Biodiversity Externality Costs Through Supply Chain: A Pass-Through Input-Output Framework for Biodiversity Financial Impact Assessment*

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Abstract

Transition biodiversity risk is increasingly recognised as a source of financial risk, yet no framework exists to translate firm-level biodiversity impacts into credit risk metrics comparable to those developed for climate transition risk or even biodiversity dependency risk. This paper fills that gap by adapting the cost pass-through input-output methodology, established in the climate transition risk literature to biodiversity. We construct country- and sector-level biodiversity impact intensities across six pressure categories using Exiobase 3 and LC-IMPACT characterisation factors, monetise them using willingness-to-pay externality costs, and propagate the resulting cost shock through the supply chain via sector-specific pass-through rates. The propagated cost is mapped to firm-level probability of default through a Merton structural model, applied to the STOXX Europe 600. Results show that indirect supply-chain exposure dominates direct exposure by more than two to one

*The views expressed here are those of the authors and do not necessarily represent those of the European Investment Bank.

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and that land use and water consumption are the primary financial risk drivers. Weighted-average probability of default rises from 0.17% to 2.05% under the central scenario. Impacts are concentrated across a small number of firms and impact channels, with land use and climate change accounting for most of the impact. Externality cost estimates and pass-through calibration are the dominant sources of methodological uncertainty, each requiring explicit assumptions that are difficult to standardise across scenarios. In aggregate, biodiversity scenario design involves a fundamental trade-off between flexibility and supervisory comparability, one that pre-competitive collaboration can help address.

JEL classification codes: C67, G32, Q51, Q57

Keywords: Biodiversity transition risk; Cost pass-through; Input-output analysis; Credit risk

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1 Introduction

Although the economic costs of biodiversity loss are estimated to exceed those of climate change by a factor of two, policy and regulatory responses remain less developed than for climate change (van 't Klooster and Prodani, 2025; Ranger and Oliver, 2024). But regulation is recently catching up. The Corporate Sustainability Reporting Directive (European Parliament and Council of the European Union, 2022) requiring companies to disclose material biodiversity impacts, and the European Banking Authority (2025) guidelines requiring banks to assess financial resilience to environmental risks, including biodiversity. Together, these reflect a growing recognition among regulators that nature-related risk is material to both financial stability and nature recovery. The methodology to support these requirements, however, lags far behind what exists for climate.

This methodological gap is not uniform across the literature. Although microeconomic impact approaches already exist on the dependency side, applying different approaches (Crisóstomo, 2025; Gallet et al., 2024, 2026; Ranger and Oliver, 2024), on the transition side, the literature is split in different approaches to quantify biodiversity risk. Kulionis et al. (2024) and Ceglar et al. (2025) assess corporate exposure through footprint attribution, while Prodani et al. (2023) model biodiversity transition risk through a computable general equilibrium framework at the macroeconomic level. However, to the best of our knowledge, existing work has remained largely confined to dependency and impact assessment based on environmental footprints, without extending to the pricing of biodiversity-related transition risk at the micro-level. Nevertheless, this kind of micro-level cost pricing is well established for climate transition risk. Several authors (Guth et al., 2021; Mardones and Mena, 2020; Mardones, 2025; Pineau and Zuñiga, 2024; Roncalli and Semet, 2024) model how a carbon price propagates through supply chains. Bouchet and Le Guenedal (2020) extend this propagated cost into credit risk metrics through a structural default model.

By combining methods for measuring the biodiversity footprint with the methodologies for quantifying and projecting impacts used in climate research, we construct country- and sector-level biodiversity impact intensities across six pressure categories,

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monetise them using willingness-to-pay-based externality costs, and propagate the resulting cost shock through the supply chain using sector-specific pass-through rates. The propagated cost is mapped to firm-level credit risk via a Merton structural default model.

As main results, we find that land use dominates the aggregate footprint but propagates a limited share of its cost, since the sectors where it concentrates have below-average pass-through capacity; climate change generates a smaller footprint but propagates broader. In the European portfolio sample, aggregate indirect exposure exceeds direct exposure by more than two to one, in line with the dominance of manufacturing and services in the Index and confirming that footprint-only analysis understates firm-level financial risk. Results are robust to the pass-through calibration and largely insensitive to current range externality cost assumptions.

Applied to a sample of 484 STOXX Europe 600 constituents, the framework shows that aggregate weighted-average PD rises from 0.17% to 2.05% under the central scenario, with the impact highly concentrated: Materials and Health Care reach scenario PDs of 9.35% and 3.16% respectively, while median PDs remain far lower (0.39% and 0.97%), reflecting within-sector concentration rather than broad-based exposure. Indirect supply-chain exposure is the dominant channel for most portfolio firms, with land use indirect averaging 6.7% of sectoral output across the sample. These results confirm that firm-level supply-chain structure, not sector classification, is the primary determinant of biodiversity transition risk at the portfolio level.

The results carry direct implications for regulators and supervisors. The imperfect correlation between footprint magnitude and financial materiality cautions against frameworks that treat footprint as a proxy for risk. Risk concentration within sectors argues for targeted firm-level engagement. Pass-through assumptions should be treated as an explicit scenario parameter since the nature of the shock affects cost propagation as much as the underlying impact intensity. All of the above entail a trade-off between methodological flexibility and cross-institutional comparability, which pre-competitive collaboration and shared analytical infrastructure can help manage.

The rest of the paper is structured as follows. Section 2 provides a literature review

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of relevant publications in this field. Section 3 presents the methods used. Section 4 describes the data and discusses the empirical results. Finally, Section 5 concludes.

2 Literature Review

Interest in the biodiversity footprint of economic activity has grown substantially over the past decade, driven by mounting evidence that biodiversity loss is both economically material and financially relevant. The adoption of the Kunming-Montreal Global Biodiversity Framework in 2022 (CBD, 2022) has intensified regulatory scrutiny of biodiversity-related financial risks and placed them firmly on the agenda of supervisors and financial institutions. From a macroeconomic perspective, Ranger and Oliver (2024) estimate that biodiversity loss alone could reduce UK GDP by 6%, while with a microeconomic approach Crisóstomo (2025) finds that global equities could lose an average of 26.8%. These aggregate estimates motivate a growing literature seeking to measure, attribute, and ultimately price biodiversity-related risks at the sector and firm level. Gallet et al. (2024, 2026), using a proxy scenario, find that granular impacts allow for better nature-related financial stability assessments.

Financial institutions are exposed to nature-related financial risks through two primary channels. The first is physical risk, which arises from the economic dependency of counterparties on ecosystem services (Dasgupta, 2021). The second is transition risk, stemming from regulatory interventions, policy shifts and market shifts as economies adjust towards nature-positive outcomes (Dasgupta, 2021). Both channels materialise at the portfolio level, meaning that a bank's financial exposure to biodiversity loss is ultimately determined by the economic activities it finances. Quantifying the exposure, however, requires methods capable of tracing biodiversity impacts through supply chain linkages.

