# The Financial Cost of Biodiversity Loss for SMEs

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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 the Biodiversity Intactness Index – a geospatial dataset at a 10 and 1 km$^2$ developed by the Natural History Museum – we geo-locate SMEs, quantify biodiversity loss where firms operate, and assess their exposure to biodiversity-related risks over time. Our findings indicate that a one-standard-deviation decline in local biodiversity leads to a statistically significant reduction in firm operating profit by 0.74 percentage points. This effect appears to operate primarily through higher operating costs and is economically meaningful as it corresponds to about 36% of the sample's average operating profit to total assets ratio. Moreover, micro firms and SMEs located in more ecologically degraded areas are found to be more exposed to biodiversity-related risks. This reinforces our main findings, showing that biodiversity exposure is not uniform across firms but is amplified by both local ecological conditions and firm scale. The results remain robust across alternative econometric specifications and after controlling for climate risk factors.

**Keywords**: Biodiversity risk; SMEs; Geospatial finance; Environmental materiality
**JEL classifications**: G32; L25; Q57

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# 1 Introduction

Biodiversity constitutes a fundamental component of natural capital that underpins economic production and, increasingly, financial stability (Karolyi and Tobin-de la Puente, 2023; Giglio et al., 2023). It sustains the ecosystem services – pollination, water regulation, soil formation, climate moderation – on which firms rely, often implicitly, to operate efficiently. Ecological research shows that more diverse ecosystems supply these services more productively and with greater stability over time (Balvanera et al., 2006; Isbell et al., 2011; Gamfeldt et al., 2013). When biodiversity is lost, these service flows weaken, production becomes costlier, and environmental shocks have a clearer route into firms' cash flows, through the same real-to-financial transmission channels that have been documented for climate and other environmental risks (Bolton and Kacperczyk, 2021, 2023).

This mechanism matters because the stock of biodiversity is declining rapidly. Global assessments document pervasive ecosystem degradation driven by land-use change, resource extraction, and pollution (MEA, 2005; IPBES, 2019). Estimates suggest that per-capita natural-capital stocks fell by about 40% over two decades (OECD, 2021) and that global biodiversity has dropped by roughly 70% since 1970 (WWF, 2025). Such declines imply a progressive depreciation of an input into production that is only imperfectly substitutable. If ecological thresholds are crossed, the resulting economic adjustments may be abrupt and only partially reversible, which makes the issue relevant not just for environmental policy but also for financial stability.

Building on this backdrop, a recent finance and banking literature has begun to quantify whether nature-related risks are already material for firms and intermediaries. Equity-market studies show that biodiversity-related exposures can be priced once information or policy makes them salient, and that investors revise valuations for firms that are more nature-dependent or have larger biodiversity footprints (Giglio et al., 2023; Garel et al., 2024; Coqueret et al., 2025). On the credit side, better management of nature-related risks is associated with lower credit risk, while exposure to nature-related transition risk raises borrowing costs (Hoepner et al., 2023; Becker et al., 2025). Related work links firms' biodiversity exposure to weaker operating outcomes (Cosma et al., 2024;

Bach et al., 2025) and shows that natural-capital shocks can propagate to bank portfolios (Battiston et al., 2024). Evidence on small businesses points in the same direction: biodiversity-exposed US SMEs face less favourable credit conditions (Nguyen et al., 2025). These studies suggest that both physical channels (through ecosystem-service disruption) and transition channels (through regulation, taxation, or reputational pressures) can be financially material. But they have so far focused mainly on large or listed firms and have seldom exploited granular, geolocated measures of biodiversity loss.

We contribute to the biodiversity–finance literature by providing, to our knowledge, the first empirical evidence that local, geolocated biodiversity loss is financially material for SMEs. The closest antecedent is Nguyen et al. (2025), who show that US small-business lenders charge higher rates to firms in sectors with high ENCORE-based nature dependency. Their measure, however, is sectoral and activity-level rather than spatially matched to the firm's location, and their outcome is credit conditions, not operating performance. By contrast, we use the Natural History Museum's Biodiversity Intactness Index (BII), link it to UK and Irish SME postcodes, and follow the same firms over 2006–2023. This setup allows us to observe how *actual biodiversity degradation where a firm operates* feeds through to its profitability, and it shifts the empirical focus from listed, globally diversified firms to the part of the economy that is most location-bound and financially fragile.

Therefore, our focus is on biodiversity *dependency* risk, rather than biodiversity *impact* risk. Much of the existing finance work has asked how markets price firms' biodiversity footprints or nature impacts, typically capturing transition channels (e.g., Garel et al., 2024; Coqueret et al., 2025). We show instead that firms can lose value because the ecosystems they rely on deteriorate, even when their own impact on nature is limited. This identifies a production-based channel through which biodiversity loss affects business outcomes and complements the listed-firm and banking evidence on nature-related financial risks.

Our second contribution is to show that the biodiversity loss effect is not only economically large but also heterogeneous. A one–standard-deviation increase in local bio-

diversity loss lowers the operating profit over total assets ratio by about 0.74 percentage points – roughly 36% of the ratio's sample mean – and the mechanism runs mainly through higher operating costs, consistent with degraded ecosystems making natural inputs scarcer or more expensive. The effect is stronger (i) for micro firms, (ii) for firms located in more ecologically degraded areas, and (iii) in sectors that ENCORE classifies as nature-dependent. This pattern matters for supply-chain transmission, because listed firms often face biodiversity risk through their SME suppliers.

Our third contribution is to examine how the spatial resolution of biodiversity data affects inferences about firms' exposure. To our knowledge, we are among the first with Cornaggia et al. (2025) to use high resolution data on biodiversity in a finance setting. The finer 1 $km^2$ grid captures very local ecological deterioration and therefore reveals stronger cost effects for firms that operate in, or directly affect, a narrow area. However, such high resolution can understate vulnerabilities that arise from wider, geographically distributed dependencies – for example, SMEs whose inputs or customers are drawn from a broader catchment will be better represented by the 10 $km^2$ measure. Comparing the two resolutions therefore highlights a trade-off: higher spatial precision improves detection of immediate, site-specific risks, whereas coarser grids better reflect ecosystem conditions in the wider area on which SMEs may still depend. Analysing both resolutions gives a more accurate picture of SME vulnerability to biodiversity loss and reinforces our central result that biodiversity loss is a material, location-specific risk.

Because much of the existing evidence on biodiversity risk is based on listed or very large firms, it is important to ask how biodiversity loss affects firms that are smaller, more financially fragile, and less diversified. Our objective is not to assume that biodiversity dependency is necessarily stronger (or weaker) for SMEs than for listed firms, but to examine how the same environmental shock operates when firms have fewer margins of adjustment. Large, listed firms can diversify across plants and geographies, switch suppliers, or absorb shocks with internal liquidity. SMEs, by contrast, are more geographically anchored, source a higher share of inputs locally, rely more on local ecosystem services (water availability, soil quality, flood protection, pollination), and face tighter financial

and managerial constraints for adaptation. Under these conditions, a local biodiversity shock can translate more directly into operating costs – which is the mechanism we document. This suggests that evidence based solely on listed firms may give a partial picture of the financial materiality of biodiversity loss, because it focuses on the segment of the corporate sector best equipped to smooth such shocks. Our results are therefore not at odds with the listed-firm literature; they complement it by showing how size, localisation, and financial flexibility shape the transmission of biodiversity risk. Finally, because SMEs account for a large share of UK turnover and employment (Office of National Statistics (ONS), 2023) and are embedded in the supply chains of listed companies, biodiversity-related cost increases or disruptions at the SME level can propagate upstream, revealing exposure that is not visible when analysing only large firms.

Our paper is structured as follows: section 2 surveys the literature on biodiversity finance, outlines recent economic theory on the relationship between biodiversity and the economy, 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 presents a series of extensive robustness checks to validate the main findings; section 6 concludes with some financial implications and recommendation.

## 2 Literature review and hypotheses development

The emergence of biodiversity finance is often linked to the call by Karolyi and Tobin-de la Puente (2023) for finance scholars to study how nature is financed in a nature-positive transition. Since then, research has increasingly examined how firms depend on and affect nature (e.g., Kulionis et al., 2024) and how investors value biodiversity-related projects (Flammer et al., 2025).

Recent work shows that biodiversity risk is increasingly priced. Creditors charge higher rates to borrowers with greater biodiversity exposure (Becker et al., 2025), and similar effects are documented for US small businesses (Nguyen et al., 2025). Investors also demand a biodiversity premium in equity markets (Giglio et al., 2023; Garel et al.,

2024), and biodiversity risk increases stock-price crash risk (Bassen et al., 2024) and bond spreads (Cherief et al., 2025). Although some studies find no pricing effects (Xin et al., 2025), in general, evidence for large firms suggests growing materiality.

Much less is known about SMEs. These firms play a central role in credit transmission (Cathcart et al., 2020; Barro et al., 2025) and will soon face mandatory environmental disclosures (European Commission, 2022). Existing SME-focused work mainly covers sustainability reporting (Rodríguez-Gutiérrez et al., 2021) or ESG assessments (Barro et al., 2025). Climate-finance studies show that physical risk affects SME profitability and default risk (Cathcart et al., 2022, 2023), suggesting that biodiversity loss may have similar effects – especially in natural-capital-dependent sectors. However, this remains largely unexplored.

Theoretical models incorporating natural capital (Stiglitz, 1974; Markandya and Pedroso-Galinato, 2007) typically overlook the role of biodiversity in generating ecosystem services. Ecological research, however, shows that biodiversity is essential for these services (Isbell et al., 2011; Lefcheck et al., 2015). Giglio et al. (2024) bridge this gap by modelling how species richness sustains ecosystem-service flows and, in turn, firm productivity. Biodiversity loss thus degrades natural capital, raising costs and reducing output.

Giglio et al. (2024)'s model provides a theoretical framework showing how biodiversity decline adversely affects firm production. Biodiversity underpins a wide range of ecosystem services and firms depend on these services – such as pollination, water purification, and soil fertility – to sustain their economic activities. Consequently, when biodiversity is lost, these services degrade, and their degradation directly undermines productivity and erodes profit. This dependence is particularly pronounced for SMEs, which typically operate at a local scale, are more geographically concentrated (Nguyen et al., 2025) and have limited capacity to absorb shocks (Koporcic et al., 2025). Consequently, an index capturing biodiversity loss should reflect the erosion of these ecosystem services across space and time, and for SMEs in particular, the depletion of natural capital is expected to translate more directly into lower profitability. Based on this premise, our main hypothesis is as follows:

**H1**. Firms located in areas with stronger localised biodiversity loss experience a negative impact on their operating profit.

