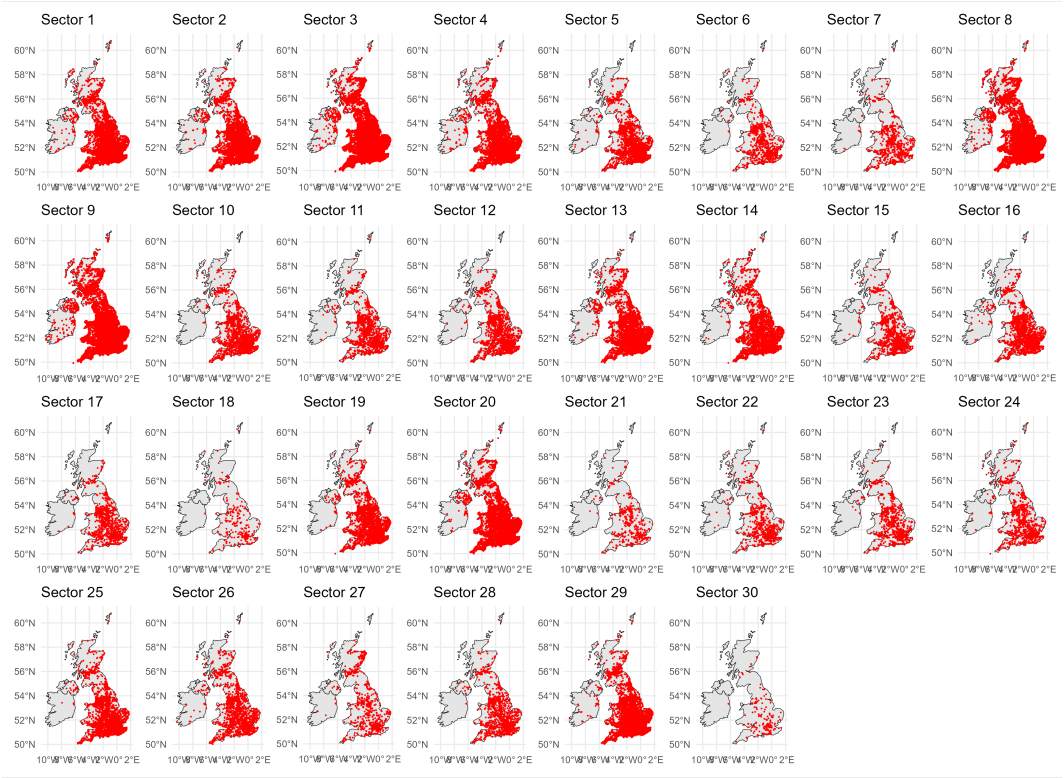


Figure 2: Location of SMEs by sector

Note: This figure presents the location of the SMEs in our database for the UK and Ireland. Sector 1: Property Services; Sector 2: Wholesale; Sector 3: Business Services; Sector 4: Unknown; Sector 5: Banking, Insurance & Financial Services; Sector 6: Textiles & Clothing Manufacturing; Sector 7: Transport Manufacturing; Sector 8: Public Administration, Education, Health Social Services; Sector 9: Travel, Personal & Leisure; Sector 10: Printing & Publishing; Sector 11: Metals & Metal Products; Sector 12: Miscellaneous Manufacturing; Sector 13: Retail; Sector 14: Agriculture, Horticulture & Livestock; Sector 15: Communications; Sector 16: Industrial, Electric & Electronic Machinery; Sector 17: Chemicals, Petroleum, Rubber & Plastic; Sector 18: Information Services; Sector 19: Transport, Freight & Storage; Sector 20: Construction; Sector 21: Leather, Stone, Clay & Glass products; Sector 22: Biotechnology and Life Sciences; Sector 23: Waste Management & Treatment; Sector 24: Utilities; Sector 25: Media & Broadcasting; Sector 26: Food & Tobacco Manufacturing; Sector 27: Mining & Extraction; Sector 28: Wood, Furniture & Paper Manufacturing; Sector 29: Computer Software; Sector 30: Computer Hardware;