Early contributions to the financial exposure literature rely on spatial assessment of protected areas to define transition risk, overlapping between economic activities and biodiversity-sensitive areas. van Toor et al. (2020) find that the biodiversity footprint

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of Dutch financial institutions is equivalent to the loss of over 58.000 km^2 of pristine nature, and Svartzman et al. (2021), extended in Hadji-Lazaro et al. (2024), report 130.000 km^2 annually for French institutions and further showing that while the most biodiversity-damaging firms operate in agriculture, forestry, and mining; food processing, chemicals, and construction contribute substantially through their supply chains. Bank and Malaysia (2022) find that up to 38% of loans may be exposed to biodiversity transition risk, a figure mirrored by Calice et al. (2021) for Brazilian banks. Broer et al. (2021) identify climate change and land use as the primary drivers of the MSCI World biodiversity footprint. While this stream of literature offers a tractable first approximation, it is limited to current or projected protected area boundaries.

There has however been a shift to the methodological approach to expand to synthetic metrics. The use of biodiversity characterisation factors — typically expressed as potentially disappeared fractions of species (PDF) or mean species abundance (MSA) — represents a methodological advancement by enabling the transition from purely spatial exposure assessment to impact-oriented assessment, translating environmental pressures into comparable biodiversity impact metrics improving comparability across activities and regions. Kulionis et al. (2024) apply this approach at the company level using a life-cycle assessment (LCA) approach linked to Multi-Regional Input-Output (MRIO) data, finding that land use dominates biodiversity impact, followed by climate change and water stress. Ceglar et al. (2025) apply a similar framework to the euro area banking system, finding that 100 out of 2,500 banks are responsible for 87% of the total biodiversity footprint through their lending.

However, due to the relative lack of clarity in biodiversity policy pathways, existing studies rely either in environmental footprints or ad hoc scenario definitions to characterise the exposure but do not elicit the impact for companies or sectors. Translating environmental risk into firm-level financial impact is a well-established feature of climate transition risk research (Reinders et al., 2023; Guth et al., 2021; Mardones, 2025; Mardones and Mena, 2020; Pineau and Zuñiga, 2024; Roncalli and Semet, 2024; Vermeulen et al., 2018) but has not been applied to biodiversity. While footprint analysis provides

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a comprehensive view of the total impact embodied in economic activity, the Leontief-based footprint approach attributes the entire upstream impact to final demand it does not model how the financial cost of internalising that impact would distribute across firms along the value chain if biodiversity externalities were priced. As van 't Klooster and Prodani (2025) note, the absence of a standardised metric linking firm-level activity to biodiversity loss makes it difficult to quantify biodiversity transition risk in a manner comparable to climate risk.

Notably, one forward-looking study has attempted to quantify the financial impact of biodiversity policy scenarios. Prodani et al. (2023), using a computable general equilibrium model, simulates scenarios including half-Earth area protection, a deforestation tax, and pollination decline, finding impacts on bank capital ratios of 5–30 basis points — substantially below climate stress results. Although this does not model how the financial cost of internalising that impact would distribute along the value chain under a pricing mechanism.

Despite the lack of maturity in measuring biodiversity transition risk and regulatory frameworks, financial markets are already beginning to price biodiversity-related risks. Following the Kunming Declaration, Garel et al. (2023) identify a biodiversity footprint premium in a global cross-sector sample, and Coqueret et al. (2025) document a biodiversity risk premium in the United States concentrated in high-impact sectors. Guidolin and Pedio (2026) find that high-biodiversity-impact commodities carry risk premiums but suffered abnormal losses after Kunming, and Visentin (2026) shows that investors are beginning to demand a premium from firms exposed to biodiversity's double materiality. Giglio et al. (2023), using textual analysis, find that portfolio returns rise with growing biodiversity risk exposure, though these risks appear underpriced. Hirschbühl et al. (2024) find evidence of adjustment at the bank level, with institutions reducing loan-to-value ratios in response to biodiversity-related pollution risks. Together, these findings suggest that markets and financial institutions are responding to biodiversity risk even in the absence of a standardised metric or frameworks.

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3 Methods

Companies that impact ecosystems and biodiversity face both transition and reputational risks, analogous to the transition and physical risks of climate change (van Toor et al., 2020). As discussed in Section 2, while some frameworks have begun to translate nature-related risks into firm-level financial costs (Crisóstomo, 2025; Gallet et al., 2024, 2026), no equivalent approach exists for the impact side.

We address this gap in four steps. First, we construct country- and sector-level biodiversity impact intensities using an environmentally extended MRIO framework following Kulionis et al. (2024). Second, we monetise these impacts using externality cost estimates from CE Delft (2024). Third, we propagate the resulting cost shock through the supply chain using a cost pass-through input-output model with sector-specific pass-through rates, following Roncalli and Semet (2024). Fourth, we translate the propagated costs into firm-level financial impact measures relevant for credit risk assessment, following Bouchet and Le Guenedal (2020).

This approach treats biodiversity loss as a shadow price applied uniformly across all impacting activities, rather than modelling specific policy interventions or area-based restrictions. It is therefore more closely analogous to carbon pricing frameworks (Guth et al., 2021; Mardones and Mena, 2020; Pineau and Zuñiga, 2024; Roncalli and Semet, 2024) than to the CGE-based scenario analysis of Prodani et al. (2023), and is particularly suited to shorter-term transition risk assessments where sector-level cost propagation is more tractable than macroeconomic general equilibrium adjustment.

3.1 Biodiversity footprint intensity

Our analysis begins by estimating country- and sector-level biodiversity impact intensities using Environmentally Extended Multi-Regional Input- Output (EEMRIO) data (Kulionis et al., 2024; Leontief, 1970; Miller and Blair, 2021). While ecosystem losses are often quantified using MSA (Ceglar et al., 2025; Coqueret et al., 2025; Garel et al., 2023; Hadji-Lazaro et al., 2024; Kok and Alkemade, 2014), LCA methods standardize biodiver-

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sity impact through PDF (Crenna et al., 2020). We employ PDF characterization factors from Verones et al. (2020). This approach enables us to address six pressure categories: climate change (CC), land use (LU), terrestrial acidification (TA), water consumption (WC), freshwater eutrophication (FE), and marine eutrophication (ME).

For all the different pressure factors, biodiversity impact intensities are constructed by combining the characterisation factor matrix B, which maps physical pressures into PDF·yr, with the stressor matrix F from the EEMRIO system, normalised by monetary output x. This yields the direct biodiversity impact intensity matrix:

$$S_i = B \circ F\hat{x}^{-1} \tag{1}$$

where S_i represents the direct biodiversity impact per million euros of sectoral output (PDF·yr / M€) for each pressure category i. The incorporation of indirect, supply-chain-embedded impacts is addressed through the cost pass-through framework developed in Section 3.3.

