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DeNederlandscheBank

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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Abstract

This paper introduces a new framework for integrating dependence on nature (ecosystem services) and the degree of nature degradation in estimations of credit risk-related losses for banks. The framework brings the field of nature-related financial risks forward by proposing a capital-based sensitivity indicator to nature degradation, thereby moving from an "exposure" approach to a "financial risk" approach. This ecosystem service degradation sensitivity indicator (EDSI) shows how much of a bank's available capital buffer on top of its minimum requirements is lost due to a shock on nature. It enables cross-bank and cross-country comparison of potential financial losses related to nature degradation. Our results indicate that incorporating nature degradation into financial risk estimates adds an important - and currently missing - layer of risk and offers additional differentiation in capital impact among banks and countries. While in this paper the framework uses hypothetical shocks on nature and can therefore only produce comparative sensitivity indicators, upon calibrating a shock on different ecosystem services the framework can be used to stress-test financial institutions' solvency position.

Keywords: nature degradation, ecosystem services, biodiversity loss, dependence score, financial stability, risk, credit risk losses, Merton model

JEL classification: G21, G28, Q57

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1. Introduction

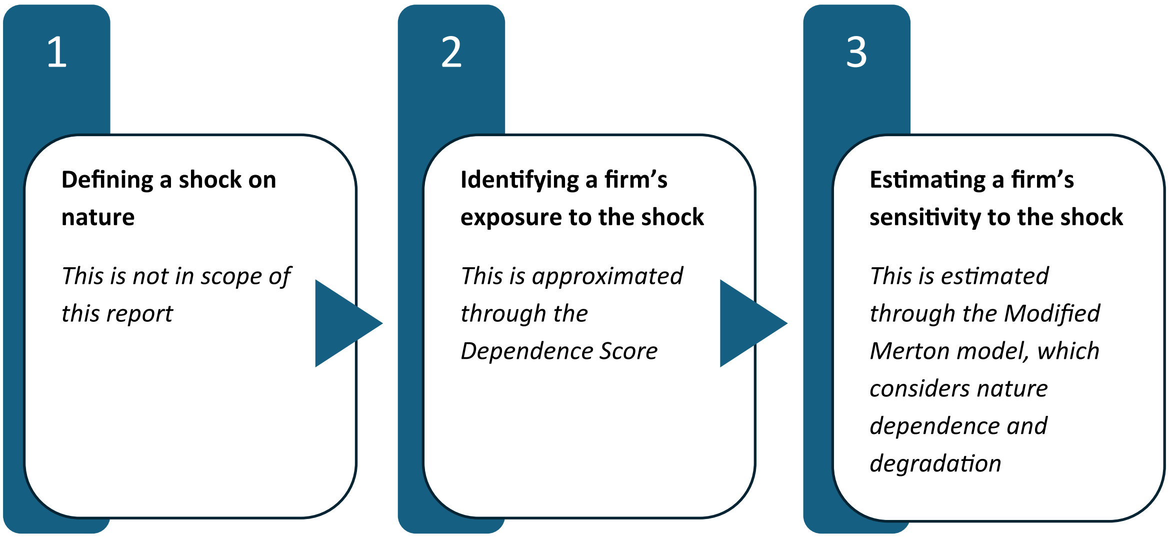
It is now widely recognized within the central banking community that nature-related risks can have implications for financial institutions and financial stability at large. In 2022, the NGFS shared that 'nature-related risks, including those associated with biodiversity loss, could have significant macroeconomic implications, and that failure to account for, mitigate, and adapt to these implications is a source of risks relevant for financial stability' (NGFS, 2022). This realization followed the 2019 publication of the Global Assessment Report of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services, which outlined the worldwide degradation of nature and the services nature provides to people, the so-called ecosystem services (ES), such as pollination or water quality (IPBES, 2019). Supervisory expectations related to the management of nature-related risks are also increasing (ECB, 2020; DNB, 2023).

Nature degradation, similarly to climate change, can pose physical or transition-related financial risks (NGFS, 2024). Physical risks are those resulting from the degradation of ecosystem services on which economic activities depend, while transition risks are those resulting from misalignment with actions aimed at protecting, restoring, and/or reducing negative impacts on nature, such as regulation or consumer preferences. The dependence of a firm on ecosystem services is a good starting point for evaluating physical risks; the more highly dependent a firm is on a certain ecosystem service, the more it will be exposed when that ecosystem service degrades. These physical and transition-related risks have macroeconomic repercussions - such as higher inflation - and microeconomic repercussions - such as cost increases for a corporate. These economic impacts then filter into the traditional risk categories of financial institutions. As an example, an increase in costs for a corporate that is dependent on water for cooling its heavy machinery might affect its repayment capacity and therefore lead to increased credit risk for the bank that has lent to it. The aggregation of microeconomic impacts, and their interaction with macroeconomic impacts, can lead to financial system-wide shocks and therefore pose a threat to financial stability.

As nature degradation is a forward-looking, uncertain phenomena, scenario analysis is a useful tool to estimate possible losses for financial institutions. To enable such analysis, three steps are needed: (1) defining a shock on nature, (2) identifying a firm's exposure to the shock, and (3) estimating a firm's sensitivity to the shock (see Figure 1) (Svartzman et al., 2021; Hadji-Lazaro et al., 2024). Literature that focuses on identifying shocks on nature, such as the acute or chronic degradation of a particular ecosystem service, has done so through scenario analyses on nature futures (physical vs transition) (IPBES, 2016). Nonetheless, a general or ecosystem service-specific shock or hazard on nature remains complicated to model, not least because of its non-linearity and second-round and cascading effects (Maurin et al., 2022). Current literature on nature-related financial risks largely focuses on "dependence-and-impact analysis", also called "exposure" analysis. This type of analysis identifies exposures of financial institutions that are dependent on nature and/or impact nature (step 2 in Figure 1), without providing a measure of risk (van Toor et al., 2020; Svartzman et al., 2021; Calice et al., 2021; World Bank and Bank Negara Malaysia, 2022). While there have been two main attempts to estimate financial risks posed to financial institutions, they have identified major methodological limitations in using nature-to-macroeconomy models (Prodani et al., 2023; Ranger & Oliver, 2024).