To explore the mechanism linking biodiversity loss to firm profitability in greater detail, we decompose operating profit into its two components: revenues from operations and operating expenses. Since operating profit is defined as revenues minus operating expenses, a negative impact of biodiversity loss on operating profit must arise either through lower revenues, higher costs, or both. An alternative possibility is that revenues increase when firms exploit ecosystem services more intensively, generating higher output, but at the same time costs rise disproportionately, offsetting the gains in revenues. To anchor this intuition in theory, Giglio et al. (2024) develop a two-period model in which agents maximise production by exploiting land. While greater land use raises output, it simultaneously degrades ecosystem services[1], which enter the production function, thereby driving up input costs. To test this mechanism, we formulate the following two hypotheses:

**H2**. Revenue channel: Firms located in areas with stronger localised biodiversity loss face higher revenues (leading to higher operating profit).

**H3**. Cost channel: Firms located in areas with stronger localised biodiversity loss face higher costs (leading to lower operating profit).

Each of the two hypotheses translates into a distinct empirical specification. In the first case, where we test whether biodiversity loss increases firm revenues, the dependent variable is revenues from operations. In the second case, where we assess whether biodiversity loss increases firm costs, the dependent variable is operating expenses. Estimating these models separately allows us to disentangle whether the effect of biodiversity loss on operating profit operates primarily through the revenue channel, the cost channel, or a combination of both.

[1]One way to interpret this is that, as the population of each species decreases because of land use (e.g., through deforestation), the likelihood of extinction rises. In fact, ecological studies have shown that the smaller a species' population, the higher its chance of local extinction (Cleland, 2012).

Furthermore, if localised biodiversity loss reduces SMEs' operating profits, this effect should strengthen under certain firm characteristics. We expect firms with high *dependence* on ecosystem services to be more adversely affected, as biodiversity degradation directly disrupts inputs such as water, soil fertility, and pollination. This vulnerability is likely amplified for SMEs, which typically have limited financial and managerial capacity to absorb environmental shocks. Consistent with this view, Nguyen et al. (2025) find that SMEs highly dependent on ecosystem services face higher borrowing costs. By contrast, firms with a high *impact* on natural capital are less likely to experience direct losses from biodiversity decline. Their main exposure is transition risk – arising from tighter environmental regulation, shifts in consumer preferences, or reputational pressures. Such risks tend to be more relevant for large firms due to their higher visibility, while SMEs may face them only once regulation becomes widespread. Thus, we hypothesise:

**H4**. The negative association between localised biodiversity loss and firms' operating profit is stronger for firms that have a high dependency on biodiversity.

**H5**. The strength of the negative association between localised biodiversity loss and firms' operating profit does not significantly depend on firms' biodiversity impact.

Finally, as smaller firms are more impacted by financial crises (Chang, 2010; Sydnor et al., 2017; Koporcic et al., 2025) and climate shocks (Berg et al., 2025) than larger firms, similarly, we deem plausible that smaller firms are disproportionally affected by biodiversity loss. Indeed, micro firms may be more likely to be influenced by the biodiversity outlook of limited geographic areas. Micro firms tend to be more location-bound than small and medium enterprises and have even more limited capacity to invest in adaptation or mitigation strategies. Moreover, they typically have lower capital reserves and less access to credit, thus being less resilient to disruptions caused by biodiversity loss. For this reason, we hypothesise the following:

**H6**. The negative association between localised biodiversity loss and firms' operating profit is stronger for micro firms.

Testing whether micro firms are more severely impacted by biodiversity loss also allows us to address the possible problem of multi-establishment firms. Indeed, while SMEs may occasionally operate more than one branch, they generally have only a single location, and this is even more so for micro firms.

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

# 3 Data and methodology

## 3.1 The Biodiversity Intactness Index

To analyse the effect of localised biodiversity loss on SMEs' operating profit, we combine different datasets from various sources. To quantify biodiversity, we use the Biodiversity Intactness Index (BII). The BII is a biodiversity index that combines information on species identity and abundance, and 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 was 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 project uses ecological data from around the world to measure and forecast biodiversity changes 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, data are 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 (De Palma et al., 2024): one assessing how human activities – including land use, landscape simplification, and management intensity – 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 and landscape simplification, to produce maps of abundance and compositional similarity, which are then multiplied to estimate the BII. 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).

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 $S_{ref}$, respectively, 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 2021 is represented in Figure 1. The UK presents substantial regional variation in biodiversity decline across the country. Notably, southern and especially eastern England exhibit very high levels of biodiversity loss, particularly in and around large urban areas, in some cases to the extent that almost no biodiversity remains (e.g., London and its surroundings). In contrast, Wales and Ireland retain comparatively more of their native biodiversity, though, in general, biodiversity loss remains substantial (over 60%), with urban areas again showing more pronounced declines. Scotland displays the highest levels of biodiversity, with the Highlands preserving over 50% of their original biodiversity. Importantly, the UK and Ireland present remarkable variability within a relatively small territory. The combination of severe biodiversity loss, substantial regional variation, and an economically important and dense SME presence (see Office of National Statistics (ONS), 2023) makes the UK and Ireland an ideal empirical setting to study the impact of biodiversity on SMEs.

[Insert Figure 1]

All in all, the BII is a comprehensive index that allows for an in-depth assessment of

biodiversity loss at the local level. Indeed, the BII represents one of the leading indicators of biodiversity loss and a "cutting-edge indicator of ecosystem integrity" (Taskforce on Nature-related Financial Disclosures (TNFD), 2025).

## 3.2 Firm-level 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 profit, our main dependent variable, is available in at least one year. This results in an initial sample 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. Finally, the estimation sample is reduced to 397,648 due to missing values in key variables. 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. Note that firms located in England account for approximately 90% of the sample.

[Insert Table 1]

[Insert Table 2]

We obtain annual BII data 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 SME locations 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. In the robustness checks (section 5), we repeat the analysis excluding extrapolated data and show that the results of our empirical analysis hold.

[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[2] 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 control for climate change specific effects to provide support that our documented results are driven by biodiversity dependency and not by climate change. In particular, we collect a heat index, the annual 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 in a year[3]. 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 illustrate the spatial distribution of the heat and rain indices across the UK and Ireland over 2006–2023. Hotter areas, particularly in southern and eastern England, tend to coincide with regions that exhibit more severe biodiversity loss, while cooler and wetter regions such as parts of Scotland, Wales, and Ireland show

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

[3]Using maximum temperature aligns with standard climate-science indices highlighted by the IPCC (Seneviratne et al., 2021) and is supported by Katz and Brown (1992), who demonstrate that extreme temperatures – rather than mean temperature – drive the most significant ecological and economic impacts. Similarly, the SDII is widely used in climate science as a standard extreme-precipitation metric, and is included in the IPCC AR6 as a core indicator for assessing changes in rainfall intensity (IPCC, 2021).

comparatively lower biodiversity loss. This pattern is consistent with the correlations reported in Table 6, where biodiversity loss is positively related to the heat index and negatively related to rainfall.

[Insert Figure 3]

[Insert Figure 4]

The list of variables, including climate and financial controls, is reported in Table 3. To exclude outliers, following Nguyen et al. (2025), all the continuous variables are winsorised at the 2.5% and 97.5% levels[4].

[Insert Table 3]

Finally, we also collect levels of sectoral dependencies and impact on biodiversity using ENCORE[5] (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 follow two procedures. First, we calculate the average of the dependency scores across the 25 ecosystem services and the impact scores across the 13 impact drivers, rounding the resulting values to the nearest integer. Second, following Nguyen et al. (2025), we

[4]The variables were initially winsorised at the 1% and 99% levels, but as several extreme values persisted, we winsorised at the 2.5% and 97.5% levels instead.

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

count the total number of ecosystem services for which sectoral dependency, and the total number of impact drivers for which sectoral impact, are assessed as medium or higher.

Table 4 reports the summary dependency score and impact score computed using ENCORE. For the average scores, values range from 1 (low dependency/impact) to 3 (high dependency/impact), with most sectors taking a value of 1. No sector records a value of 0, indicating that all sectors are at least partially dependent on, or exert some impact on, biodiversity. For the count scores, values range from 0 to 16 for dependency and from 0 to 10 for impact. Based on both the average and count scores, the sectors most dependent on biodiversity are Agriculture, Horticulture & Livestock, which records the maximum values across both measures (average = 3; count = 16), followed by Mining and Extraction (average = 2; count = 9) and Biotechnology and Life Sciences (average = 2; count = 7). Mining and Extraction scores relatively high because it relies on several biodiversity-related ecosystem services, such as water supply and water quality regulation, soil stability and erosion control. In terms of impact, Agriculture, Horticulture & Livestock again shows the highest scores (average = 3; count = 10), while Mining and Extraction (average = 3; count = 7), Waste Management & Treatment (average = 2; count = 8), and Construction (average = 2; count = 6) also display relatively high impact levels. Overall, the count scores are consistent with the average scores in identifying the sectors most dependent on, and most impacting, biodiversity.

[Insert Table 4]

## 3.3 Empirical models

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 profitability 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:

$$Profit_{i,t} = \beta_0 + \beta_1 BL_{i,t-1} + \beta_2 \boldsymbol{X}_{i,t-1} + \theta_j + \mu_c + \gamma_t + \epsilon_{i,t} \tag{3}$$

where $Profit_{i,t}$ is operating profit to total assets of firm $i$ at year $t$, $BL_{i,t-1}$ 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 including cash, interest coverage, the natural log of total assets, age, and the FCP index of financial constraint (Schauer et al., 2019), and $\theta_j$, $\mu_c$, and $\gamma_t$ 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, $\beta_1$ in model (3) should be negative and significant.

Next, we examine the channels through which biodiversity loss affects profitability, focusing on its potential impact on revenues (H2) and costs (H3). The empirical model used to test hypothesis H2 is specified as follows:

$$Revenues_{i,t} = \beta_0 + \beta_1 BL_{i,t-1} + \beta_2 \boldsymbol{X}_{i,t-1} + \theta_j + \mu_c + \gamma_t + \epsilon_{i,t} \tag{4}$$

where $Revenues_{i,t}$ indicates revenues to total assets of firm $i$ in year $t$. The model includes the same control variables and sector, county, and year fixed effects used to estimate equation (3). Standard errors are double clustered at the firm and time levels. If hypothesis H2 holds, $\beta_1$ in model (4) should be positive and significant.

To test the cost channel, we adopt the following specification:

$$Costs_{i,t} = \beta_0 + \beta_1 BL_{i,t-1} + \beta_2 \boldsymbol{X}_{i,t-1} + \theta_j + \mu_c + \gamma_t + \epsilon_{i,t} \tag{5}$$

where $Costs_{i,t}$ indicates operating costs to total assets of firm $i$ in year $t$. Again, model (5) includes the same control variables and sector, county, and year fixed effects used to estimate equation (3). Standard errors are double clustered at the firm and time levels. If hypothesis H3 is confirmed by the data, $\beta_1$ in model (5) should be positive and significant.