3.2 Externality cost

Biodiversity transition risks arise when economic actors fail to align with efforts to protect, restore, or reduce harm to nature, driven by shifts in regulation, technology, or consumer and investor preferences (Prodani et al., 2023; NGFS, 2023). Translating the PDF-based impact intensity into a financial measure requires a shadow price for biodiversity loss. In practice, no such price exists: biodiversity lacks a market, damage-cost estimates remain highly uncertain, and valuation methods differ substantially. We follow CE Delft (2024) in adopting externality cost estimates based on willingness-to-pay (WTP). WTP-based valuation carries two offsetting biases: it holds production technology fixed, ignoring firms' capacity to adapt processes, which overstates costs; and it reflects perceived rather than productive value of ecosystems, which understates them. We treat WTP-based valuation as the best available proxy, with the net direction of this bias left unresolved.

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CE Delft (2024) express this valuation per unit of species per year rather than per unit of PDF directly. Converting our PDF-based intensities into this metric requires multiplying PDF by the species count implicit in the underlying ReCiPe characterisation (Goedkoop et al., 2008). We assign each pressure category to a realm following the taxonomic coverage reported in Verones et al. (2020) and apply the corresponding realm-specific valuation per species per year. This yields the monetised biodiversity impact:

$$\varepsilon_{i,s} = S_i \cdot N_{r(i)} \cdot \lambda_{s,r(i)} \tag{2}$$

where $N_{r(i)}$ is the ReCiPe species count for the realm $r(i)$ assigned to category i, $\lambda_{s,r(i)}$ represents the externality cost under scenario s (€ / species·yr), so that ε_s gives the biodiversity externality for pressure category i under scenario s (€ / M€) at country and sector level.

Since the CE Delft (2024) estimates reflect European WTP, applying them uniformly across all regions would overstate the monetary burden in lower-income countries, where the same nominal cost represents a proportionally larger real burden relative to local price levels. We therefore apply a purchasing power parity correction following Feenstra et al. (2015), scaling λ_s to local price levels before monetisation. The adjusted externality cost remains expressed in euros but reflects the biodiversity cost in local economic terms, ensuring comparability across the 49 regions covered by the EEMRIO system.

To the best of our knowledge, the CE Delft (2024) WTP-based estimates represent the best currently available monetisation at the required scale. The framework is nonetheless designed to accommodate more refined cost estimates as biodiversity shadow pricing methods mature. A sensitivity analysis further contextualises the uncertainty inherent in this choice.

3.3 Cost pass-through

For several sectors, biodiversity financial impacts materialise primarily through supply chain linkages (Visentin, 2026), yet firms differ substantially in their ability to pass cost

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increases forward to buyers. While exposure-based studies such as Kulionis et al. (2024) and Ceglar et al. (2025) account for the full embodied footprint using the standard Leontief inverse, this approach attributes the entire upstream impact to final demand, effectively counting the same exposure multiple times at different points in the value chain. This is appropriate for footprint accounting but does not reflect how costs would actually distribute across firms if biodiversity externalities were priced.

We therefore build on Roncalli and Semet (2024), who introduced a cost-push pass-through mechanism to model the cascading price effects of a carbon tax through the supply chain, and extend it to the case of biodiversity externality costs. A diagonal pass-through matrix $\Theta = \text{diag}(\theta)$ is defined, where each element $\theta_j \in [0, 1]$ represents the fraction of a cost shock in sector j transmitted forward to its buyers, with the complement θ_j absorbed internally. The portion of the biodiversity externality cost borne directly by each sector is then:

$$\varepsilon_s^{direct} = (I - \Theta)\varepsilon_s \tag{3}$$

The propagation of residual cost shocks through the supply chain follows a recursive structure: at each tier, a sector passes a fraction θ_j of its cost increase forward while retaining the rest. Summing across all tiers yields the total cost-push impact under partial pass-through:

$$\varepsilon_s^{indirect} = (I - A^\top \Theta)^{-1} \Theta \varepsilon_s \tag{4}$$

Following Adenot et al. (2022), we assume that input proportions remain fixed and that the monetary value of trade is unaffected by the introduction of the externality cost, consistent with the standard cost-push input-output framework. Pass-through rates θ_j are calibrated at the sector level, reflecting observed differences in market power and pricing behaviour across industries. Given the limited availability of sector-specific pass-through estimates for biodiversity costs, this approach contrast with the one used in footprint exposure literature (Ceglar et al., 2025; Kulionis et al., 2024). These consider the entire footprint generated throughout the supply chain, counting the same exposure multiple times at different points in the value chain for different activities.

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No global dataset of sector-level price elasticities at consistent sectoral disaggregation currently exists, so for most sectors we derive θ_j from the own-price elasticities reported by Guth et al. (2021), who estimate these across all NACE sectors in the context of a carbon price stress test — the best available single-source calibration, even though it reflects a specific European economy. Two sectors are treated separately: for electricity, Fabra and Reguant (2014) find that costs are almost fully passed through to prices, and for water supply and waste management cost-reflective tariff settings under regulatory frameworks similarly ensures near-full pass-through; we assign both sectors a pass-through rate of 1.

Alternatively, other authors, such as Reinders et al. (2023), apply a common pass-through rate uniformly across all sectors, with a central value of $\theta = 0.5$. Sensitivity analysis considering both approaches are included in Appendix B.

3.4 Financial impact

To translate the propagated biodiversity externality costs into firm-level credit risk metrics, we follow the standard approach in climate stress testing and adopt a Merton (1973) structural model of default. This framework has been applied to climate transition risk (Bouchet and Le Guenedal, 2020; Reinders et al., 2023) and, more recently, to biodiversity dependency risk (Gallet et al., 2024, 2026).

Starting from each company's observed probability of default, the baseline distance to default is recovered as:

$$DtD_i = \ -N^{-1}PD_i \tag{5}$$

which, following Merton (1973), can be expressed in terms of firm fundamentals as:

$$DtD_i = \frac{ln\left(\frac{A_i}{L_i}\right) + \left(\mu_i - \frac{{\sigma_i}^2}{2}\right)\tau}{\sigma_i\sqrt{\tau}} \tag{6}$$

where DtD_i is the distance to default for company i in the period τ, A_i represents the value of the company assets, L_i represents the value of the company liabilities, σ_i is the volatility of assets, τ is the period of assessment and μ_i is the expected return of assets.

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The assessment horizon is set to one year ($\tau = 1$), consistent with standard stress testing practice (Guth et al., 2021; Reinders et al., 2023). Within this horizon, firms' input structures and supply chain relationships are unlikely to adjust significantly in response to a biodiversity pricing shock.

The biodiversity shock enters through an effective reduction in asset value. Firms with greater biodiversity impact face higher transition risk as externality costs erode their financial position (Svartzman et al., 2023). Following Bouchet and Le Guenedal (2020) and Gallet et al. (2024), the cost impact — both direct and indirect — is incorporated as a proportional reduction $\varepsilon_{i,s}$ in asset value, yielding the scenario distance to default:

$$DtD_{i,s} = \frac{ln\left(\frac{(1-\varepsilon_{i,s})*A_i}{L_i}\right) + \left(\mu_i - \frac{{\sigma_i}^2}{2}\right)}{\sigma_i} \tag{7}$$

Since $\varepsilon_{i,s} \in (0,1)$, $\ln(1-\varepsilon_{i,s})$ is strictly negative, so $DtD_{i,s} < DtD_i$ in all cases. Biodiversity externality costs unambiguously move firms closer to default, with the magnitude of the reduction depending on the size of the shock $\varepsilon_{i,s}$ and the asset volatility σ_i and the firm's distance from default in the baseline.