Our proposed framework brings the field of nature-related financial risks forward, by introducing a new way of incorporating firms' dependence on nature into a traditional risk assessment model used by financial institutions. This brings dependence "exposure" analysis a step further. Specifically, the framework approximates the vulnerability of a firm to nature degradation (step 3 of Figure 1), which is necessary to arrive at a risk, i.e. financial loss, estimation. To approximate a firm's, i.e. bank counterparty's, vulnerability, we integrate both i. the dependence on nature of the economic sector in which a firm operates and ii. the degree of nature degradation in the countries where a firm and its supply chain operate into a firm's estimated probability of default. This probability of default is the main driver of a bank's credit risk-related common equity tier 1 (CET1) ratio depletion. We then compare banks based on a new proposed indicator – the ecosystem service degradation sensitivity indicator (EDSI) – that approximates a sort of "distance to the breach of minimum requirements". The EDSI does this by taking into account not only the banks' extent of CET1 ratio depletion, but also a bank's CET1 capital "cushion" above minimum requirements.

Figure 1: Three steps needed for a nature-related scenario analysis



We find that taking into account the extent of nature degradation into financial risk estimations adds a needed - and currently missing - layer of risk. Adding nature degradation as a driver of financial losses - in addition to dependence on nature - produces more heterogeneity in the level of CET1 ratio depletion across banks and countries.[1] It also results in a better proxy of financial risk. We identify mass stabilization and erosion control, climate regulation, flood and storm protection, ground water, and surface water as the ecosystem services to which banks are most sensitive in terms of credit risk related capital depletion. Our results point to different sensitivity to a shock on these ecosystem services across Single Supervisory Mechanism (SSM) banks and countries.

Section 2 presents the rationale of the paper and the justification for following this approach. Section 3 describes the data and methodology used for translating a firm's dependence on nature and extent of nature degradation across its supply chain to asset depreciation that decreases the firm's distance to default. This is done by modifying the Merton model used for credit risk assessments (Merton, 1973). We then estimate how the change in the probabilities of default implied by this model gives rise to changes in loss-given-defaults and subsequently credit losses and increases in risk weighted

[1] Countries are approximated by a theoretical bank that aggregates all the capital and risk weighted assets of the significant banks in that country.

assets for banks that lend to this firms, which ultimately lead to a capital ratio depletion. Section 4 presents an application of the proposed framework and subsequent results. Section 5 is used to discuss the meaning and use of the framework and results, and potential next steps needed to move to a full-fledged stress test. Section 6 concludes.

2. Related literature

Work on nature-related financial risks beyond climate change has been proliferating since 2019. (World Economic Forum, 2021; World Bank and Bank Negara Malaysia, 2022; WWF, 2021; OECD, 2019; Dasgupta, 2021; Taskforce on Nature-related Financial Disclosure, 2021; Borges & Laurinaitytė, 2023; OECD, 2023) In 2020, DNB was the first central bank to conduct a study on Dutch financial institutions' dependencies and impacts on nature (van Toor et al., 2020). The study focused on direct dependencies of primary economic sectors on nature. A wave of similar "exposure" analyses followed, which also took into account indirect dependencies throughout supply chains for non-primary economic sectors, approximated through input-output databases (Svartzman et al., 2021; Calice et al., 2021; World Bank and Bank Negara Malaysia, 2022; Boldrini et al., 2023; Hadji-Lazaro et al., 2024). Such analyses map the exposures of financial institutions to different degrees of dependence and impact on nature, and infer that financial institutions with higher exposures to high-dependence and high-impact corporations face a larger financial risk.

More recently, publications have focused on the assessment of financial losses through macroeconomic scenarios. In 2023, DNB conducted a first estimation of nature-related financial losses for Dutch financial institutions, thereby moving from an "exposure" analysis to a "risk/financial loss" approach (Prodani et al., 2023). The DNB study tried to translate nature-related transition-risk shocks to a macroeconomic impact and then using these macroeconomic impacts to obtain potential financial losses for Dutch financial institutions. In line with the NGFS Recommendations for the development of nature-related scenarios, the DNB study highlighted many of the limitations of i. current nature models in capturing the multi-dimensionality and interconnectedness of nature components and ii. the linkages between nature and (macro)economic models (NGFS, 2023b). Other recent analyses have also used exploratory methodologies in trying to move beyond the pure exposure analysis by adding a degree of risk quantification (Boldrini et al., 2023; Ranger & Oliver, 2024).

As there is currently no mainstream way for translating nature degradation to financial losses for financial institutions, this study offers an intuitive framework for doing so. This work builds on the ECB Occasional Study (OS) on nature-related physical risks, which is itself based on the Silent Spring report of the Banque de France (Svartzman et al., 2021). It introduces two main innovations compared to existing research, and specifically the ECB OS. First, it takes the extent of geographical degradation as an additional component that affects a firm's sensitivity to nature. Second, it does so by proposing a new framework that integrates dependence on nature and the extent of nature degradation into a traditional credit risk assessment model. This Merton model has been introduced by Robert C. Merton in 1973 as a way to assess the credit risk of a non-financial corporates (Merton, 1973). In this model, default occurs when the value of a firm's assets falls below a pre-determined threshold of liabilities. Subsequent research has shown the applicability of such a model to other types of entities - sovereigns and financial institutions -, to which we will also apply this framework (Gray, Bodie, & Merton, 2007; Chan-Lau & Sy, 2006). More recently, work has been done to integrate climate-related transition risks, and more specifically climate-related taxes, into this model (Reinders et al., 2023). Our proposed framework aims to synthesize and refine this work into a quantification model that builds on an already widely-used model for risk professionals while allowing for enough flexibility to incorporate broader nature-related risks.