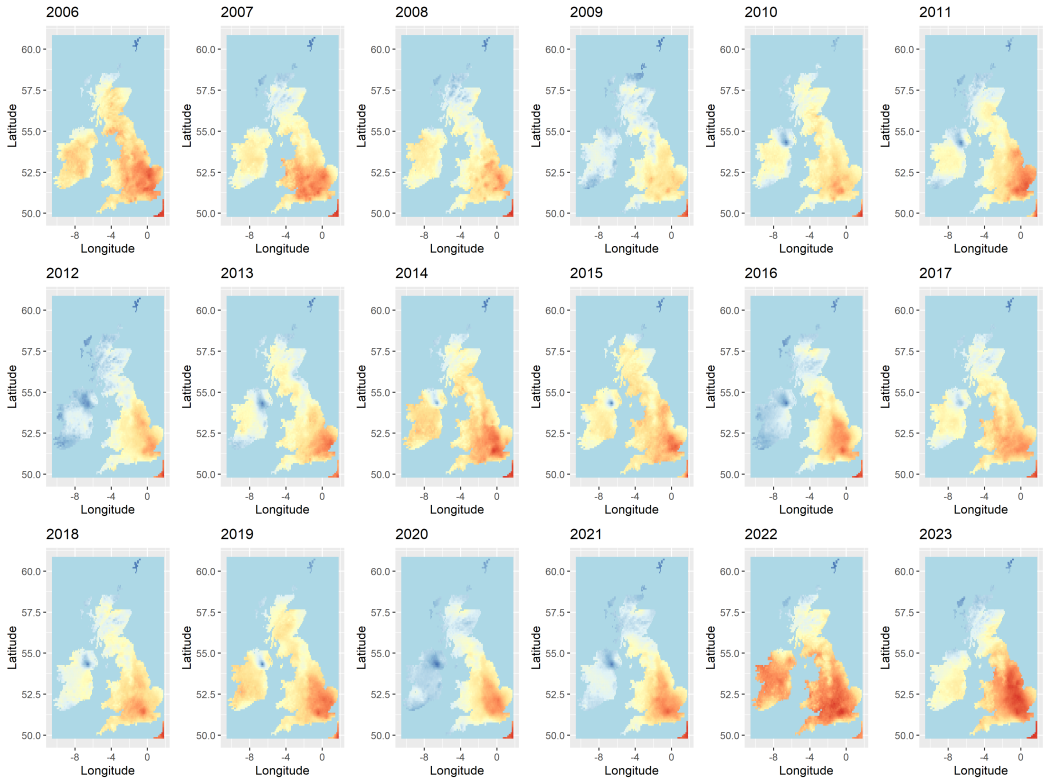


Figure 3: Heat index for the UK and Ireland

Note: This figure presents the annual median of the maximum of daily maximum temperature for the UK and Ireland. The period spans from 2006 to 2023. Data are at 10 km^2 resolution.

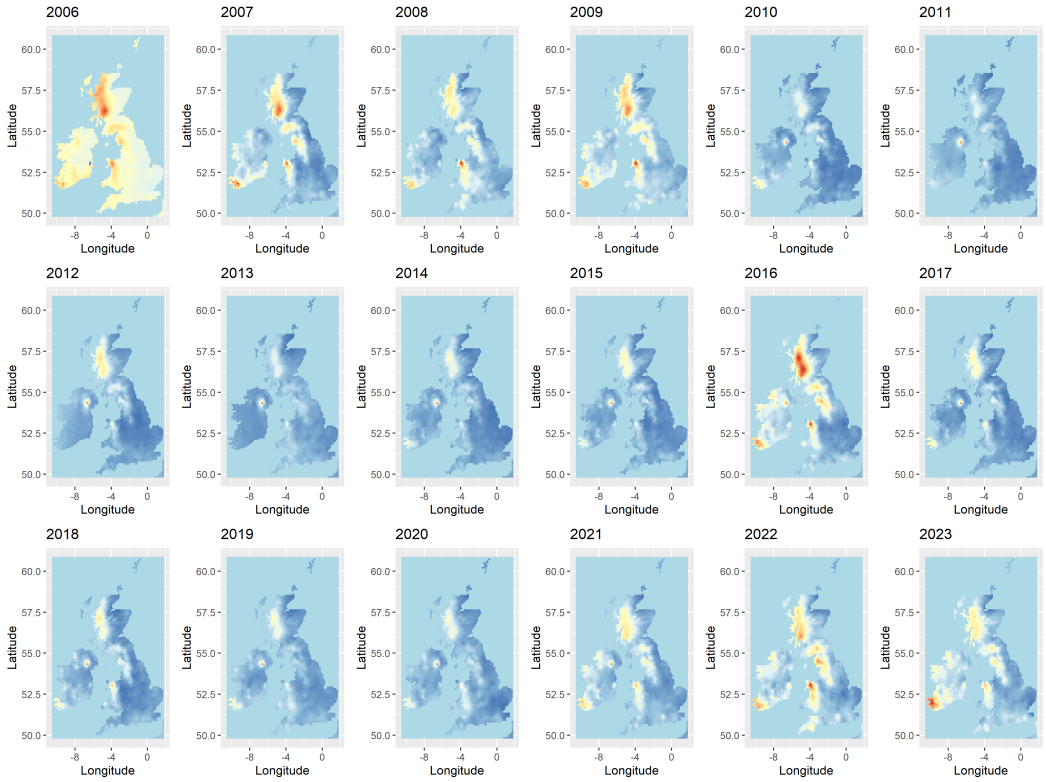


Figure 4: Rain index for the UK and Ireland

Note: This figure presents the annual median of the Simple Daily Intensity Index for the UK and Ireland. The period spans from 2006 to 2023. Data are at 10 km^2 resolution.