4 Data and results

4.1 Data

We draw on the Exiobase 3 multi-regional input-output database (Stadler et al., 2018), which provides supply-use tables covering 49 countries and regions and 163 industry sectors, yielding 7,987 unique sector-country combinations. Exiobase 3 includes physical satellite accounts for five pressure categories used in this study: CC, WC, ME, FE, and TA, as well as three LU categories — cropland, grazing land, and forest. Urban land use is not covered by the satellite accounts and are therefore excluded from the analysis.

Biodiversity characterisation factors are drawn from LC-IMPACT (Verones et al., 2020), which provides spatially explicit endpoint characterisation factors expressed in

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PDF·yr per unit of pressure, differentiated by country and activity across all six pressure categories. For land use, the characterisation factor is applied to occupied land stocks rather than land use transitions, and the median factor serves as a best-available proxy for the unobservable transition dynamic. The source for the externality cost is CE Delft (2024) as explained in Section 3.4.

For the sample portfolio, we extracted financial data from S&P Capital IQ, while PD values were obtained from the Credit Research Initiative (Duan et al., 2012).

σ_i is assumed uniform across firms, so cross-sectional variation in the scenario impact is driven entirely by heterogeneity in biodiversity exposure. Otherwise, firms with higher asset volatility would, under a firm-specific calibration, show a smaller reduction in DtD for a given biodiversity shock.

4.2 Input-Output results

Fig. 1 shows the distribution of biodiversity-related economic impact as a share of sectoral output, weighted by monetary output, across the sector-country observations under the central scenario. Impact is decomposed into direct exposure and indirect exposure, inherited through supply-chain price propagation following Roncalli and Semet (2024). Detailed statistics are in Table A.1. The central externality cost for this analysis is equivalent to a carbon price of 84.75 €/tCO2e for climate change.

With propagating the externality cost through the value chain, analogous to the carbon price, we see that (Table A.1) land use dominates total average exposure at 23.9% of sectoral output, followed by water consumption (8.7%) and climate change (6.9%); terrestrial acidification, freshwater eutrophication, and marine eutrophication are negligible. Total average impact reaches 33.3%, reflecting the simultaneous internalisation of all six externalities: each sector absorbs its own shock plus all upstream shocks propagated through inter-sectoral linkages.

The direct/indirect split reveals meaningful differences across categories. LU has the highest total average, but its sectors show a lower ability to pass on cost (indicated by a larger share of output within the extreme bucket for direct impacts). So, although

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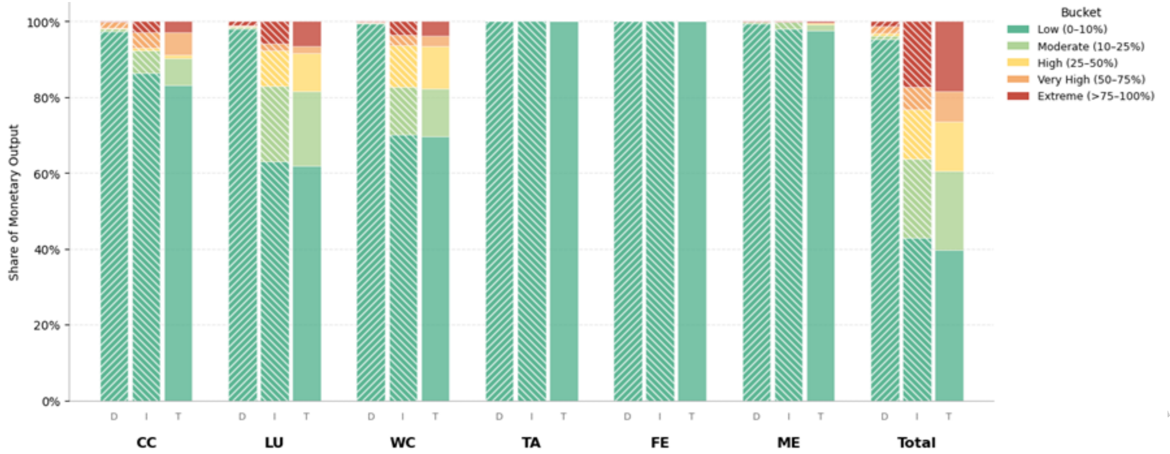

Figure 1: Distribution of economic impact buckets by pressure category.
Note: Each bar represents the share of weighted Exiobase 3 sector-country combinations falling within each exposure bucket, where bucket assignment is based on the ratio of category-specific economic impact to total economic impact across all pressure categories for that sector-country row. D = direct (cost absorbed at source); I = indirect (cost passed through the supply chain); T = total. Results for Guth et al. (2021) central pass-through estimates and central externality cost.

the cost pass-through is lower, the indirect impact footprint is significant because the footprint intensity is so high that even a low pass-through rate generates a significant absolute indirect impact. In the case of CC, the spread is due to the fact that the sectors most affected have a greater ability to pass on the cost. The aggregate total indirect impact of 24.9% is more than twice the total direct exposure of 11.5%, confirming that a direct-footprint-only framework would substantially understate financial risk, which is aligned with Roncalli and Semet (2024) findings for a climate scenario (see Table A.1).

With respect to the cost pass-through sensitivity analysis, total exposure rankings are robust to this choice, reflecting that the cross-sectoral ordering of θ drives total rankings. The amplification effect from supply-chain propagation is also visible across all Guth specifications: indirect exposure consistently exceeds direct, growing with θ as more cost enters the propagation mechanism. For the Reinders extreme cases (no cost pass-through and total pass-through), Agriculture is the activity most affected when there is no pass-through while downstream services inheriting the largest burden at θ=1 (see Fig. B.1).

In contrast to the pass-through calibration, varying the CE Delft valuation scenario leaves both the structure and magnitude of results largely unchanged (Figure B.2). Valuation uncertainty is therefore not a binding source of uncertainty in this framework; broader limitations of the WTP-based approach were discussed in Section 3.2.

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4.3 Portfolio application results

As an example for an investment portfolio, we used the companies that are part of the STOXX Europe 600 as of December 31, 2025, drawing financial data from S&P Capital IQ. Breakdown by country and sector are in Table C.1.

Table 1: Sample composition based on STOXX Europe 600.

	Number of Companies	Total Assets (Billion €)
Total	600	52,112.7
Financial services	111	38,650.7
Non-financial Companies	489	13,474.6
Data Quality*	5	18.2
Sample	484	13,456.3

Note: Constituents as of 31 December 2025. Data quality issues refer to missing data on DtD.

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When comparing the sectors and countries in the sample with the global sample, the sectoral distribution shows no notable differences in the footprint; however, a smaller impact is observed in the countries represented in the STOXX Europe 600. The main factor mitigating the impact on the STOXX Europe 600 is that the sectors of the index map to multiple Exiobase 3 activities, diluting exposure through diversification across activity classifications.