3. Methodology

A shock on ecosystem services depreciates the assets of a firm that relies on those ecosystem services. This "negative" change in a firm's balance sheet affects the credit risk borne by the bank that lends to this firm. For the credit risk estimation, we rely on the Merton model. Our innovation involves incorporating asset depreciation related to the decline of ecosystem services into this model. This asset depreciation is proportional to i. a shock on ecosystem services relevant to a firm, ii. the extent to which a firm depends on those ecosystem services, and iii. the degree of degradation of ecosystem services in the countries where the firm and its supply chain operate. As the calibration of a shock on ecosystem services is out of the scope of our work, we impose assumed shocks. Section 3.2 explains how we use two approaches in imposing such shocks: one iteration where the same shock is assumed across ecosystem services, and one iteration where a total asset depreciation per ecosystem service at the SSM level is assumed and then the needed shocks on ecosystem services are reverse-calibrated.

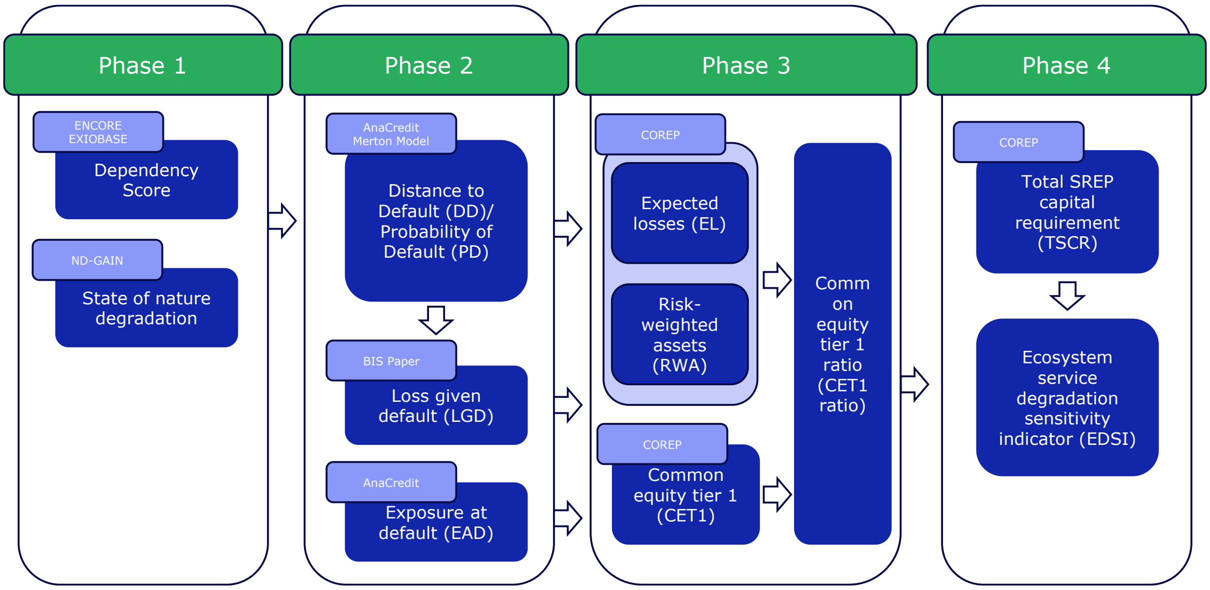
Our methodological approach consists of four main phases: (1) gathering the nature dependence and nature degradation indexes per exposure, (2) incorporating these into each firm's distance to default estimation through the Merton model, (3) estimating banks' CET1 ratio depletion, and (4) estimating the ecosystem service degradation sensitivity indicator (EDSI) (Figure 2, (Section 3.2)). Phase 1 consists of using the dependence score (DS) from the ENCORE dataset, which includes the *direct* exposure of an economic sector to an ecosystem service, enhanced with the indirect exposure of an economic sector to an ecosystem service, which is made possible through linking ENCORE to the EXIOBASE input-output database so as to take into account supply-chain information.[2] The ENCORE and EXIOBASE methodology is the same as the ECB methodology used in their OS on Nature-related physical risks (Boldrini et al., 2023). We enrich that existing methodology by adding, in this same step, an index of ecosystem degradation per country to take into account the extent to which an ecosystem service is degraded in different regions of the world.[3] Phase 2 consists of estimating the lower distance to default of a firm due to the nature shock. This is done by modifying the traditional Merton model to account for the asset depreciation that results from dependence on nature and nature degradation (through the indicators mentioned in step 1). Phase 3 consists of estimating the impact on banks' CET1 ratios. Here, we consider the impact that results from credit losses and risk-weighted assets (both through probabilities of default (PD) and losses given default (LGD)) . As a last phase, in order to have a better view of risk at the bank-level, when making a cross-bank/cross-country comparison, we also take into account banks' capital headroom – i.e. the CET1 capital above a bank's total Supervisory Review and

[2] The new ENCORE version published in July includes direct and indirect dependencies of an economic sector to an ecosystem service. Partly due to methodological choices we had made in this paper before the updated ENCORE version, we have decided to proceed here with using the previous ENCORE version.

[3] The ND-GAIN Index, developed by the Notre Dame Global Adaptation Initiative, assesses a country's vulnerability to climate change and other global challenges, its readiness to adapt by evaluating exposure to climate-related risks and adaptive capacity. It focuses on key sectors such as agriculture, water, and infrastructure, and includes data on over 180 countries, offering insights into how various nations are equipped to handle climate-related challenges and vulnerabilities. Country Index // Notre Dame Global Adaptation Initiative // University of Notre Dame

Evaluation Process (SREP) capital requirement (TSCR). Specifically, we compare the newly (depleted) CET1 ratio estimated in phase 3 to each bank's TSCR. The TSCR is the sum of each bank's pillar 1 and pillar 2 capital requirement. This last step allows us to build our proposed indicator – the EDSI –, which allows us to see how much of a bank's available CET1 capital buffer on top of the TSCR requirement is lost due to nature degradation.

Figure 2: The four phases of the proposed framework



Note: The above phases show in a more detailed manner how we apply Step 2 (identifying exposure to nature) and 3 (estimating sensitivity to a shock on nature) of Figure 1, leaving out of scope Step 1 of Figure 1 (defining the shock on nature).

3.1 Data

There are five main databases we use in our analysis.