We test whether firms in sectors highly dependent on biodiversity earn lower profits (H4) and whether firms in sectors with high biodiversity impact do not earn lower profits (H5). Sector-level dependency and impact scores come from ENCORE (see Section 3.2). We classify sectors as highly dependent ($HD_j = 1$) and highly impacting ($HI_j = 1$) biodiversity using two methods. With the average score approach, dependency (impact) dummies equal 1 when the average score is at least 2. With the count score approach, dependency (impact) dummies equal 1 when at least one third of ecosystem services (impact drivers) are flagged. We then estimate equation (3) including first the interaction term $BL_{i,t-1} \times HD_j$ to test H4, and then $BL_{i,t-1} \times HI_j$ to test H5. Support for H4 requires a negative, significant interaction coefficient, while support for H5 requires the interaction coefficient to be statistically indistinguishable from zero.

Finally, we investigate the impact that biodiversity loss has on micro enterprises and test hypothesis H6. To do so, we define a dummy variable that takes the value of 1 if total assets of firm $i$ is less than or equal to £500,000. This threshold captures the smallest firms in our sample and corresponds to the micro-enterprise category[6]. Then, we add to equation (3) the interaction term $BL_{i,t-1} \times Micro_i$, where $Micro_i$ is equal to 1 if firm $i$ is a micro firm, and 0 otherwise. Hypothesis H6 is empirically validated if the coefficient on the interaction term $BL_{i,t-1} \times Micro_i$ is negative and significant. In this way, we also account for the potential issue of multi-establishment firms, since micro firms are even more likely than small and medium-sized enterprises to operate as single-location businesses.

# 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, using the 10 km$^2$ BII, the average biodiversity loss is 83.19, indicating

[6]The UK company law defines micro enterprises as firms that meet at least two of the following criteria: a turnover of £1 million or less, a balance sheet total of £500,000 or less, and no more than 10 employees (see https://www.gov.uk/annual-accounts/microentities-small-and-dormant-companies). Our threshold of £500,000 in total assets reflects the paucity of available data on employment and turnover.

that SMEs in the UK typically operate in areas where approximately only 17% of the original biodiversity is intact. Using the 1 km$^2$ BII, the average biodiversity loss rises to 89.55, highlighting even more serious ecosystem degradation at a very granular level[7]. The average operating profit to total assets is 0.02, with a standard deviation equal to 0.948. These firm-level figures are consistent with those reported by Cathcart et al. (2022) for European SMEs.

[Insert Table 5]

Table 6 reports the correlation matrix for all the variables. Biodiversity loss (10 km$^2$) is negatively correlated with both operating profit (-0.052) and net profit (-0.058), which supports our initial hypothesis (H1). By contrast, the climate variables show weaker correlations with the measures of profitability. It is also interesting to observe that biodiversity loss is positively correlated with the temperature variable (0.283) and negatively correlated with the rain variable (-0.356). This suggests that biodiversity loss tends to be higher in hotter areas, where rising temperatures can stress ecosystems. By contrast, greater rainfall is generally associated with more intact habitats and helps reduce the risk of droughts, thereby limiting biodiversity loss. These figures remain consistent using the finer 1 km$^2$ BII.

[Insert Table 6]

## 4.2 Regression analysis

Table 7, Column 1, reports the results from our baseline regression of operating profit over total assets on biodiversity loss, including fixed effects but no additional firm-level controls. The coefficient on biodiversity loss is negative and significant at the 1% level,

[7]This difference reflects the fact that SMEs tend to be located in the most heavily degraded 1 km$^2$ pixels within each broader 10 km$^2$ grid cell, so the finer-resolution measure captures local degradation around firms more precisely.

hence, on average, a larger biodiversity loss in a localised area is associated with a lower operating profit of SMEs operating in this area. In Column 2, all the control variables are introduced and, again, the coefficient on biodiversity loss remains negative and significant, but this time is equal to -0.001. Thus, a one-standard-deviation increase in biodiversity loss is associated with a decrease in operating profit to total assets of 0.74 percentage points ($0.001 \times 7.72 \approx 0.0074$), which corresponds to a 36% drop in the average value of the dependent variable (0.02). This effect is not only statistically significant but also economically significant. Indeed, these results suggest that degradation of ecosystem services can directly impair SME profitability, thereby confirming hypothesis H1.

[Insert Table 7]

In Columns 3-4, we use biodiversity loss lagged by 2 years. The results remain robust and the coefficient on biodiversity loss retains its magnitude (-0.001) and significance. The fact that biodiversity loss from two 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[8].

## 4.3 Transmission channels

We conduct tests to understand the underlying mechanisms through which biodiversity loss affects SME profitability. Given the negative relationship we found between operating profit and biodiversity loss, it is natural to infer that the depletion of natural resources translates into either reduced revenues, increased costs, or both.

To formally test these channels, we estimate two different regression models. In the first, the dependent variable is revenues (model (4)), and in the second it is operating costs (model (5)). Both revenues and operating costs are expressed as ratios to total assets. The models include control variables and fixed effects identical to those used in the baseline model (equation (3)).

[8]We also estimate a model where biodiversity loss is lagged by 5 years. The results remain robust, confirming the delayed impact that biodiversity loss has on firm profitability.

Table 8 displays the results. When the dependent variable is revenues, the coefficient on biodiversity loss is positive but not statistically significant, while it is positive and significant at the 5% for costs (0.0027). Biodiversity loss can increase costs for SMEs because it reduces natural resources and ecosystem services they rely on, forcing them to spend more on inputs, substitutes, and risk management. For example, a furniture maker that mainly sources locally may face higher timber prices as forest biodiversity declines and wood becomes scarcer. A one-standard-deviation increase in biodiversity loss is associated with a 2.08 percentage points increase in the costs to total assets ratio, which corresponds to roughly 0.8% of its sample mean (2.598). In monetary terms, the one-standard-deviation increase in biodiversity loss is associated with an increase of about £208,000 in operating costs for a firm with £10 million in assets.

[Insert Table 8]

In summary, our results reinforce the link between biodiversity loss and SME operating profit, highlighting the mechanisms through which this relationship materialises. In particular, we find that exploiting ecosystem services more intensively, which causes a higher biodiversity loss, does not significantly increase revenues, but instead manifests as higher operating costs. These results do not support the validity of hypothesis H2, but they do provide evidence in support of hypothesis H3. Although not statistically significant, it is noteworthy that the coefficient of biodiversity loss in the revenue regression is smaller than that for costs, suggesting that biodiversity loss increases costs in a way that more than offsets any revenue gains.

## 4.4 Heterogeneity analysis: sectoral dependency and impact

We conduct a sectoral analysis to further investigate the mechanism through which biodiversity loss affects operating profit. To construct a variable that identifies the sectors most dependent on, and most impacting, biodiversity, we use ENCORE (see section 3.2 for the description of the score construction and section 3.3 for the construction of the dummy variables).

Table 9 reports regression estimates where we extend our baseline specification (equation (3)) by interacting biodiversity loss with the high dependence and high impact sector dummies. This allows us to disentangle the influence of biodiversity *physical risk* (captured by high dependence) from *transition risk* (captured by high impact), the latter arising from regulatory, market, or reputational responses to firms' impacts on nature.

[Insert Table 9]

Our results show that firms in sectors that are highly dependent on ecosystem services exhibit lower operating profit compared with firms in sectors that are not highly dependent. The combined marginal effect for high-dependence firms is in the range of -0.0035 to -0.0037, which is substantially larger in magnitude than the baseline effect estimated in previous specifications (around -0.001, see Table 7). In economic terms, the sensitivity of operating profit to biodiversity deterioration is roughly three to four times larger for biodiversity-dependent firms compared to the average firm.

Conversely, firms in sectors with a high impact on nature do not display lower profitability. These findings confirm hypotheses H4 and H5 and point to the mechanism behind the effect of biodiversity loss on operating profit: the degradation of ecosystem services reduces the profitability of firms that rely on those services to conduct their operations. By contrast, firms that strongly impact nature are not necessarily directly affected by the loss of natural capital, so biodiversity loss need not influence their profitability unless regulation makes such impacts financially material. For example, waste management companies affect ecosystems but rely only marginally on natural capital (see Table 4). In such cases, the materiality of transition risk largely depends on regulatory action to protect nature (Boissinot et al., 2022).

Overall, our evidence supports the materiality of physical risk for SMEs in the UK and Ireland, in line with the theoretical framework of Giglio et al. (2024), where firm output depends on ecosystem services. Notably, biodiversity risk appears material not only for large and very large firms (e.g., Garel et al., 2024; Coqueret et al., 2025) but also for SMEs. A key distinction, however, is that SMEs seem primarily exposed to

physical risk, whereas larger firms are more subject to transition risk – for instance Garel et al. (2024) show that firms with a large environmental footprint lose value following the Kunming Declaration. Large firms typically have complex, diversified supply chains, so biodiversity loss in any single location may only marginally affect overall profitability. In contrast, SMEs operate at a local scale, so local biodiversity loss can materially affect their operating conditions and financial performance, as reflected in the decline in profitability we document.

## 4.5 Heterogeneity analysis: micro firms

Next, we examine the impact of biodiversity loss on micro firms. Table 10 presents the results from our baseline regression (equation (3)) with the addition of an interaction term between biodiversity loss and the dummy identifying micro firms. The coefficient of interest is equal to -0.0008, and is statistically significant at the 1% level, further confirming that micro firms experience a disproportionately large negative effect from biodiversity loss. The combined marginal effect for micro enterprises is -0.0017, substantially larger in magnitude than the estimated baseline effect (-0.001). For micro firms, a one-standard deviation increase in biodiversity loss (7.72 units) is associated with a reduction of about -0.013 in operating profit – over 50% of the sample mean – suggesting that micro firms are extremely vulnerable to biodiversity pressures. These findings further validate our hypothesis H6.

[Insert Table 10]

## 4.6 Addressing potential reverse causality

We have shown that the impact of biodiversity loss on SME economic activities is material. However, SME activities may also influence local biodiversity conditions—for example, through land use, water extraction, or other environmentally intensive operations – which can be associated with higher profitability. This raises the possibility of reverse causality,

whereby more profitable firms also contribute more to local biodiversity loss. To corroborate our findings on the effect of biodiversity loss on SME operating profit, we therefore address potential endogeneity by implementing an instrumental variable (IV) approach. This requires instruments that are strongly correlated with biodiversity loss (relevance), but that affect operating profit only through their impact on biodiversity loss and not through any other channel (exogeneity).