Fig. 2 reports firm-level biodiversity economic impact by pressure category and channel across the 484-firm sample, on a log scale. The portfolio composition — dominated by manufacturing, services, and technology firms — shapes the results structurally: direct impacts are small across all categories, while indirect supply-chain exposure is the primary channel through which biodiversity transition risk reaches portfolio companies.

Land use indirect dominates, with an average of 6.7% of sectoral output and a tail extending to 100% for a small number of firms. Water consumption indirect and climate change indirect follow at 2.9% and 0.9% respectively, with similarly fat-tailed distributions. Terrestrial acidification, marine eutrophication, and freshwater eutrophication are negligible at the portfolio level, with marine eutrophication indirect a partial exception.

Within-column dispersion is wide for every meaningful category, and no single industry dominates any channel's distribution. Supply-chain structure at the firm level, rather

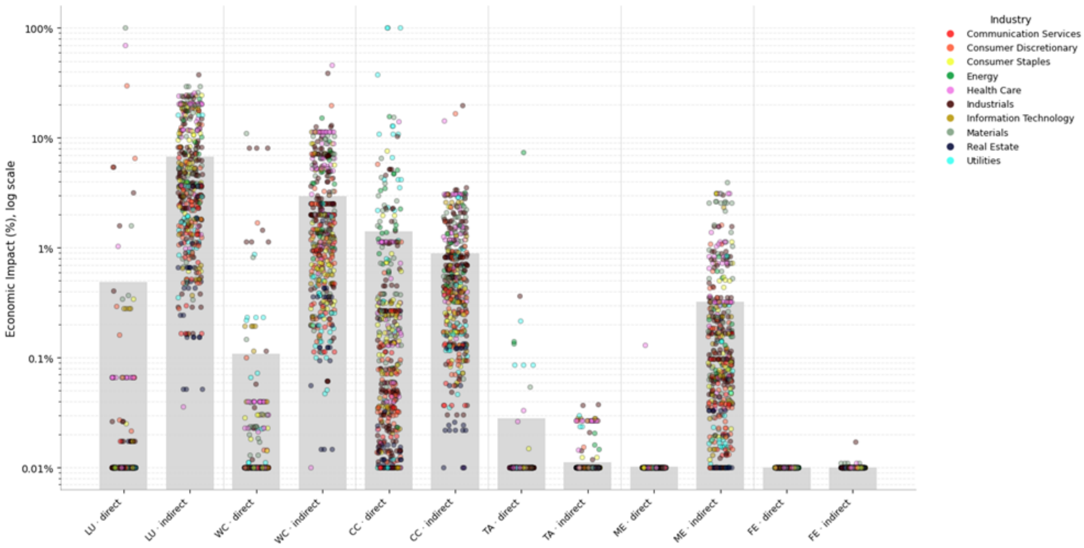

Figure 2: Weighted average biodiversity economic impact by pressure category and channel.
Note: Log scale. Values at 0 are floored for log display.

than industry classification, is the primary driver of individual biodiversity transition risk exposure within this sample.

Table 2 reports baseline and scenario probability of default by GICS Industry. Across the full sample, weighted-average PD rises from 0.17% to 2.05% under the central scenario, while median PD increases more modestly from 0.06% to 0.22%, indicating that the aggregate impact is driven by a subset of highly exposed firms rather than a broad-based shift.

Materials and Health Care show the largest weighted-average increases — to 9.35% and 3.16% respectively — but their median PD scenarios remain comparatively low (0.39% and 0.97%), confirming high within-sector concentration. Utilities, Energy, and Industrials form a second tier with weighted-average scenario PDs between 1.0% and 2.6%. Real Estate and Communication Services show minimal impact on both metrics.

The divergence between weighted-average and median PD is a consistent feature across sectors: in every case, the mean scenario PD substantially exceeds the median, reflecting the fat-tailed, concentrated nature of biodiversity transition risk documented in Fig. 2. Sector classification is therefore a weak summary statistic for this risk — within-sector dispersion is as informative as the cross-sector ranking.

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Table 2: Biodiversity Transition Risk Impact on Probability of Default by Industry

Industry	Weighted avg PD	Median PD	Weighted avg PD scenario	Median PD scenario
Communication Services	0.15%	0.09%	0.22%	0.12%
Consumer Discretionary	0.42%	0.12%	0.87%	0.28%
Consumer Staples	0.07%	0.04%	0.43%	0.25%
Energy	0.11%	0.09%	1.01%	0.70%
Health Care	0.16%	0.03%	3.16%	0.97%
Industrials	0.12%	0.06%	1.53%	0.21%
Information Technology	0.10%	0.05%	0.82%	0.14%
Materials	0.10%	0.07%	9.35%	0.39%
Real Estate	0.07%	0.02%	0.10%	0.02%
Utilities	0.25%	0.04%	2.64%	0.12%
Total	0.17%	0.06%	2.05%	0.22%

5 Conclusions and policy implications

This paper proposes a framework for translating biodiversity impacts embedded in economic activity into firm-level credit risk impacts. The connection from biodiversity impact to credit-relevant financial pressure runs through four elements: i) the intensity of biodiversity impact per unit of sectoral output; ii) its monetisation using willingness-to-pay externality cost estimates adjusted for purchasing power; iii) the propagation of the resulting cost shock through the supply chain via a cost pass-through input-output model; iv) and the translation of the propagated cost into firm-level credit risk metrics through a structural default model. The result is a tractable and scalable estimate of the financial burden firms would face if biodiversity externalities were internalised through a pricing mechanism.

Applied to 484 STOXX Europe 600 constituents, the framework reveals three findings with broader relevance beyond the specific sample. First, indirect supply-chain exposure dominates total biodiversity transition risk for most firms in the sample, exceeding direct exposure by more than two to one at the portfolio level. Second, the impact is highly concentrated: weighted-average scenario PD rises from 0.17% to 2.05% across the sample, but within-sector dispersion is large, with Materials and Health Care reaching scenario PDs of 9.35% and 3.16% respectively, while their medians remain far lower. Third, the pressure category driving most of this exposure is land use, but its financial reach operates

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almost entirely through the supply chain rather than through firms' own operations.

In this sample, land use dominates the physical footprint and generates the largest absolute indirect exposure but propagates a smaller share of its cost relative to its footprint size. Climate change, in comparison reaches a broader set of sectors with higher pass-through capacity and translates a smaller footprint into comparably large financial exposure. Water consumption emerges as an additional driver of financial risk, and the combination of pressure categories compounds the overall impact substantially. It can be seen that footprint metrics gain interpretive traction when anchored to financial metrics. Supervisors should prioritize requiring financial impact contextualization – quantifying impacts across distinct pressure categories rather than aggregating them - over footprint disclosure or scoring metrics. Similarly, banks should define materiality through risk appetite metrics rather than relying on biodiversity scores.

Three limitations bound the interpretation of results. First, sector-country average biodiversity intensities are assigned to all firms within the same sector and country, since firm-level data does not yet exist at scale, making within-sector heterogeneity driven by idiosyncratic production technology or supplier choices invisible to the model. Second, pass-through calibration is static and draws on elasticity estimates from a single economy, the dominant source of uncertainty in the results. Third, willingness-to-pay externality costs reflect perceived societal value rather than the productive value of ecosystems to the economy, introducing a directional bias whose net sign is unresolved. Each limitation has a clear path towards improvement, and the modular structure of the framework allows components to be updated independently as better data becomes available.