For nature-related data, we use ENCORE, EXIOBASE, and ND-GAIN (Notre Dame Global Adaptation Initiative) (Phase 1 of Figure 2). Our subset of ENCORE describes the direct dependence of 86 types of production processes on 21 ecosystem services.[4] The dependence is categorized into five different scales that range from very high to very low. ENCORE itself translates the dependence of the production processes into a dependence for economic sub-sectors.[5] We translate this categorization into numerical scales linearly, meaning that a DS of 1 is used for the highly dependent category and a DS of 0 is used for very low dependence[6]. The direct score obtained by ENCORE is complemented with information taken from EXIOBASE on the value chains of each production sector in each region. In this way, we can derive indirect dependence scores for sectors not directly dependent on nature. An example would be the food processing sector in the Netherlands, which is indirectly dependent on, among others, the agricultural sector of the Netherlands but also of Brazil because it uses Brazilian

[4] ENCORE (encorenature.org)
[5] The ENCORE database contains both dependencies and impacts on ecosystem services. In this analysis, we focus only on the dependencies. The database itself maps the production processes to economic sectors using the Global Industry Classification Standard (GICS) classification. Building on that, we mapped the GICS to the NACE classification building on the work done by the ECB in their Occasional Study on nature-related physical risks.
[6] We also use a dependence score of 0 for production processes not included in the ENCORE database.

agricultural output (e.g. soy) as an input in its production process (e.g. to produce soy milk). We use the ND-GAIN database, which ranks countries annually based on their degree of nature degradation, to retrieve an index that approximates the extent to which the ecosystem services of different countries are degraded. In this analysis we consider nature degradation across all countries where a firm's supply chain operates.[7] While there are several databases that could be used to proxy the extent of nature degradation across countries, our choice of ND-GAIN was made based on two main considerations: the relatively broad coverage of nature categories and the extensive geographical coverage of all major producing countries.[8] The mapping between ND-GAIN categories and the ENCORE ecosystem services is explained in section 3.2.2.2.

For bank-level data, we use the Eurosystem COREP, FINREP, and AnaCredit databases, which have information on euro area banks (Phase 2 and 3 in Figure 2). We use COREP for extracting bank-level data that is also publicly available in Pillar 3 reports, namely CET1, TSCR, and Risk-Weighted Assets (RWA) amounts as of 31 December 2023.[9] We use FINREP for extracting publicly available data on total assets. We use AnaCredit loan-level data for extracting the outstanding amount of loans as a proxy for the exposure at default (EAD) and the PD per loan. As the dataset only includes PDs estimated through the internal ratings-based (IRB) approach for credit risk, we approximate missing PDs – estimated through the standardized approach (SA) - with the average PD of the economic sector in which the firm operates.[10] The AnaCredit dataset includes loans to non-financial corporations, sovereigns, and financial institutions.

Our sample covers 200 banks and a total amount of 5.25 trillion loans extended to approximately 1.6 million creditors across 20 countries (Table 1). We restrict our sample to SSM banks and filter for (i) on-balance sheet loans, (ii) loans that are not defaulted and not impaired, (iii) amount outstanding of loans, and (iv) reference date 31-12-2023. We use the ECB's list of supervised entities as per December 2023[11] as a guiding reference to ensure alignment with the AnaCredit and COREP datasets. Specifically, we start by filtering for unique banks within the AnaCredit sample and then check for overlaps with our COREP data, retaining only those banks for which COREP information is available. We further refine our sample by cross-checking with the ECB's list to ensure we include only significant institutions (SIs). When the highest level of consolidation used in the ECB's SI list is available in our AnaCredit and COREP merge, we include that entity in our final sample. When the highest level of consolidation used in the ECB's SI list is not available in our AnaCredit and COREP merge, we include the lower levels of consolidation available in the ECB list. We then filter the COREP dataset to include only the highest level of consolidation and merge this with our filtered AnaCredit data. This approach results in a representative sample of SSM SIs.

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[7] The location of the supply chains is approximated using an input-output table, as we do not have firm specific location data for supply chains.

[8] For clarity purposes, it should be noted that ND-GAIN names the degradation scores we use as vulnerability indices. The database includes indices – from 0 to 1 - for six nature categories.

[9] For this we use a bank's RIAD code as identifier.

[10] The loans reported in AnaCredit are those above the reporting threshold of €25,000. The average PD of the economic sector in which a firm operates is calculated as a weighted average of the PDs of the sector that are included in AnaCredit.

[11] List of supervised banks (europa.eu)

Table 1: Overview of the selected sample based on AnaCredit and COREP data as of 31 December 2023

Country	Total Nominal Amount Outstanding in bn	Average CET1 Ratio (%)	Size of portfolio considered as % of total assets
BE	182.02	14.5	0.28
CY	17.86	20.0	0.31
DE	844.83	14.8	0.28
EE	16.27	23.3	0.42
ES	580.18	12.5	0.17
FI	179.97	26.8	0.24
FR	1 445.90	17.8	0.17
GR	81.54	14.5	0.29
IE	217.57	17.4	0.35
IT	679.91	14.9	0.26
LU	55.14	19.3	0.41
NL	898.93	16.5	0.49
PT	37.75	17.8	0.16
SI	13.98	17.3	0.34
	5 251.85	16.3	0.24

Note: The results presented in this table and section 4 exclude outliers, defined as the countries for which i. less than three banks are part of our sample (AT, HR, MT, SK) or ii. the size of the portfolio considered as % of total assets is ≤15% or ≥50% (LV, LT).

3.2 Structural credit risk models

Credit risk models are tools used to estimate the future default probabilities and loss distribution of values of a (bank's) portfolio of investments. These models are divided into two main categories: reduced form and structural models (Oyamienlen, 2024). Reduced form models treat default as exogenous, while structural models treat default as endogenous. In this report we focus on structural credit risk models, which determine a firm's probability of default based on the value of its assets and liabilities, assuming default occurs when the value of the assets is less than the value of liabilities.