To instrument biodiversity loss, we rely on the number of wildfires within 10 km of the SME (WF) and the number of consecutive dry days (CDD), as proxies for the occurrence of droughts, in the area where the SMEs operate. We collect wildfire locations over time from EFFIS[9] and the number of consecutive dry days from E-OBS. These shocks are directly linked to ecosystem degradation and thus provide relevant variation in biodiversity loss, while being plausibly exogenous to firm-level operating profit. Since the wildfires occur within the surrounding 10 km area and never at the SME's own location[10], they should affect operating profit only through their impact on biodiversity (for example, by reducing the availability of natural resources that SMEs rely on). Similarly, droughts can impair local ecosystems that support raw materials. Nevertheless, potential caveats remain. First, even if wildfires do not occur directly at the SME's location, they may still generate economic effects beyond biodiversity, such as local infrastructure damage. Second, droughts could influence firms not only via biodiversity loss but also through reduced water availability for production processes. We mitigate these risks to the exclusion restriction through three design choices and diagnostics. (i) We use lagged values of both WF and CDD (t-1), so the instruments shift local ecological conditions without coinciding with contemporaneous, firm-specific shocks. (ii) All IV specifications include sector, county, and year fixed effects together with our standard firm controls, absorbing local demand and cost shocks that are unrelated to biodiversity. (iii) Instrument diagnostics indicate relevance and validity: first-stage coefficients are strong, Kleibergen-Paap statistics exceed conventional thresholds in most cases, and (where applicable) Hansen

[9] See https://forest-fire.emergency.copernicus.eu/.

[10] We geolocated both the wildfires and the SME locations and verified that none of the wildfire areas overlap with any SME location.

J tests do not reject the null hypothesis of validity of the instruments. Taken together, these features support the interpretation that wildfire incidence and consecutive dry days provide plausibly exogenous variation in biodiversity loss that identifies its causal effect on SME operating performance.

[Insert Table 11]

Table 11 reports the estimates of the first stage of our IV regressions. In Column 1, the instrument is the number of wildfires. The coefficient on WF is negative and highly significant ($p < 0.01$), indicating that a higher number of wildfires is associated with lower measured biodiversity loss. While this result may seem counterintuitive at first, it likely reflects the fact that wildfires predominantly occur in forested or natural areas, which inherently exhibit higher levels of biodiversity compared to more urbanised regions. On the other hand, the coefficient on CDD in column 2 is positive and highly significant ($p < 0.01$), suggesting that a greater number of consecutive dry days (and thus more severe drought conditions) is associated with higher biodiversity loss. In column 3, both WF and CDD are significant at the 1% level and in column 4 the interaction term WF $\times$ CDD is negative and significant, indicating that the effect of dry days on biodiversity loss becomes weaker when the number of wildfires increases. In other words, a higher frequency of wildfires mitigates the negative impact of droughts on biodiversity. From an interpretative standpoint, this may suggest that in areas prone to frequent wildfires (typically more natural or forested regions) biodiversity is already higher or responds differently to climatic stress, or that biodiversity loss associated with drought is less pronounced where fires are more common[11].

[Insert Table 12]

The estimates of the second stage of the IV regressions are reported in Table 12. The coefficient on biodiversity loss is negative and significant across all the estimated models

[11]In this regard, it is interesting to observe that recent research has found that more frequent, smaller fires are likely to contribute to healthier forests, water ecosystems, and overall biodiversity (see Stephens et al., 2021; Climate Working Group, 2025).

(the coefficient ranges from -0.0057 to -0.0104 depending on the instrument) and, notably, it is higher than the coefficient estimated using OLS (-0.001). For example, in the case of the model where we use WF, CDD and WF×CDD (Column 4), a one-standard-deviation in biodiversity loss is associated with a decrease of approximately 4.48 percentage points in the operating profit to total assets ratio, corresponding to about £448,000 for a firm with £10 million in assets. This highlights a substantial economic impact of biodiversity loss on SME performance. Using instruments such as wildfires and droughts, the coefficient on biodiversity loss is larger than in OLS because 2SLS corrects for endogeneity, isolating exogenous variation in biodiversity and capturing its true causal impact on operating profit.

# 5 Robustness checks

## 5.1 Robustness analysis with finer spatial resolution data

We begin the robustness analysis using BII data at 1 $km^2$ resolution. Fine-grained biodiversity data are valuable because they capture highly localised ecological variation and can provide insights into firms' direct impacts on the surrounding environment. For instance, a 1 $km^2$ grid can identify specific areas where economic activity coincides with habitat degradation, highlighting the immediate ecological footprint of firms. On the other hand, as we focus on dependency risk, our main analysis relies on the BII at 10 $km^2$, which offers a more relevant perspective on biodiversity-related dependencies. At this resolution, the index reflects the broader ecological systems on which firms ultimately depend for resources and ecosystem services. Very fine spatial data, while informative about local impacts, may overemphasise micro-level anomalies that are not representative of the wider ecological context, consistent with Levin (1992), who cautions that analyses at very fine scales can obscure the larger-scale patterns that structure ecological systems. Aggregating biodiversity over a 10 $km^2$ grid smooths these local distortions and captures the landscape-scale processes that underpin long-term business resilience. The two measures are therefore complementary: the 1 $km^2$ data provide finer insight into where firms

exert direct pressure on local biodiversity, whereas the 10 $km^2$ data capture how firms are situated within, and reliant on, the broader ecological landscape that supports their activities.

Since our main analysis is on biodiversity dependency risk, we employ the 1 $km^2$ data as a robustness check. Specifically, we re-estimate equations (3), (4), and (5) to verify that the effect of biodiversity loss on operating profit, as well as the channels through which this effect materialises, remain robust.

[Insert Table 13]

Table 13 reports the estimates of equations (3)-(5) using BII data at a 1 $km^2$ resolution. In Column 1, biodiversity loss has a negative and highly significant effect on operating profit (-0.0007), close in magnitude to that obtained with the 10 $km^2$ data (-0.001), confirming that biodiversity degradation hampers SME performance.

In Column 2, where the dependent variable is revenues, the coefficient on biodiversity loss (0.0072) is positive and significant at the 1% level – unlike in the 10 $km^2$ specification. This confirms our hypothesis H2 and suggests that at finer spatial scales, revenues may be increased through intensive resource use or land exploitation (in line with Giglio et al. (2024)'s framework).

However, the estimated effect on operating costs (0.0078) exceeds that on revenues, implying that any gains from exploiting biodiversity are more than offset by higher costs. Notably, the difference between the two coefficients ($0.0078 - 0.0072 \approx 0.0006$) matches the estimated impact on operating profit, confirming internal consistency with the 10 $km^2$ results.

## 5.2 Robustness to climate risk: inclusion of climate change variables

Based on the results of Garel et al. (2024)[12], 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 natural 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 our baseline specification, as an additional robustness check. Following Addoum et al. (2020), we employ variables representing changes in heat and rain, described in Section 3.2.

[Insert Table 14]

Table 14 reports the results. 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 only the rain variable is 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 coefficients are also similar in magnitude to those found in Section 4.2.

The results found provide further evidence in favour of hypothesis H1, and aligns with prior research documenting the materiality of biodiversity risk for listed firms (e.g., Garel et al., 2024; Coqueret et al., 2025).

## 5.3 Biodiversity quartiles, low and high biodiversity loss areas, and exclusion of large urban centres

We also estimate an alternative version of our baseline model to further test whether SMEs operating in ecologically degraded areas exhibit lower profit levels compared to

[12] 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.

those situated in regions with higher biodiversity. We first construct firm-level quartile dummies based on the biodiversity loss variable. We then replace the variable $BL$ with such dummies in equation (3). In addition, we estimate our baseline model only for firms that operate in areas where the biodiversity loss is higher than average biodiversity loss.

In Table 15, Column 1, we present the estimates of the alternative specification of model (3) that includes firm-level quartile dummies based on biodiversity loss. Firms in the second quartile exhibit an operating profit that is 0.005 lower than that of firms in the first quartile, in absolute terms. This difference is statistically significant at the 10% level. This negative effect increases across quartiles: firms in the third and fourth quartiles report operating profits that are 0.0111 and 0.03 lower, respectively, compared to firms in the first quartile ($p < 0.01$).

In Column 2, regression (3) is estimated only on firms that operate in areas where biodiversity loss is higher than the mean (83.195). Consistently with the results of Column 1, the coefficient (-0.0028) is higher in absolute terms than that found for the whole sample (-0.001), revealing that for SMEs that operate in highly degraded areas biodiversity loss has a greater effect on operating profit. On the other hand, for firms operating in areas where biodiversity loss is below the sample mean, the coefficient on biodiversity loss is not statistically significant (Column 3). This may suggest that firms located in more degraded areas are disproportionately affected by biodiversity loss. These results strengthen the validity of hypothesis H1.

[Insert Table 15]

Additionally, to ensure that the results are not driven by large cities – where biodiversity loss tends to be higher – and to verify that the findings reflect the actual impact of biodiversity loss, in Column 4 and 5 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, statistically 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.

### 5.4 Further robustness tests: sample period, competition controls, and alternative profitability measure

Finally, to corroborate our findings, we conduct a range of additional robustness tests. The results are presented in Table 16. Column 1 reports the results with the sample period 2006-2021, which excludes extrapolated biodiversity loss 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[13] (Hadlock and Pierce, 2010) as a financial constraint dummy and in Column 4 we replace operating profit with net profit. The results remain largely unvaried. Finally, in unreported results, we also employ a different set of fixed effects encompassing sector-year and county-year fixed effects. This approach accounts for shocks or trends affecting all firms within a sector or county in a given year, such as regulatory changes or local economic conditions. The results remain largely unchanged, indicating that our findings are robust to different ways of capturing time-varying sectoral and geographic effects.

[Insert Table 16]

## 6 Conclusions

This paper documents that local biodiversity loss is financially material for small and medium-sized enterprises in the United Kingdom and Ireland. Using geolocated SME accounts linked to the Biodiversity Intactness Index, we show that a one-standard-deviation

[13]One advantage of the SA index is that it requires only firm size and age, which are available for most of the firms in our sample. In addition, Kaplan and Zingales (1997) show that size and age are particularly useful predictors of financial constraints.

increase in biodiversity loss lowers the operating profit to total assets ratio by around 0.74 percentage points, which corresponds to about 36% of the sample's average operating profit to total assets ratio. This is an economically meaningful effect: it implies that the erosion of local ecosystem services can translate into sizable and persistent reductions in SMEs' operating income.

We find that this impact works primarily through higher operating costs rather than lower revenues. Biodiversity loss appears to make production more expensive by degrading ecosystem services and natural inputs on which firms rely, even if their own direct impact on nature is limited. The effect is stronger for micro firms, for firms operating in ecologically degraded areas, and for sectors that ENCORE classifies as highly dependent on ecosystem services, underscoring that biodiversity exposure is location-specific and heterogeneous across activities. Importantly, the relationship between biodiversity loss and profitability remains robust when we include local climate variables such as heat and rainfall, when we exploit shocks related to wildfires and droughts, and when we use finer-resolution biodiversity data. This suggests that biodiversity-related channels provide additional information beyond standard climate risk proxies and should be considered alongside them in risk assessments.