Pass-through assumptions matter as much as the underlying impact intensity, yet they are inherently difficult to standardise. The nature of the shock (regulatory, technological, or social) may also affect the ability to pass on the cost along the value chain. Supervisors and financial institutions, scenario design must include assumptions regarding how pass-through costs may change depending on the scenario. For policymakers, this type of approach can be useful in policy-making processes themselves.

Finally, firm-level impact of this kind are useful even when based on input-output

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proxies rather than company-reported data. Within-sector dispersion can tell us that a small number of firms drive most of each sector's aggregate scenario PD - consistent with Ceglar et al. (2025) and Kulionis et al. (2024). This concentration suggests that targeted engagement with the most exposed counterparties, rather than broad sector-level action, enables financial institutions to manage biodiversity risk without incurring in a significant operational cost. It also raises a governance question: discretion over materiality definitions allows institutions to align assessments with conventional risk management practices but the same flexibility creates headroom for selective framing. To avoid the latter, Supervisors should promote pre-competitive collaboration through shared data and open methodological frameworks, lowering the operational burden and creating at the same time minimum methodological standards while preserving the flexibility to deviate for well-grounded reasons.

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A Appendix

Table A.1: Statistics for economic impact.

Pressure Factor and Channel	Buckets					Average	Median	90th Percentile
	0–10%	10–25%	25–50%	50–75%	75–100%			
CC direct	5573	248	132	56	112	4.5%	0.1%	8.0%
CC indirect	5796	259	40	12	14	2.5%	0.6%	6.7%
CC total	5231	507	180	74	129	6.9%	1.5%	15.3%
WC direct	5914	53	38	21	95	2.2%	0.0%	0.1%
WC indirect	5256	442	206	81	136	6.8%	1.2%	16.0%
WC total	5100	460	242	94	225	8.7%	1.3%	22.2%
ME direct	6005	38	18	10	50	1.2%	0.0%	0.0%
ME indirect	6051	44	13	5	8	0.8%	0.1%	1.0%
ME total	5945	75	32	10	59	1.9%	0.1%	1.5%
FE direct	6118	1	0	1	1	0.0%	0.0%	0.0%
FE indirect	6121	0	0	0	0	0.0%	0.0%	0.0%
FE total	6118	1	0	1	0	0.0%	0.0%	0.0%
TA direct	6114	4	1	0	2	0.1%	0.0%	0.0%
TA indirect	6121	0	0	0	0	0.0%	0.0%	0.0%
TA total	6114	4	1	0	2	0.1%	0.0%	0.1%
LU direct	5582	106	82	53	298	6.2%	0.0%	4.4%
LU indirect	3923	888	468	181	661	19.5%	5.3%	84.4%
LU total	3598	906	491	224	902	23.9%	6.6%	100.0%
Total direct	5075	266	180	102	498	11.5%	0.2%	47.8%
Total indirect	3359	1063	546	269	884	24.9%	8.2%	100.0%
Total	2662	1130	657	355	1317	33.3%	13.3%	100.0%

Note: Results for Guth et al. (2021) central pass-through estimates and central externality cost. Segments with no activity in Exiobase 3 have been removed, so the total number of segments is 6,121 out of 7,987.

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B Appendix: Sensitivity analysis

The results presented in the main text rely on two sets of parameters that are subject to meaningful uncertainty: the sector-level cost pass-through rates θ and the externality cost λ. This appendix documents the calibration of both and presents the full sensitivity analysis across all scenarios assessed.

Sector-level pass-through rates are derived from the own-price elasticities reported by

Guth et al. (2021) using:

$$\theta = \frac{1}{1 - \frac{1}{\eta}}$$

Low and high bounds are constructed by applying a ±20% perturbation to each elasticity estimate.

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Table B.1: Sector-level pass-through rates.

Code	NACE Sector	Guth low	Guth central	Guth high
A	Agriculture, forestry and fishing	0.42	0.47	0.52
B	Mining and quarrying	0.19	0.23	0.27
C	Manufacturing	0.32	0.38	0.42
D	Electricity, gas, steam	0.77	0.86	1.00
E	Water supply; waste management	0.90	1.00	1.00
F	Construction	0.51	0.57	0.61
G	Wholesale and retail trade	0.19	0.23	0.27
H	Transportation and storage	0.62	0.67	0.71
I	Accommodation and food services	0.62	0.67	0.71
J	Information and communication	0.44	0.50	0.55
K	Financial and insurance	0.07	0.09	0.11
L	Real estate	0.44	0.50	0.55
M	Professional and technical	0.44	0.50	0.55
N	Administrative services	0.50	0.56	0.60
O	Public administration	0.24	0.29	0.32
P	Education	0.29	0.33	0.38
Q	Human health and social work	0.14	0.17	0.19
R	Arts and recreation	0.50	0.56	0.60
S	Other services	0.29	0.33	0.38

Source: Guth et al. (2021), Authors.

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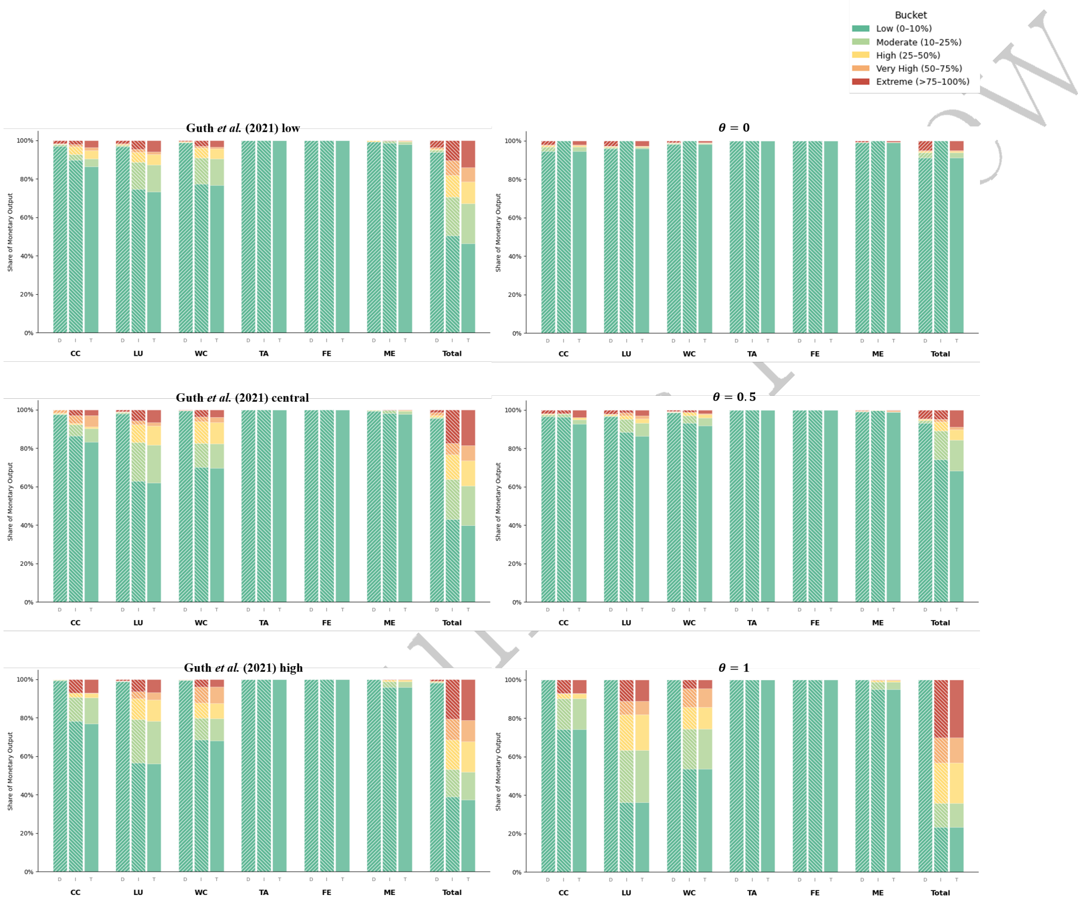