3.2.1 The "traditional" Merton model

Structural models, pioneered by Merton (Merton, 1973), employ the Black-Scholes option pricing framework to describe default behavior. This is done by defining and estimating a credit risk measure called distance to default (DTD) as per the below equation. The intuition behind the model is that a firm *i* is closer to default the lower its assets are compared to its liabilities.

$$DTD_i = \frac{\ln\left(\frac{A_i}{D_i}\right) + \left(\mu_i - \frac{{\sigma_i}^2}{2}\right)\tau}{\sigma_i\sqrt{\tau}} \tag{1}$$

with

- DTD_i, the distance to default for firm *i* over the period τ
- A_i, the firm's asset value
- D_i, the firm's total debt value

- σ_i, volatility of the assets[12], which is considered as constant over the time period
- τ, period until assessment of the possible default, which will be considered one year for the rest of the study as per regulatory standards[13]
- μ_i, the expected return of assets, set equal to the risk-free rate

The Merton model (Merton, 1973) is especially useful for estimating a bank's credit-related losses, as the distance to default it produces can be readily translated into a probability of default for the bank's counterparty.

$$PD_i = \Phi(-DTD_i) \tag{2}$$

where Φ (.) is the standard normal cumulative distribution function.

Since this first definition, the model has evolved towards greater realism, for example by redefining how to take into account different debt maturities, as with the Kealhofer-Merton-Vasicek (KMV) model.[14]

Originally designed for estimating credit risk for non-financial corporates, the model uses a simplified non-financial corporate's balance sheet summarizing two items: assets and debts. This approach has been adapted and used for other sectors, such as sovereign credit risk (Gray, Bodie, & Merton, 2007) and banks (Chan-Lau & Sy, 2006). This literature show that the Merton approach can be adapted by adjusting the definitions of assets and liabilities. In our approach, we do not use data from debtors' balance sheets but rather use default probabilities obtained from AnaCredit or rating agencies. This is done under the assumption that sector-specific adaptations of the Merton model are already taken into account in the PDs we use. Therefore, we use the same model as in equation (1) to estimate the risk of default for non-financial corporates, financial institutions, and governments, all of which are referred to as "firms" below.[15]

3.2.2 The modified Merton model, integrating dependence on nature and state of nature degradation

3.2.2.1 Introducing asset depreciation into the Merton model

We adapt the Merton model to account for the firms' utilization of natural services, i.e. ecosystem services.[16] Firms operate optimally, freely utilizing ecosystem services. A degradation of the ecosystem services on which a firm relies results in productivity loss for the firm. This productivity loss depreciates the asset value of the firm, leaving the firm with the option to offset this depreciation through new investments, financed through either debt or equity. We choose to show the lower productivity in

[12] We derive the volatility of assets using the relation between the volatility of assets and the volatility of equity, as deduced from the Merton model. A firm's volatility of equity is proxied through sectoral volatility data obtained from Bloomberg, while a firm's debt ratio is proxied through sectoral debt ratios obtained from ReadyRatios.
[13] Probability of default: CRE32 - IRB approach: risk components (bis.org)
[14] KMV was originally a financial technology firm founded in 1989 by Stephen Kealhofer, John McQuown, and Oldrich Vasicek. In 2002, KMV was acquired by Moody's Corporation and became part of Moody's Analytics
[15] For the time being, we do not extend this analysis to exposures to households (retail and real estate exposures), given that they are not part of AnaCredit.
[16] Such proposed adaptation is made under the assumption that credit risks due to nature degradation are not already captured in credit risk assessments.

terms of higher – extra – asset depreciation resulting from nature degradation. Simplifying the notation to account for a one year time horizon, the new equation looks as follows:

$$DTD_i^{dep} = \frac{\ln\left(\frac{A_i . e^{-dep_i}}{D_i}\right) + \left(\mu - \frac{{\sigma_i}^2}{2}\right)}{\sigma_i} = \frac{\ln\left(\frac{A_i}{D_i}\right) + \left(\mu - \frac{{\sigma_i}^2}{2}\right)}{\sigma_i} - \frac{dep_i}{\sigma_i} \qquad (3)$$

with dep_i being the "extra" depreciation rate resulting from nature degradation applied to firm *i* and where $0 \leq dep_i < 1$, with 0 illustrating a state of no depreciation due to nature degradation and 1 illustrating a state of stranded assets with no remaining value. From equation (3) one can also note that a loss on assets - A_i -, an increase in debts - D_i -, or a drop of the expected return on assets - μ_i – are equivalent.

The new DTD resulting from nature degradation can now be easily expressed as the initial *DTD*, diminished by a multiple of the depreciation rate resulting from nature degradation over the specified time period:

$$DTD_i^{dep} = DTD_i - dep_i/\sigma_i \qquad (4)$$

where dep_i is defined and estimated as in section 3.2.2.2, DTD_i is calculated based on the known or proxied PD and σ_i – assumed to be equal across firms within the same sector for simplification reasons - is derived from sectoral volatilities retrieved from Bloomberg.[17]

This paper presents the theoretical framework for quantifying the sensitivity of banks to a shock on ecosystem services which their counterparties depend on. Here, the depreciation parameter dep_i represents a loss on the counterparty's balance sheet. Ideally, the calibration of the link between this loss and a shock on ecosystem services would use external data on how shocks on nature affect the productivity of specific economic sectors. This study does not focus on calibration and therefore introduces a framework with an assumed shock on ecosystem services (section 3.2.2.2 and 3.2.2.3).

3.2.2.2 Specifying how asset depreciation is affected by Vulnerability to nature degradation

As per Phase 1 of Figure 2, for each firm we define the extra depreciation rate stemming from a shock on nature as introduced in equation (3) as a product of:

- a theoretical shock on a firm's balance sheet due to an ecosystem service on which the firm depends (α_{ES}) on (see section 3.2.2.3), and
- the vulnerability of the firm to that shock ($Vuln_{ES,i}$), where the vulnerability is proxied by the dependence of the firm's main process (via the NACE code) on that ecosystem service and the country of that firm – through a dependence score ($DS_{ES,i}$) - and the degree of nature degradation in the countries where the firm and its supply chain operate ($Degr_{ES,i}$)

$$dep_i = \alpha_{ES}\, Vuln_{ES,i} \qquad (5)$$

As per Phase 2 of Figure 2, we can express the new distance to default for a firm i as a function of Vulnerability to nature degradation (equation (6)). From this definition, we can see how the vulnerability ($Vuln_{ES,i}$), which has a range from 0 to 1, can be seen as a mitigation of the shock α_{ES}.