These results have clear implications for policy, supervision, and corporate practice. Because SMEs are central to employment, regional development, and large-firm supply chains, biodiversity-related cost shocks at the SME level can propagate through the real economy and the financial system. Policymakers and regulators may therefore wish to integrate biodiversity metrics into SME support schemes, nature-related disclosure frameworks, and financial stability assessments. For lenders and investors, incorporating local biodiversity conditions and sectoral dependency into credit and risk models could improve the pricing of nature-related risks and help identify vulnerable borrowers, especially among micro and highly nature-dependent firms.

Our analysis also points to several avenues for future research. First, richer biodiversity metrics – for example, indicators that differentiate functional roles or explicitly treat invasive species – could refine the measurement of nature-related dependencies at the

firm level. Second, combining biodiversity data with supply-chain and input–output information would allow researchers to track how local ecological shocks propagate through production networks and into banks' and investors' portfolios. Third, studying dynamic adaptation – such as relocation, supplier switching, or investment in natural capital – would shed light on how firms re-optimise in response to biodiversity decline. Finally, extending this framework beyond the UK and Ireland, and comparing biodiversity and climate channels in different institutional settings, would help build a more global understanding of nature-related financial risks for SMEs.

## 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: SME sample composition by sector

| Sector | Firm-year observations | Percent |
|---|---|---|
| Agriculture, Horticulture & Livestock | 19,425 | 0.99 |
| Biotechnology and Life Sciences | 11,250 | 0.57 |
| Business Services | 666,096 | 34.01 |
| Chemicals, Petroleum, Rubber & Plastic | 21,110 | 1.08 |
| Communications | 14,711 | 0.75 |
| Computer Hardware | 1,397 | 0.07 |
| Computer Software | 75,000 | 3.83 |
| Construction | 176,160 | 9.00 |
| Food & Tobacco Manufacturing | 17,250 | 0.88 |
| Industrial, Electric & Electronic Mac.. | 34,139 | 1.74 |
| Information Services | 2,367 | 0.12 |
| Leather, Stone, Clay & Glass products | 3,802 | 0.19 |
| Media & Broadcasting | 43,876 | 2.24 |
| Metals & Metal Products | 24,568 | 1.25 |
| Mining & Extraction | 14,124 | 0.72 |
| Miscellaneous Manufacturing | 20,977 | 1.07 |
| Printing & Publishing | 23,230 | 1.19 |
| Property Services | 173,433 | 8.86 |
| Retail | 62,835 | 3.21 |
| Textiles & Clothing Manufacturing | 7,903 | 0.40 |
| Transport Manufacturing | 6,907 | 0.35 |
| Transport, Freight & Storage | 58,111 | 2.97 |
| Travel, Personal & Leisure | 305,913 | 15.62 |
| Utilities | 23,541 | 1.20 |
| Waste Management & Treatment | 8,931 | 0.46 |
| Wholesale | 129,334 | 6.60 |
| Wood, Furniture & Paper Manufacturing | 11,966 | 0.61 |
| Total | 1,958,356 | 100 |

Note: This table reports the composition of our sample by sector. Column 2 reports the number of firm-year observations by sector, and Column 3 the percentage.

Table 2: SME sample composition by country

| Country | Firm-year observations | Percent |
|---|---|---|
| England | 1,763,299 | 90.04 |
| Northern Ireland | 12,707 | 0.65 |
| Republic of Ireland | 15,955 | 0.81 |
| Scotland | 120,349 | 6.15 |
| Wales | 46,046 | 2.35 |
| Total | 1,958,356 | 100 |

Table 3: Description of regression variables

| Variable | Type | Description | Source |
|---|---|---|---|
| Operating profit | Dependent | Operating profit to total assets | Fame |
| Net profit | Dependent | Net profit to total assets | Fame |
| Revenues | Dependent | Revenues to total assets | Fame |
| Costs | Dependent | Operating costs 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 | Maximum of daily maximum temperature in a year at each location on the weather grid | E-OBS |
| Rain | Control | 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 defines the variables employed in our regression analyses and their source.

Table 4: ENCORE dependency scores and impact scores in our SME sample

| Sector | Dependency | | Impact | |
|---|---|---|---|---|
| | Average | Count | Average | Count |
| Agriculture, Horticulture & Livestock | 3 | 16 | 3 | 10 |
| Biotechnology and Life Sciences | 2 | 7 | 1 | 1 |
| Business Services | 1 | 1 | 1 | 0 |
| Chemicals, Petroleum, Rubber & Plastic | 1 | 5 | 1 | 2 |
| Communications | 1 | 0 | 1 | 0 |
| Computer Hardware | 1 | 5 | 1 | 2 |
| Computer Software | 1 | 0 | 1 | 0 |
| Construction | 1 | 7 | 2 | 6 |
| Food & Tobacco Manufacturing | 1 | 5 | 1 | 2 |
| Industrial, Electric & Electronic Machinery | 1 | 5 | 1 | 2 |
| Information Services | 1 | 0 | 1 | 0 |
| Leather, Stone, Clay & Glass products | 1 | 5 | 1 | 2 |
| Media & Broadcasting | 1 | 0 | 1 | 0 |
| Metals & Metal Products | 1 | 5 | 1 | 2 |
| Mining & Extraction | 2 | 9 | 3 | 7 |
| Miscellaneous Manufacturing | 1 | 5 | 1 | 2 |
| Printing & Publishing | 1 | 0 | 1 | 0 |
| Property Services | 1 | 2 | 1 | 0 |
| Retail | 1 | 2 | 1 | 3 |
| Textiles & Clothing Manufacturing | 1 | 5 | 1 | 2 |
| Transport Manufacturing | 1 | 5 | 1 | 2 |
| Transport, Freight & Storage | 1 | 1 | 2 | 3 |
| Travel, Personal & Leisure | 1 | 3 | 1 | 2 |
| Utilities | 1 | 4 | 2 | 4 |
| Waste Management & Treatment | 1 | 4 | 2 | 8 |
| Wholesale | 1 | 2 | 1 | 4 |
| Wood, Furniture & Paper Manufacturing | 1 | 5 | 1 | 2 |

Note: This table reports the ENCORE dependency score and impact score for each sector represented in our SME sample. The *Average dependency score* is the average of the 25 individual ecosystem services dependency scores available in ENCORE. Values are rounded to the nearest integer. The *Count dependency score* is the total number of ecosystem services for which sectoral dependency is assessed as medium or higher. The *Average impact scores* is the average of the 13 individual impact drivers scores available in ENCORE. Values are rounded to the nearest integer number. The *Count impact score* is the total number of impact drivers whose sectoral impact is assessed as medium or higher.

Table 5: Descriptive statistics of financial, biodiversity and climate variables used in the analysis

| Variable | Obs. | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| Operating profit | 1,958,356 | 0.020 | 0.948 | -3.905 | 2.651 |
| Biodiversity loss (10 km$^2$) | 1,958,356 | 83.195 | 7.720 | 64.290 | 92.960 |
| Biodiversity loss (1 km$^2$) | 1,923,215 | 89.553 | 9.015 | 65.040 | 99.850 |
| Heat | 1,907,397 | 30.929 | 3.369 | 24.740 | 38.970 |
| Rain | 1,907,398 | 5.625 | 0.662 | 4.447 | 7.356 |
| Cash | 1,563,105 | 0.321 | 0.344 | 0.000 | 1.000 |
| Interest coverage | 688,083 | 36.484 | 95.273 | -36.322 | 461.536 |
| Ln(total assets) | 1,958,343 | 13.063 | 3.446 | 5.609 | 18.958 |
| Age | 1,958,192 | 15.881 | 15.756 | 1.000 | 67.000 |
| SA index | 1,958,179 | -2.397 | 1.273 | -4.551 | 0.930 |
| FCP index | 604,096 | -23.002 | 83.932 | -266.162 | 248.497 |
| Net profit | 1,900,972 | 0.105 | 0.605 | -1.749 | 2.167 |
| Revenues | 1,612,803 | 2.736 | 4.678 | 0.014 | 25.466 |
| Costs | 1,612,803 | 2.598 | 4.660 | 0.001 | 25.366 |

Note: This table reports the descriptive statistics for the regression variables used in this study. Operating profit, net profit, revenues, costs, and cash are given as ratios to total assets. Costs refer to operating costs. 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 at 10 km$^2$ resolution. Heat is the maximum of daily maximum temperature at 10 km$^2$ resolution. Rain is the Simple Daily Intensity Index at 10 km$^2$ resolution. The observations are annual. The sample period is 2006-2023.

Table 6: Correlation matrix of financial, biodiversity, and climate variables

| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Operating profit | 1 | | | | | | | | | | | | | |
| 2 | Biodiversity loss (10 km$^2$) | -0.052 | 1 | | | | | | | | | | | | |
| 3 | Biodiversity loss (1 km$^2$) | -0.044 | 0.626 | 1 | | | | | | | | | | | |
| 4 | Heat | -0.024 | 0.283 | 0.133 | 1 | | | | | | | | | | |
| 5 | Rain | 0.008 | -0.356 | -0.184 | -0.215 | 1 | | | | | | | | | |
| 6 | Cash | 0.114 | 0.008 | 0.001 | 0.048 | 0.011 | 1 | | | | | | | | |
| 7 | Interest coverage | 0.257 | -0.023 | -0.015 | 0.009 | 0.004 | 0.221 | 1 | | | | | | | |
| 8 | Ln(total assets) | -0.120 | 0.109 | 0.111 | 0.098 | -0.003 | -0.316 | -0.076 | 1 | | | | | | |
| 9 | Age | -0.013 | -0.085 | -0.073 | -0.058 | 0.014 | -0.055 | 0.041 | 0.131 | 1 | | | | | |
| 10 | SA index | -0.070 | 0.152 | 0.138 | 0.131 | -0.014 | -0.196 | -0.093 | 0.735 | -0.521 | 1 | | | | |
| 11 | FCP index | -0.741 | 0.067 | 0.051 | 0.035 | -0.008 | -0.177 | -0.423 | 0.130 | -0.019 | 0.110 | 1 | | | |
| 12 | Net profit | 0.881 | -0.058 | -0.047 | -0.031 | 0.007 | 0.135 | 0.324 | -0.128 | 0.007 | -0.091 | -0.885 | 1 | | |
| 13 | Revenues | 0.163 | -0.061 | -0.031 | -0.047 | -0.001 | 0.195 | 0.092 | -0.406 | -0.043 | -0.280 | -0.159 | 0.158 | 1 | |
| 14 | Costs | -0.024 | -0.053 | -0.024 | -0.044 | -0.002 | 0.177 | 0.047 | -0.388 | -0.041 | -0.271 | -0.030 | -0.001 | 0.978 | 1 |

Note: This table reports the correlation matrix for the variables used in this study. Operating profit, net profit, revenues, costs and cash are given as ratios to total assets. Costs refer to operating costs. 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 at 10 km$^2$ resolution. Heat is the maximum of daily maximum temperature at 10 km$^2$ resolution. Rain is the Simple Daily Intensity Index at 10 km$^2$ resolution. The observations are annual. The sample period is 2006-2023.