Figure B.1: Distribution of economic impact buckets by impact channel for different sector-level pass-through rates.

Note: Each figure panel corresponds to one of six pass-through presented above. Within each panel, pressure categories (CC: climate change; WC: water consumption; ME: marine eutrophication; FE: freshwater eutrophication; TA: terrestrial acidification; LU: land use) are shown along the horizontal axis. For each category, bars show the distribution of sector-country rows across impact buckets — Low (0–10%), Moderate (10–25%), High (25–50%), Very High (50–75%), and Extreme (>75%) — where each bucket reflects the impact of that pressure category in terms of the monetary output. D, I, and T denote direct, indirect, and total impact channel.

Figure B.2: Distribution of economic impact buckets by impact channel for different externality costs.

Note: Each figure panel corresponds to one of six pass-through presented above. Within each panel, pressure categories (CC: climate change; WC: water consumption; ME: marine eutrophication; FE: freshwater eutrophication; TA: terrestrial acidification; LU: land use) are shown along the horizontal axis. For each category, bars show the distribution of sector-country rows across impact buckets — Low (0–10%), Moderate (10–25%), High (25–50%), Very High (50–75%), and Extreme (>75%) — where each bucket reflects the impact of that pressure category in terms of the monetary output. D, I, and T denote direct, indirect, and total impact channel.

C Appendix: Portfolio sample details

Table C.1: Country and Sector breakdown.

Country		Industry	
Austria	6	Communication Services	32
Belgium	11	Consumer Discretionary	67
Cyprus	1	Consumer Staples	46
Denmark	19	Energy	20
Finland	15	Health Care	54
France	64	Industrials	115
Germany	63	Information Technology	31
Guernsey	1	Materials	53
Ireland	9	Real Estate	33
Isle of Man	1	Utilities	33
Italy	20		
Luxembourg	8		
Netherlands	26		
Norway	12		
Poland	4		
Portugal	3		
Spain	20		
Sweden	53		
Switzerland	44		
United Kingdom	100		
United States of America	3		
Total			484

Note: The table shows the sample composition for observations with an available DtD in NUS-CRI.

List of Abbreviations

CBD Convention on Biological Diversity

CC Climate Change

EEMRIO Environmental Extended Multi-regional Input Output

FE Freshwater Eutrophication

LU Land-use

LCA Life-cycle Assessment

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ME Marine Eutrophication

MRIO Multi-regional Input Output

MSA Mean Species Abundance

PDF Potentially disappeared fractions of species

TA Terrestrial Acidification

WC Water Consumption

WTP Willingness-to-pay

EU European Union

PD Probability to default

GDP Gross Domestic Product

CRediT authorship contribution statement

Daniel Ramos-García: Writing – review & editing, Writing – original draft, Methodology, Data curation, Software, Formal analysis. **Lisa Mayer:** Writing – review & editing, Writing – original draft, Methodology, Data curation, Software, Formal analysis.

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

During the preparation of this work, the authors used Claude Sonnet 5 (Anthropic) to improve language and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

None.

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Data Availability Statement

EXIOBASE version 3.10.2 can be downloaded from https://zenodo.org/records/20051562, LC-IMPACT version 1.3 can be downloaded from https://lc-impact.eu. Financial data has been retrieved from S&P IQ Capital, which requires a license. Distance-to-default can be obtained from CRI database, available at: http://nuscri.org.

References

Adenot, T., Briere, M., Counathe, P., Jouanneau, M., Le Berthe, T., and Le Guenedal, T. (2022). Cascading effects of carbon price through the value chain: Impact on firm's valuation. *SSRN Electronic Journal*.

Bank, W. and Malaysia, B. N. (2022). *An Exploration of Nature-Related Financial Risks in Malaysia*. World Bank, Washington, DC.

Bouchet, V. and Le Guenedal, T. (2020). Credit risk sensitivity to carbon price. *SSRN Electron. J.*

Broer, W., Kan, D., Patel, R., van Lenders, C., and Melis, K. (2021). Biodiversity footprint for financial institutions: Exploring biodiversity assessment. Technical report, The Netherlands Enterprise Agency.

Calice, P., Diaz Kalan, F., and Miguel, F. (2021). *Nature-Related Financial Risks in Brazil*. World Bank, Washington, DC.

CBD (2022). Decision 15/4. kunming-montreal global biodiversity framework.

CE Delft (2024). Environmental prices handbook 2024: Eu27 version.

Ceglar, A., Marques, A., Boldrini, S., Lelli, C., Toreti, A., Parisi, L., and Heemskerk, I. (2025). European banks face significant vulnerability to ecosystem degradation and climate change. *Communications Earth & Environment*, 6(1).

Preprint under review

Coqueret, G., Giroux, T., and Zerbib, O. D. (2025). The biodiversity premium. *Ecological Economics*, 228:108435.

Crenna, E., Marques, A., La Notte, A., and Sala, S. (2020). Biodiversity assessment of value chains: State of the art and emerging challenges. *Environmental Science & Technology*, 54(16):9715–9728.

Crisóstomo, R. (2025). Quantifying firm-level risks from nature deterioration. Technical report, Comisión Nacional del Mercado de Valores.

Dasgupta, P. (2021). *The Economics of Biodiversity: The Dasgupta Review.* HM Treasury, London.

Duan, J.-C., Sun, J., and Wang, T. (2012). Multiperiod corporate default prediction—a forward intensity approach. *Journal of Econometrics*, 170(1):191–209.

European Banking Authority (2025). Final guidelines on the management of environmental, social and governance (esg) risks. Technical Report EBA/GL/2025/01, European Banking Authority.

European Parliament and Council of the European Union (2022). Directive (eu) 2022/2464 of the european parliament and of the council of 14 december 2022 as regards corporate sustainability reporting. Official Journal of the European Union, L322, 16 December 2022, pp. 15–80.