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[17] See section 3.1 on how the missing PDs are approximated at the sectoral-country level.

$$DTD_i^{dep} = DTD_i - \frac{\alpha_{ES}\, Vuln_{ES,i}}{\sigma_i} \tag{6}$$

The estimation of the vulnerability of a firm to nature degradation ($Vul_{ES,i}$) involves the estimation of the direct DS and the estimation of the indirect DS, both enriched with the extent of degradation of ecosystem services across different countries. The DS is a metric illustrating the degree to which a given production process relies upon a specific ecosystem service. A low DS (close to zero) indicates little to no reliance, whereas a high score (close to one) shows that the ecosystem service is crucial for the functioning of the economic activity. The direct DS is obtained directly from ENCORE, while the indirect DS is generated by intersecting ENCORE with EXIOBASE, considering the supply chain at a country and sector level. The DS methodology (direct and indirect) is the same as that followed in the ECB Occasional Study on nature-related physical risks (see Appendix A and B in Boldrini et al., 2023). We enrich the DS by adding a new component that takes into account the extent of degradation of ecosystem services in each country.

The estimation of the vulnerability of a firm to nature degradation ($Vul_{ES,i}$) happens in four sub-steps. These sub-steps clarify how a firm's vulnerability varies based on the firm's economic activity and location, and those of its supply chain.

Sub-step 1 in estimating a firm's vulnerability to nature degradation: Direct DS

The first sub-step consists of estimating the direct DS by matching the firm's NACE code with the Global Industry Classification Standard (GICS) in the ENCORE database. While we use level two NACE codes for simplicity reasons, a finer granularity is also possible. ENCORE allows us to have the dependence score of each economic sector on each ecosystem service included in the database, as shown below.

$$ENCORE : \begin{bmatrix} DS_{ES1,NACE1} & \cdots & DS_{ES1,NACEj} \\ \vdots & \ddots & \vdots \\ DS_{ES21,NACE1} & \cdots & DS_{ES21,NACEj} \end{bmatrix},$$

where ES*1* to ES*21* denotes the 21 ecosystem services included in the ENCORE database and *NACE j* denotes NACE level 2 economic sectors. This DS matrix is the same across countries, as the direct DS is not location specific.

Sub-step 2 in estimating a firm's vulnerability to nature degradation: Direct Vulnerability

The second sub-step involves enhancing the direct DS with an index which accounts for each country's extent of ecosystem service degradation. To do this, we choose the ND-GAIN index given its global coverage and simple mapping to the ecosystem services included in ENCORE. While ND-GAIN assesses vulnerability and readiness of countries across six nature-related categories using 45 indicators, this study focuses on the categories "ecosystems" and "water" within the ND-GAIN Vulnerability Score. The "ecosystems" and "water" scores per country are mapped to the ENCORE ecosystem services as presented in Appendix 7.5. This mapping approach could be further improved by using more nature-related categories from ND-Gain or using other more granular nature degradation indices.

For this second step, we first start with the extent of degradation $Degr_{ES,cntry_i}$, proxied by the ND-Gain index. We can then define the Vulnerability index using direct dependencies (DS direct) and the extent of degradation of a country's ecosystem services (equation (7)). The direct vulnerability of each firm - $Vuln_{ES,i}^{direct}$- introduced above is then mapped to a vulnerability index that takes into account the country and economic sector (NACE) of firm *i* - $Vuln\,^{direct}_{ES,\,cntry_i,\,NACE_i}$ – corresponding to the data breakdown coming from ENCORE and EXIOBASE. Then by definition:

$$Vuln\,^{direct}_{ES,i} \stackrel{\text{def}}{=} Vuln\,^{direct}_{ES,\,cntry_i,NACE_i} \stackrel{\text{def}}{=} DS^{direct}_{ES,NACE_i}\,.\,Degr_{ES\,,cntry_i} \tag{7}$$

Following this formulation, the newly produced Vulnerability index takes into account not only the dependency of a firm[18] - through the economic sector to which it belongs - on ecosystem services, but also the extent of nature degradation relevant to the firm's direct process in the firm's country as stipulated in AnaCredit.

Sub-step 3 in estimating a firm's vulnerability to nature degradation: Indirect DS and Indirect Vulnerability

The third sub-step consists of estimating vulnerability to nature degradation also for indirect dependencies on nature ($Vuln\,^{indirect}_{ES,\,cntry_i,NACE_i}$). The process to integrate the impact of the supply chain and define indirect vulnerabilities is the same as the one for estimating indirect DS based on direct DS and incorporating supply chain effects through EXIOBASE, as used in Svartzman et al. (2021) and the ECB OS on nature-related physical risks (Boldrini et al., 2023). The only difference is that instead of using $DS^{direct}_{ES,NACE_i}$ to estimate $DS^{indirect}_{ES,NACE_i}$, we now use $Vuln\,^{direct}_{ES,\,cntry_i,NACE_i}$ to estimate $Vuln\,^{indirect}_{ES,\,cntry_i,NACE_i}$. Through following that same process, nature degradation is also taken into account throughout the location of the supply chains.