Table 7: Effect of local biodiversity loss on SME profitability

| | Operating profit | | | |
|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) |
| Biodiversity loss$_{t-1}$ | -0.0018*** | -0.0010*** | | |
| | (0.000) | (0.000) | | |
| Biodiversity loss$_{t-2}$ | | | -0.0014*** | -0.0010*** |
| | | | (0.000) | (0.000) |
| Ln(total assets)$_{t-1}$ | | -0.0062** | | -0.0068** |
| | | (0.002) | | (0.002) |
| Cash$_{t-1}$ | | -0.0675*** | | -0.0542** |
| | | (0.013) | | (0.019) |
| Interest coverage$_{t-1}$ | | 0.0004*** | | 0.0004*** |
| | | (0.000) | | (0.000) |
| Age$_{t-1}$ | | -0.0003*** | | -0.0003*** |
| | | (0.000) | | (0.000) |
| FCP index dummy$_{t-1}$ | | -0.2006*** | | -0.1979*** |
| | | (0.006) | | (0.006) |
| Constant | 0.1624*** | 0.2523*** | 0.1296*** | 0.2587*** |
| | (0.022) | (0.037) | (0.024) | (0.038) |
| Obs. | 1,560,707 | 532,330 | 1,307,055 | 466,364 |
| Adj. R square | 0.019 | 0.061 | 0.017 | 0.061 |
| 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 the baseline regression (3) estimated by OLS. The dependent variable is operating profit over total assets. Cash is cash plus cash equivalent instruments over 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 at 10 km$^2$ resolution. The observations are annual. The sample period is 2006-2023. Standard errors are double clustered at the firm and year levels and are reported in parentheses. $*$, $**$ and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 8: Transmission channels: effects of biodiversity loss on revenues and operating costs

| | Revenues | Costs |
|---|---|---|
| Variable | (1) | (2) |
| Biodiversity loss$_{t-1}$ | 0.0019 | 0.0027** |
| | (0.001) | (0.001) |
| Cash$_{t-1}$ | 0.6143*** | 0.5960*** |
| | (0.052) | (0.051) |
| Interest coverage$_{t-1}$ | 0.0004*** | -0.0000 |
| | (0.000) | (0.056) |
| Ln(total assets)$_{t-1}$ | -0.3749*** | -0.3546*** |
| | (0.012) | (0.012) |
| Age$_{t-1}$ | -0.0050*** | -0.0046*** |
| | (0.000) | (0.424) |
| FCP index dummy$_{t-1}$ | -0.0242 | 0.1749*** |
| | (0.016) | (0.019) |
| Constant | 7.4197*** | 6.9490*** |
| | (0.221) | (0.213) |
| Obs. | 471,204 | 471,204 |
| Adj. R squared | 0.188 | 0.174 |
| Sector FE | Yes | Yes |
| County FE | Yes | Yes |
| Year FE | Yes | Yes |

Note: This table reports the results for regressions (4) and (5) estimated by OLS. In model (1) the dependent variable is revenues over total assets. In model (2) the dependent variable is operating costs over total assets. Cash is cash plus cash equivalent instruments over 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 at 10 km$^2$ resolution. The observations are annual. The sample period is 2006-2023. Standard errors are double clustered at the firm and year levels and are reported in parentheses. $*$, $**$ and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 9: Heterogeneity by dependency and impact: interactions with ENCORE-based sector classifications

| | Operating profit | | | |
|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) |
| Biodiversity loss$_{t-1}$ | -0.0009*** | -0.0009*** | -0.0009*** | -0.0009*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Biodiversity loss$_{t-1}$ × High dependence | -0.0028** | -0.0026** | | |
| | (0.001) | (0.001) | | |
| Biodiversity loss$_{t-1}$ × High impact | | | -0.0005 | -0.0003 |
| | | | (0.000) | (0.000) |
| Cash$_{t-1}$ | -0.0674*** | -0.0674*** | -0.0676*** | -0.0675*** |
| | (0.019) | (0.019) | (0.019) | (0.019) |
| Interest coverage$_{t-1}$ | 0.0004*** | 0.0004*** | 0.0004*** | 0.0004*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Ln(total assets)$_{t-1}$ | -0.0063** | -0.0063** | -0.0063** | -0.0063** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Age$_{t-1}$ | -0.0003*** | -0.0003*** | -0.0003*** | -0.0003*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| FCP index dummy$_{t-1}$ | -0.2006*** | -0.2006*** | -0.2006*** | -0.2007*** |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| Constant | 0.2518*** | 0.2516*** | 0.2521*** | 0.2521*** |
| | (0.037) | (0.037) | (0.037) | (0.037) |
| Obs. | 532,330 | 532,330 | 532,330 | 532,330 |
| Adj. R squared | 0.061 | 0.061 | 0.061 | 0.061 |
| 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 regressions (3), including the interaction term between biodiversity loss and the High dependence dummy and the interaction term between biodiversity loss and the High impact dummy, estimated by OLS. The dependent variable is operating profit over total assets. The variables *High dependence* and *High impact* are constructed using ENCORE. In models (1) and (3), we use the Average dependency/impact score, with the dummy variable equal to 1 when the average score is at least 2 (medium dependency/impact). In models (2) and (4), we use the Count dependency/impact score, with the dummy variable equal to 1 when the count is at least 8 for ecosystem services and 4 for impact drivers (corresponding to one third of the total), respectively. Cash is cash plus cash equivalent instruments over 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 at 10 km$^2$ resolution. The observations are annual. The sample period is 2006-2023. Standard errors are double clustered at the firm and year levels and are reported in parentheses. $*$, $**$ and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 10: Firm size heterogeneity: impact of biodiversity loss on micro firms

| | Operating profit |
|---|---|
| Variable | (1) |
| Biodiversity loss$_{t-1}$ | -0.0009*** |
| | (0.000) |
| Biodiversity loss$_{t-1}$ × Micro | -0.0008*** |
| | (0.000) |
| Cash$_{t-1}$ | -0.0622*** |
| | (0.019) |
| Interest coverage$_{t-1}$ | 0.0004*** |
| | (0.000) |
| Ln(total assets)$_{t-1}$ | -0.0136*** |
| | (0.002) |
| Age$_{t-1}$ | -0.0004*** |
| | (0.000) |
| FCP index dummy$_{t-1}$ | -0.1994*** |
| | (0.006) |
| Constant | 0.3685*** |
| | (0.029) |
| Obs. | 532,330 |
| Adj. R squared | 0.063 |
| Sector FE | Yes |
| County FE | Yes |
| Year FE | Yes |

Note: This table reports the results for regressions (3) including the interaction term between biodiversity loss and the dummy identifying micro firms, estimated by OLS. The dependent variable is operating profit over total assets. Cash is cash plus cash equivalent instruments over 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 at 10 km$^2$ resolution. Micro is a dummy variable indicating whether the SME is a micro firm. The observations are annual. The sample period is 2006-2023. Standard errors are double clustered at the firm and year levels and are reported in parentheses. $*$, $**$ and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 11: First-stage results: instruments for local biodiversity loss (wildfires and dry days)

| | Biodiversity loss | | | |
|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) |
| $WF_{t-1}$ | -1.3030*** | | -1.2797*** | 0.1086 |
| | (0.380) | | (0.377) | (0.494) |
| $CDD_{t-1}$ | | 0.0464*** | 0.0436*** | 0.0447*** |
| | | (0.014) | (0.013) | (0.013) |
| $WF_{t-1} \times CDD_{t-1}$ | | | | -0.0677*** |
| | | | | (0.011) |
| $Cash_{t-1}$ | 0.2829*** | 0.3070*** | 0.3151*** | 0.3145*** |
| | (0.078) | (0.080) | (0.080) | (0.080) |
| Interest $coverage_{t-1}$ | -0.0003** | -0.0003** | -0.0003** | -0.0003** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| $Ln(total\ assets)_{t-1}$ | 0.1373*** | 0.1376*** | 0.1383*** | 0.1384*** |
| | (0.010) | (0.011) | (0.011) | (0.011) |
| $Age_{t-1}$ | -0.0073*** | -0.0069*** | -0.0068*** | -0.0068*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| FCP index $dummy_{t-1}$ | 0.2178*** | 0.2196*** | 0.2191*** | 0.2184*** |
| | (0.028) | (0.029) | (0.029) | (0.029) |
| Constant | 81.4193*** | 80.4277*** | 80.5022*** | 80.4777*** |
| | (0.168) | (0.391) | (0.380) | (0.379) |
| Obs. | 532,330 | 520,528 | 520,528 | 520,528 |
| Adj. R squared | 0.598 | 0.601 | 0.601 | 0.601 |
| Sector FE | Yes | Yes | Yes | Yes |
| County FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

Note: This table reports the results of the first stage for the baseline regression (3) estimated by 2SLS. WF is the number of wildfires within 10 km where the SME operates. CDD is the number of consecutive dry days as a proxy for droughts. In model (1) the instrument is WF. In model (2) the instrument is CDD. In model (3) the instruments are WF and CDD. In model (4) the instruments are WF, CDD, and WF×CDD. The dependent variable is biodiversity loss. Cash is cash plus cash equivalent instruments over 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 at 10 $km^2$ resolution. The observations are annual. The sample period is 2006-2023. Standard errors are double clustered at the firm and year levels and are reported in parentheses. $*$, $**$ and $***$ denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 12: Instrumental-variables estimates: causal effect of biodiversity loss on SME profitability

| | Operating profit | | | |
|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) |
| Biodiversity loss$_{t-1}$ | -0.0057** | -0.0104** | -0.0069*** | -0.0058*** |
| | (0.002) | (0.004) | (0.001) | (0.001) |
| Cash$_{t-1}$ | -0.0662*** | -0.0629*** | -0.0639*** | -0.0643*** |
| | (0.019) | (0.019) | (0.019) | (0.019) |
| Interest coverage$_{t-1}$ | 0.0004*** | 0.0004*** | 0.0004*** | 0.0004*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Ln(total assets)$_{t-1}$ | -0.0056** | -0.0049* | -0.0054** | -0.0056** |
| | (0.002) | (0.002) | (0.002) | (0.002) |
| Age$_{t-1}$ | -0.0004*** | -0.0004*** | -0.0004*** | -0.0004*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| FCP index dummy$_{t-1}$ | -0.1996*** | -0.1989*** | -0.1997*** | -0.1999*** |
| | (0.006) | (0.006) | (0.006) | (0.006) |
| Obs. | 532,330 | 520,528 | 520,528 | 520,528 |
| R squared | 0.045 | 0.038 | 0.044 | 0.045 |
| Sector FE | Yes | Yes | Yes | Yes |
| County FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Instrument | WF | CDD | WF, CDD | WF, CDD |
| | | | | WF × CDD |
| Kleibergen-Paap LM stat | 3.574* | 9.571*** | 9.572*** | 10.548** |
| Kleibergen-Paap F stat | 11.760 | 11.528 | 13.915 | 32.266 |
| Stock-Yogo 10 % crit. Val. | 16.380 | 16.380 | 19.930 | 22.300 |
| Hansen J stat | | | 1.140 | 2.901 |

Note: This table reports the results of the second stage for the baseline regression (3) estimated by 2SLS. WF is the number of wildfires within 10 km where the SME operates. CDD is the number of consecutive dry days as a proxy for droughts. In model (1) the instrument is WF. In model (2) the instrument is CDD. In model (3) the instruments are WF and CDD. In model (4) the instruments are WF, CDD, and WF×CDD. The dependent variable is operating profit over total assets. Cash is cash plus cash equivalent instruments 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 at 10 km$^2$ resolution. 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 10%, 5% and 1% levels, respectively.