Fabra, N. and Reguant, M. (2014). Pass-through of emissions costs in electricity markets. *American Economic Review*, 104(9):2872–2899.

Feenstra, R. C., Inklaar, R., and Timmer, M. P. (2015). The next generation of the penn world table. *American Economic Review*, 105(10):3150–3182.

Gallet, S., Hendricks, A., and Prodani, J. (2024). The ecosystem service degradation sensitivity indicator (edsi): A new framework for understanding the financial risk repercussions of nature degradation. Working Paper 814, De Nederlandsche Bank.

Preprint under review

Gallet, S., Hendricks, A., and Prodani, J. (2026). From nature shocks to financial stability. Working Paper 857, De Nederlandsche Bank.

Garel, A., Romec, A., Sautner, Z., and Wagner, A. F. (2023). Do investors care about biodiversity? *SSRN Electronic Journal*.

Giglio, S., Kuchler, T., Stroebel, J., and Zeng, X. (2023). Biodiversity risk.

Goedkoop, M., Heijungs, R., Huijbregts, M., Schryver, A., Struijs, J., and Zelm, R. (2008). Recipe 2008: A life cycle impact assessment method which comprises harmonised category indicators at the midpoint and the endpoint level.

Guidolin, M. and Pedio, M. (2026). The pricing of biodiversity risk in commodity markets. *Review of Finance*, 30(1):351–389.

Guth, M., Hesse, J., Königswieser, C., Krenn, G., Lipp, C., Neudorfer, B., Schneider, M., and Weiss, P. (2021). Oenb climate risk stress test – modeling a carbon price shock for the austrian banking sector. *Financial Stability Report*, 42.

Hadji-Lazaro, P., Salin, M., Svartzman, R., Espagne, E., Gauthey, J., Berger, J., Calas, J., Godin, A., and Vallier, A. (2024). Biodiversity loss and financial stability as a new frontier for central banks: An exploration for france. *Ecological Economics*, 223:108246.

Hirschbühl, D., Ceglar, A., Cojoianu, T., Emambakhsh, T., Qi, Y., Rho, C., Hu, E., Petracco, M., Biganzoli, F., de Jager, A., Garcia Herrero, L., Mandrici, A., and Pasqua, C. (2024). The climate-biodiversity-pollution nexus: The pricing of environmental credit risks for european industrial polluters. Technical report, European Central Bank.

Kok, M. and Alkemade, R. (2014). How sectors can contribute to sustainable use and conservation of biodiversity. CBD Technical Series 79, PBL Netherlands Environmental Assessment Agency, The Hague, Netherlands. PBL Report No. 01448.

Kulionis, V., Pfister, S., and Fernandez, J. (2024). Biodiversity impact assessment for finance. *Journal of Industrial Ecology*, 28(5):1321–1335.

Preprint under review

Leontief, W. (1970). Environmental repercussions and the economic structure: An input-output approach. 52(3):262–271.

Mardones, C. (2025). An input-output approach to study the impact of carbon taxes in (almost) every country. *Environmental Development*, 53:101102.

Mardones, C. and Mena, C. (2020). Economic, environmental and distributive analysis of the taxes to global and local air pollutants in chile. *Journal of Cleaner Production*, 259:120893.

Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica*, 41(5):867.

Miller, R. E. and Blair, P. D. (2021). *Input-Output Analysis: Foundations and Extensions*. Cambridge University Press.

NGFS (2023). Conceptual framework on nature-related financial risks. Technical report, Network for Greening the Financial System.

Pineau, E. and Zuñiga, E. (2024). Sectoral credit sensitivity to carbon price with value chain effects. *Review of World Economics*, 162(1):285–311.

Prodani, J., Gallet, S., Jansen, D.-J., Kearney, I., Schotten, G., Broer, G., van Zeist, W.-J., and Marques, A. (2023). The economic and financial stability repercussions of nature degradation for the netherlands: Exploring scenarios with transition shocks. Technical report, De Nederlandsche Bank.

Ranger, N. and Oliver, T. (2024). Assessing the materiality of nature-related financial risks for the uk. Technical report, Green Finance Institute.

Reinders, H. J., Schoenmaker, D., and van Dijk, M. (2023). A finance approach to climate stress testing. *Journal of International Money and Finance*, 131:102797.

Roncalli, T. and Semet, R. (2024). The economic cost of the carbon tax. Working Paper 156, Amundi Investment Institute.

Preprint under review

Stadler, K., Wood, R., Bulavskaya, T., Södersten, C., Simas, M., Schmidt, S., Usubiaga, A., Acosta-Fernández, J., Kuenen, J., Bruckner, M., Giljum, S., Lutter, S., Merciai, S., Schmidt, J. H., Theurl, M. C., Plutzar, C., Kastner, T., Eisenmenger, N., Erb, K., de Koning, A., and Tukker, A. (2018). Exiobase 3: Developing a time series of detailed environmentally extended multi-regional input-output tables. *Journal of Industrial Ecology*, 22(3):502–515.

Svartzman, R., Espagne, E., Gauthey, J., Hadji-Lazaro, P., Salin, M., Allen, T., Berger, J., Calas, J., Godin, A., and Vallier, A. (2021). A "silent spring" for the financial system? exploring biodiversity-related financial risks in france. Working Paper 826, Banque de France.

Svartzman, R., Martínez, S. J., Althouse, J., Gabet, M., Ranger, N., Alvarez, J., Freeman, A., Paulus, E., Gardes, C., and Oman, W. (2023). Recommendations toward the development of scenarios for assessing nature-related economic and financial risks. Technical report, Network for Greening the Financial System and Banque de France.

van Toor, J., Piljic, D., Schellekens, G., van Oorschot, M., and Kok, M. (2020). Indebted to nature: Exploring biodiversity risks for the dutch financial sector. (4215).

van 't Klooster, J. and Prodani, K. (2025). Planetary financial policy and the riskification of nature. *Review of International Political Economy*, 32(3):643–667.

Vermeulen, R., Schets, E., Lohuis, M., Kölbl, B., Jansen, D.-J., and Heeringa, W. (2018). An energy transition risk stress test for the financial system of the netherlands.

Verones, F., Hellweg, S., Antón, A., Azevedo, L. B., Chaudhary, A., Cosme, N., Cucurachi, S., de Baan, L., Dong, Y., Fantke, P., Golsteijn, L., Hauschild, M., Heijungs, R., Jolliet, O., Juraske, R., Larsen, H., Laurent, A., Mutel, C. L., Margni, M., Núñez, M., Owsianiak, M., Pfister, S., Ponsioen, T., Preiss, P., Rosenbaum, R. K., Roy, P., Sala, S., Steinmann, Z., van Zelm, R., Van Dingenen, R., Vieira, M., and Huijbregts, M. A. J. (2020). Lc-impact: A regionalized life cycle damage assessment method. *Journal of Industrial Ecology*, 24(6):1201–1219.

Preprint under review

Visentin, G. A. (2026). Financial risks of biodiversity loss: A review. *International Review of Economics & Finance*, 106:104894.

Preprint under review