Sub-step 4 in estimating a firm's vulnerability to nature degradation: Total Vulnerability

The fourth and final step involves computing the total vulnerability of a firm to nature degradation ($Vul_{ES,\,cntry_i,NACE_i}$) (equation (8)). This includes direct and indirect dependencies on ecosystem services, and the degradation of the ecosystem services on which the firm directly and indirectly (through its supply chain) depends on. There are alternatives to how one can estimate the total vulnerability based on direct and indirect vulnerabilities (see Appendix 7.1). We choose to estimate the total vulnerability of a firm to nature degradation using the highest of the direct and indirect vulnerabilities, hereafter referred to as *Vuln max*. The intuition behind this choice is that a firm is as vulnerable as the most vulnerable point in its supply chain, which also implies that a firm cannot change its input factors.

$$Vuln_{ES,\,cntry_i,NACE_i} = Max\left(Vuln\,^{direct}_{ES,\,cntry_i,NACE_i}\,, Vuln\,^{indirect}_{ES,\,cntry_i,NACE_i}\right) \tag{8}$$

3.2.2.3 Two approaches for calibrating the shock on ecosystem services and the resulting depreciation of assets

As per our definition in equation (5), a firm's asset depreciation rate due to nature degradation is the product of a theoretical shock on ecosystem services and a mitigating factor specific to the firm. These idiosyncratic shocks can be aggregated at a macroeconomic level. Specifically, the shocks suffered by all firms to which the SSM SIs in our sample have lent to can be aggregated to obtain an aggregated depreciation shock at the SSM level per each ES, expressed as the sum of firm's depreciation weighted by their assets (equation (9)). In our case, we define the firms as the banks' debtors and approximate

[18] The firm here is the debtor, i.e. the bank's counterpart who has taken a loan from the bank.

firms' assets by their loans' outstanding amounts. This approximation allows us to keep AnaCredit as our sole source of firm data.

$$\left(1-\frac{\Delta Assets}{Assets}\right)_{ES,SSM} = \frac{\sum_i^{firms\ in\ SSM}\left(1-\left(\frac{\Delta Assets}{Assets}\right)_i\right)A_i}{\sum_i^{firms\ in\ SSM} A_i} \tag{9}$$

Using the depreciation rate in an exponential form as expressed in equation (3), and as defined in (5), equation (9) is also equivalent to the below.

$$\left(1-\frac{\Delta Assets}{Assets}\right)_{ES,SSM} = \frac{\sum_i^{firms\ in\ SSM}\left(e^{-\alpha_{ES}\ Vul_{ES,i}}\right)A_i}{\sum_i^{firms\ in\ SSM} A_i} \tag{10}$$

To express this result in a more intuitive way for practitioners, we make use of an approximation using the Taylor series expansion for the exponential function of the first order ($e^x \approx 1+x$). This approximation is possible because the term $\left(\alpha_{ES}\ Vuln_{ES,i}\right)$ is always between 0 and 1 and much smaller than 1.[19]

$$e^{(-Vuln_i\ .\alpha_{ES})} \approx (1 - Vuln_i\ \alpha_{ES}) \tag{11}$$

Using equation (11) in equation (10) and simplifying, we get an aggregated SSM depreciation rate as per the below formula.

$$\left(\frac{\Delta Assets}{Assets}\right)_{ES,SSM} \approx \alpha_{ES}\ \frac{\sum_i^{firms\ in\ SSM} Vuln_i\ A_i}{\sum_i^{firms\ in\ SSM} A_i} \tag{12}$$

Equation (12) shows how the depreciation at the SSM level is a product of a constant α_{ES} on the defined perimeter - here SSM SIs in our sample - and the weighted average of the Vulnerability index of each firm to which the SSM SIs in our sample lend to, weighed by a firm's assets.

To clarify the dimensions used to approximate firms' vulnerability to nature degradation, the below equation shows how firms *i* are mapped to a group of firms with the same country and NACE sector $(cntry_i, NACE_i)$.

$$\left(\frac{\Delta Assets}{Assets}\right)_{ES,SSM} \approx \alpha_{ES}.\frac{\sum_{c,n}^{cntry,NACE\ in\ SSM} Vuln_{ES,c,n}\ A_{c,n}}{\sum_{c,n}^{cntry,NACE\ in\ SSM} A_{c,n}} \tag{13}$$

with country c and NACE n defining all possible country-NACE pairs (c,n).

From the above equation it is also clear that the shock calibration - α_{ES} – can be done in two different ways. A first approach would be to impose an α_{ES} to each ecosystem service, which would need to rely on modelling the relation between each ES and at least one economic sector that depends on it. The aggregated depreciation would then result from the equation. (see Option 1 below) A second approach would impose the aggregated depreciation at the SSM level per each ES, which could potentially be taken from an external macroeconomic scenario, and based on that reverse-calibrate the α_{ES}. (see Option 2 below)

[19] This is also the case in the below Option 2, when the aggregated extra asset depreciation rate at the SSM level due to nature degradation is 1% per ES.

Option 1: Assuming a constant underlying shock for all ES

A first approach would be to impose a fixed value of the alpha shock - α - across all ecosystem services for our chosen perimeter of the SSM. This approach has the upside of being simple and allowing comparability of results across ecosystem services. However, as alpha is a theoretical shock on nature, it is impossible to get a direct value of it. In addition, micro-calibration on a specific economic process is difficult to generalize to all other processes. Section 4.1 presents the results for an assumed alpha of 1% for each ES. Given that literature is more likely to provide a value for the loss of productivity or asset values that certain economic sectors would experience due to a shock on nature, we present option 2 below.

Option 2: Assuming a constant depreciation rate at aggregated SSM level per each ES