Table 13: Spatial resolution test: 1 km$^2$ biodiversity measure

| | Operating profit | Revenues | Costs |
|---|---|---|---|
| Variable | (1) | (2) | (3) |
| Biodiversity loss$_{t-1}$ | -0.0007*** | 0.0072*** | 0.0078*** |
| | (0.000) | (0.001) | (0.001) |
| Cash$_{t-1}$ | -0.0671*** | 0.6050*** | 0.5873*** |
| | (0.019) | (0.052) | (0.052) |
| Interest coverage$_{t-1}$ | 0.0004*** | 0.0004*** | 0.0000 |
| | (0.000) | (0.000) | (0.000) |
| Ln(total assets)$_{t-1}$ | -0.0064** | -0.3777*** | -0.3573*** |
| | (0.002) | (0.012) | (0.011) |
| Age$_{t-1}$ | -0.0003*** | -0.0048*** | -0.0044*** |
| | (0.000) | (0.000) | (0.000) |
| FCP index dummy$_{t-1}$ | -0.2015*** | -0.0253 | 0.1735*** |
| | (0.006) | (0.016) | (0.019) |
| Constant | 0.2398*** | 6.9710*** | 6.5130*** |
| | (0.033) | (0.186) | (0.185) |
| Obs. | 523,801 | 463,538 | 463,538 |
| Adj. R squared | 0.062 | 0.188 | 0.174 |
| Sector FE | Yes | Yes | Yes |
| County FE | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes |

Note: This table reports the results for the baseline regression (3) estimated by OLS. In model (1) the dependent variable is Operating profit over total assets. In model (2) the dependent variable is revenues over total assets. In model (3) the dependent variable is operating costs over total assets. Cash is cash plus cash equivalent instruments over 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 at 1 km$^2$ resolution. 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 10%, 5% and 1% levels, respectively.

Table 14: Robustness to climate risk: heat and rain controls in profitability

| | Operating profit | | | |
|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) |
| Biodiversity loss$_{t-1}$ | -0.0022*** | -0.0024*** | -0.0024*** | -0.0010*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Heat$_{t-1}$ | 0.0028 | | 0.0020 | 0.0008 |
| | (0.004) | | (0.004) | (0.001) |
| Rain$_{t-1}$ | | -0.0170** | -0.0156** | 0.0020 |
| | | (0.006) | (0.007) | (0.003) |
| Cash$_{t-1}$ | | | | -0.0658*** |
| | | | | (0.019) |
| Interest coverage$_{t-1}$ | | | | 0.0004*** |
| | | | | (0.000) |
| Ln(total assets)$_{t-1}$ | | | | -0.0063** |
| | | | | (0.002) |
| Age$_{t-1}$ | | | | -0.0003*** |
| | | | | (0.000) |
| FCP index dummy$_{t-1}$ | | | | -0.2010*** |
| | | | | (0.006) |
| Constant | 0.1082 | 0.3077*** | 0.2414 | 0.2195*** |
| | (0.114) | (0.046) | (0.143) | (0.040) |
| Obs. | 1,520,018 | 1,520,018 | 1,520,018 | 520,528 |
| Adj. R squared | 0.018 | 0.018 | 0.018 | 0.061 |
| 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 (3), including climate variables, estimated by OLS. The dependent variable is operating profit over total assets. Cash is cash plus cash equivalents over 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 at 10 km$^2$ resolution. Heat is the maximum of daily maximum temperature at 10 km$^2$ resolution. Rain is the Simple Daily Intensity Index at 10 km$^2$ resolution. 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 10%, 5% and 1% levels, respectively.

Table 15: Biodiversity quartiles, low and high biodiversity loss areas, and exclusion of large urban centres

| | Operating profit | | | | |
|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) |
| Biodiversity loss quartiles | | | | | |
| 2nd | -0.0050* | | | | |
| | (0.003) | | | | |
| 3rd | -0.0111*** | | | | |
| | (0.003) | | | | |
| 4th | -0.0300*** | | | | |
| | (0.006) | | | | |
| Biodiversity loss$_{t-1}$ | | -0.0028*** | -0.0004 | -0.0007*** | -0.0005*** |
| | | (0.001) | (0.000) | (0.000) | (0.000) |
| Cash$_{t-1}$ | -0.0677*** | -0.0618*** | -0.0735** | -0.0647** | -0.0634** |
| | (0.019) | (0.019) | (0.026) | (0.025) | (0.026) |
| Interest coverage$_{t-1}$ | 0.0004*** | 0.0004*** | 0.0004*** | 0.0004*** | 0.0004*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Ln(total assets)$_{t-1}$ | -0.0062** | -0.0001 | -0.0142*** | -0.0127*** | -0.0133*** |
| | (0.002) | (0.002) | (0.003) | (0.002) | (0.002) |
| Age$_{t-1}$ | -0.0003*** | -0.0002*** | -0.0004*** | -0.0004*** | -0.0005*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| FCP index dummy$_{t-1}$ | -0.2005*** | -0.2047*** | -0.1914*** | -0.1915*** | -0.1903*** |
| | (0.006) | (0.007) | (0.007) | (0.007) | (0.007) |
| Constant | 0.1823*** | 0.3146*** | 0.3322*** | 0.3366*** | 0.3311*** |
| | (0.035) | (0.092) | (0.043) | (0.037) | (0.036) |
| Obs. | 532,220 | 313,804 | 218,522 | 402,658 | 379,933 |
| Adj. R squared | 0.061 | 0.062 | 0.062 | 0.061 | 0.061 |
| Sector FE | Yes | Yes | Yes | Yes | Yes |
| County FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| London | Yes | Yes | Yes | No | No |
| Birmingham | Yes | Yes | Yes | Yes | No |
| Manchester | Yes | Yes | Yes | Yes | No |

Note: This table reports the results for the baseline regression (3) and the alternative specification of regression (3), including firm quartile dummies based on biodiversity loss, estimated by OLS. The dependent variable is operating profit over total assets. 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 or equal to the average value. In model (3) we include only firms operating in areas with a biodiversity loss lower than the average value. In model (4) we exclude London from the sample. In model (5) we exclude London, Birmingham, and Manchester from the sample. Cash is cash plus cash equivalent instruments over 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 at 10 km$^2$ resolution. 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 10%, 5% and 1% levels, respectively.

Table 16: Robustness: sample period, competition controls, and alternative profitability measure

| | Operating profit | | | Net profit |
|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) |
| Biodiversity loss$_{t-1}$ | -0.0009*** | -0.0012*** | -0.0011*** | -0.0007*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Cash$_{t-1}$ | -0.0693*** | -0.0623*** | -0.0691*** | 0.0031 |
| | (0.023) | (0.019) | (0.019) | (0.006) |
| Interest coverage$_{t-1}$ | 0.0004*** | 0.0006*** | 0.0004*** | 0.0004*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Ln(total assets)$_{t-1}$ | -0.0072** | -0.0014 | -0.0067*** | -0.0149*** |
| | (0.002) | (0.003) | (0.002) | (0.001) |
| Age$_{t-1}$ | -0.0004*** | -0.0000 | -0.0003*** | -0.0001** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| FCP index dummy$_{t-1}$ | -0.1987*** | | -0.2017*** | -0.1914*** |
| | (0.007) | | (0.007) | (0.006) |
| SA index dummy$_{t-1}$ | | 0.0003 | | |
| | | (0.006) | | |
| Number of competitors$_{t-1}$ | | | -0.0000*** | |
| | | | (0.000) | |
| Constant | 0.2633*** | 0.1438*** | 0.2719*** | 0.3543*** |
| | (0.039) | (0.046) | (0.036) | (0.026) |
| Obs. | 457,513 | 532,330 | 532,330 | 526,542 |
| Adj. R squared | 0.061 | 0.031 | 0.061 | 0.107 |
| Sector FE | Yes | Yes | Yes | Yes |
| County FE | Yes | Yes | No | No |
| Country FE | No | No | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |

Note: This table reports the results for the baseline regression (3) estimated by OLS. In model (1) the sample period is 2006-2021. In model (2) we use the SA index as a measure of financial constraint. In model (3) we control for country fixed effects and the number of firms per sector in the same county. In model (4) the dependent variable is net income over total assets. In models (1), (2) and (3) the dependent variable is operating profit over total assets. Cash is cash plus cash equivalents over 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 at 10 km$^2$ resolution. 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 10%, 5% and 1% levels, respectively.

# Figures

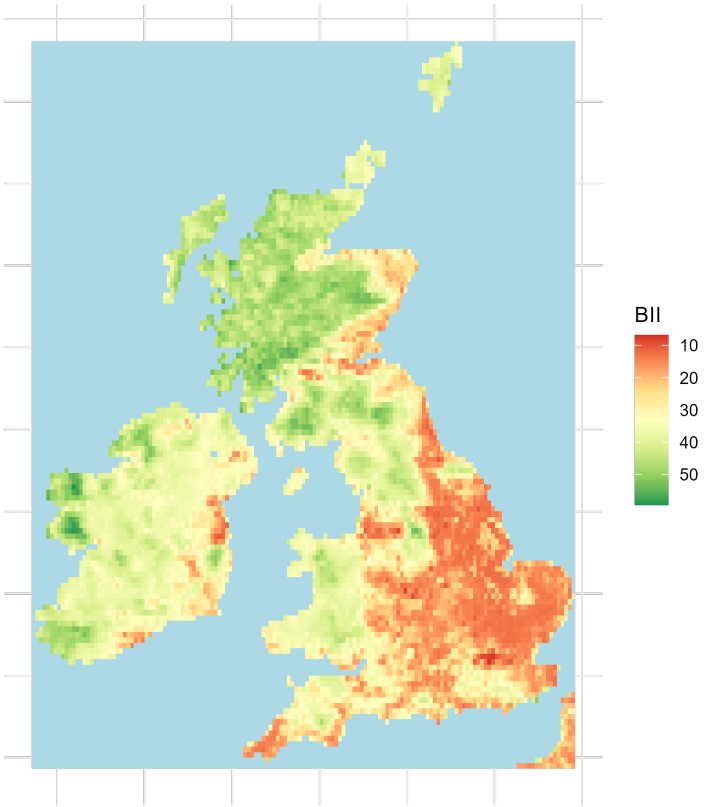



Figure 1: Biodiversity Intactness Index for the UK and Ireland

Note: This figure presents the Biodiversity Intactness Index (BII), developed by the Natural History Museum, for the UK and Ireland, in 2021. Data are at 10 $km^2$ resolution. A higher value of the Index denotes lower biodiversity loss.

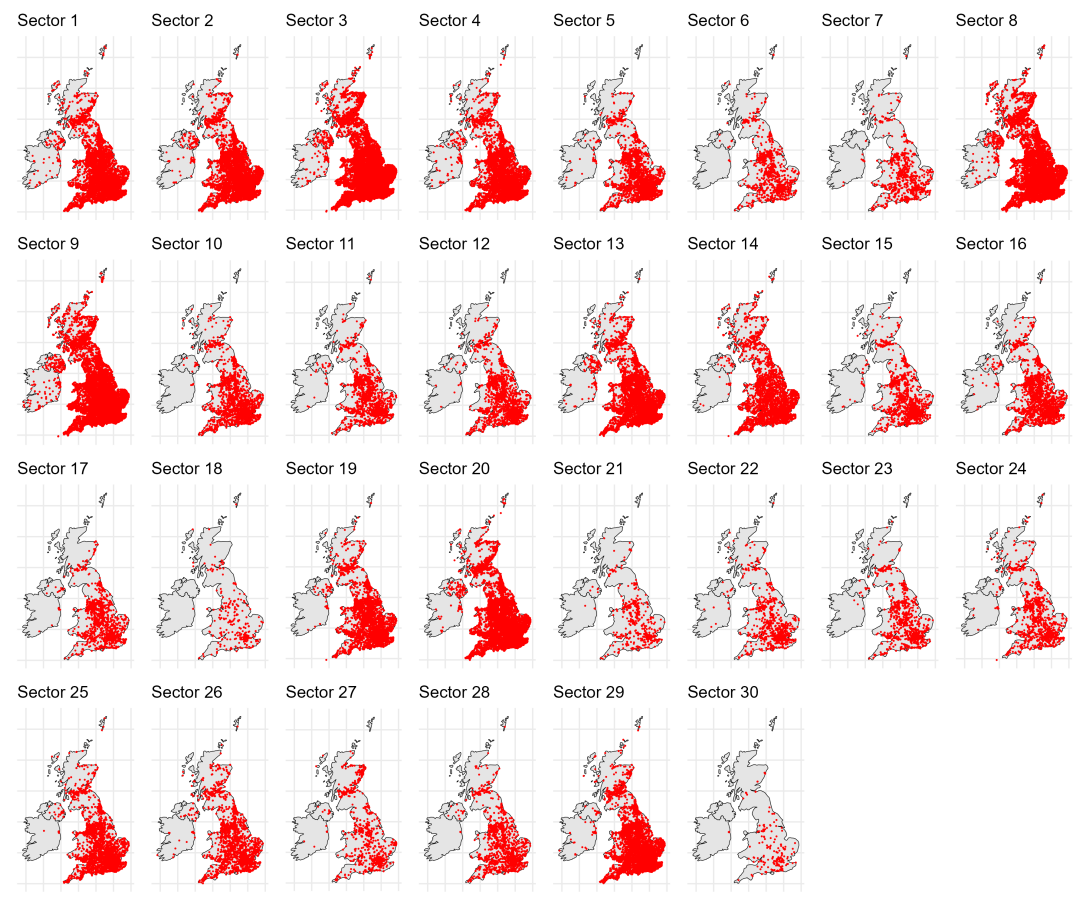



Figure 2: Location of SMEs by sector

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;

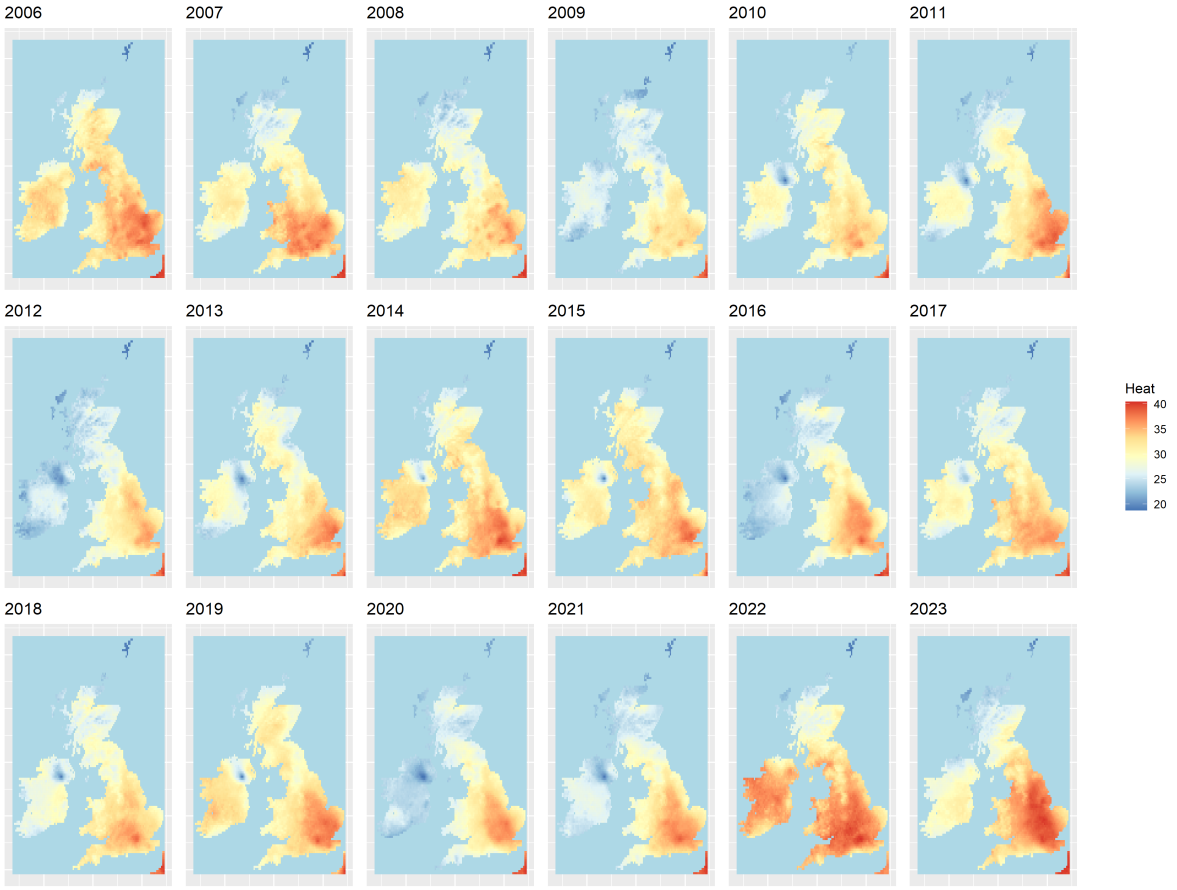



Figure 3: Heat index for the UK and Ireland

Note: This figure presents the maximum of daily maximum temperature for the UK and Ireland. Temperature is expressed in degrees Celsius (°C). The period spans from 2006 to 2023. Data are at 10 $km^2$ resolution. Source: E-OBS.

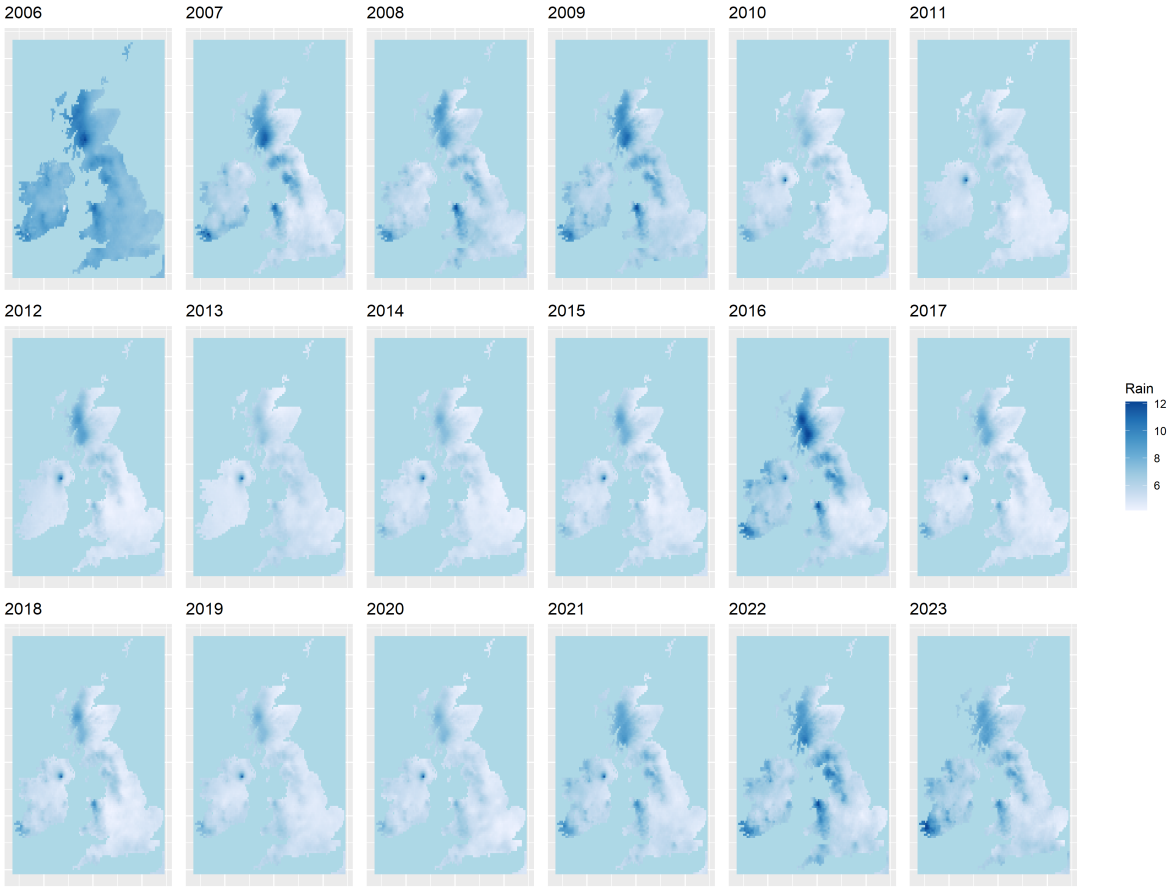



Figure 4: Rain index for the UK and Ireland

Note: This figure presents the Simple Daily Intensity Index, or average rainfall rate, for the UK and Ireland. The index is expressed in millimetres per day. The period spans from 2006 to 2023. Data are at 10 km$^2$ resolution. Source: E-OBS.