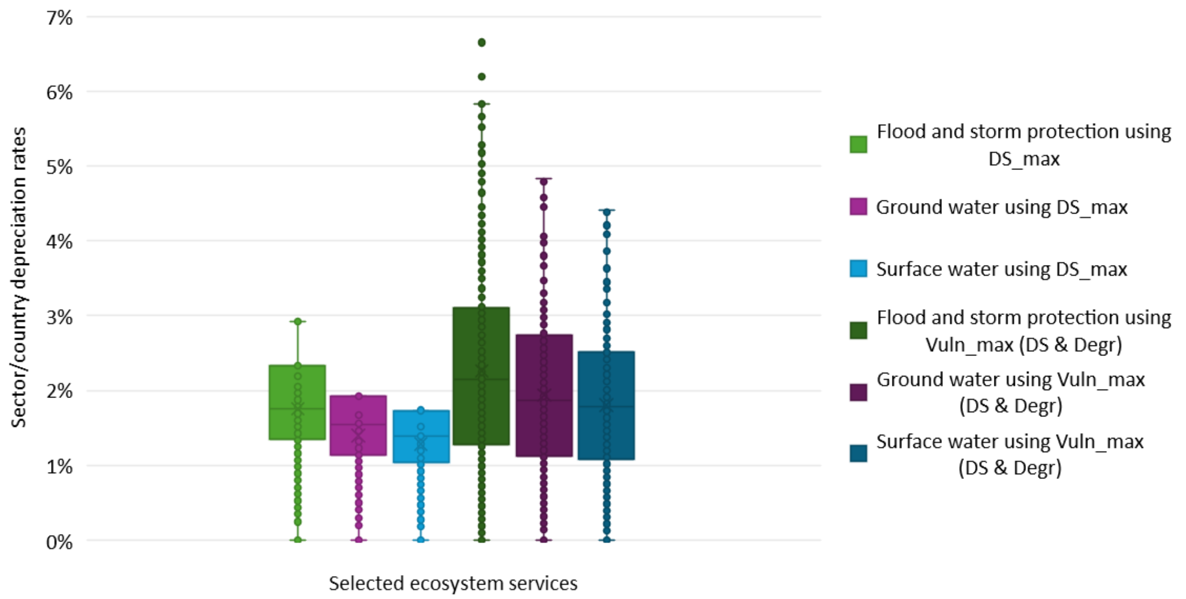
A second approach would be to impose a fixed value for the aggregated depreciation rate at a defined perimeter, here the SSM level, for each ES. This exogenous depreciation rate can be obtained by literature or nature-to-economy macro models, defined at a geographical or sectoral level, to calibrate alpha while maintaining a relative discrimination among country-sector pairs based on their Vulnerability index (see equation (14)).[20]

The caveat of this approach in our current case of an assumed depreciation rate is the counterintuitive result that in order to reach the same level of depreciation for each ES, a higher (lower) shock alpha has to be applied to lower (higher) Vulnerabilities. Section 4.2 presents the results for an assumed aggregated SSM depreciation rate of 1% for each ES.

Following Option 2, we see that taking into account the extent of degradation of different ecosystem services in different countries makes the depreciation rates incurred by different loans more divergent across countries and sectors of the debtor, and consequently also across banks (Figure 3). For three chosen ES, Figure 3 shows the depreciation rate for NACE-country pairs. In the left half of the below figure, the depreciation rate takes into account the dependence of a firm on nature and the backwards estimated shock to nature (α_{ES}) that is calibrated in order to get a certain aggregated depreciation loss at the euro area level for each ES. In the right half of the below figure, the depreciation rate also takes into account the extent of nature degradation – in addition to dependence on nature – in order to get the same aggregated depreciation loss as in the left half. The broader dispersion of results in the right side of the graph shows how taking into account the extent of nature degradation increases the divergence in the depreciation rates suffered by different firms.

[20] This Vulnerability index - ranging from 0 to 1 - is definition-dependent and qualitative (e.g. high, medium, and low for ENCORE). This means that reverse-calibrated alphas would need to change depending on the definition of the vulnerability index, to produce the same exogenous depreciation rate.

Figure 3: Spread of the depreciation rate per loan characteristic (sector-country pair of loan debtors), when assuming an aggregated 1% depreciation at SSM level per ES



3.3 The CET1 ratio impact

For estimating the impact on a bank's CET1 ratio, we use the prescribed formulas of the Basel standards for estimating expected losses (EL), RWA, and the CET 1 capital ratios (Phase 3 in Figure 2).[21] The re-evaluation of EL and RWA - including PD, LGD, and EAD - are done at the loan level. For the estimation of credit losses, we use exposure data from AnaCredit, the estimated change in PD using the Merton model, and the estimated change in the LGD using the model proposed by Frye and Jacobs (2012) as explained in Appendix 7.2 (Section 3.3.1).

For the estimation of risk-weighted assets, we use the same exposure, change in PD and change in LGD as in the EL estimation (Section 3.3.2). This is not customary, as the PD used in EL estimations needs to be a point-in-time (PIT) PD, while the PD used in RWA estimations needs to be a through-the-cycle (TTC) PD. However, we assume that the TTC PD is the same as the PIT PD, given that we expect nature degradation to be relatively permanent and assume supply chains and trade flows remain unchanged, i.e. that there is no substitution between countries, sectors, and firms within the same sector. A firm would then need time to adjust its business due to a shock on ecosystem services.

Similarly, the LGD used in EL and RWA calculations differs: the LGD used in EL estimations is a PIT LGD, while the LGD used in RWA estimations is a downturn LGD. We make the same assumption as for the PD, whereby we assume that the change in the downturn LGD is equal to the change in PIT LGD. It is important to note that most of the impact on the CET1 ratio comes from the change in RWA – as opposed to the EL – component. As the RWA is by construction a longer-term estimation, our results point to the importance of recognizing the longer-term repercussions of nature degradation (akin to what the RWA aims to capture) as opposed to the shorter-term ones (akin to what the EL aims to capture).

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[21] Basel Framework, Basel Framework (bis.org) and RWA formula: CRE31 - IRB approach: risk weight functions (bis.org)

3.3.1 Estimating the credit losses

The estimation of credit losses for the loans in scope of our analysis is done in line with the below formula as prescribed by the Basel framework and used in credit risk assessments (Boldrini et al., 2023; Chatterjee, 2015).[22]

$$EL_b = \sum_{l=1}^{Loans\ of\ b} PD_l . LGD_l . EAD_l \tag{14}$$

with

- EL_b , aggregated expected loss of bank b
- PD_l , probability of default for the borrower of a loan l [23]
- LGD_l, loss given default of loan l, which we model based on the change in PD
- EAD_l, exposure at default of loan l

The credit losses resulting from the shock on nature are derived from the variation of PDs and LGDs, as reflected by the change in expected losses.[24]

$$\Delta EL_b = \sum_{l}^{Loans\ of\ b} [\Delta PD_l . LGD_l + PD_l . \Delta LGD_l + \Delta PD_l . \Delta LGD_l] . EAD_l \tag{15}$$

The variation of PD - ΔPD - is derived from the variation of DTD before and after the nature degradation shock. The variation of DTD is estimated through the Merton model described in section 3.2, using the formula defined by the Merton model equation (1 and 4). The change in LDG - ΔLGD - is estimated based on the change in PD, as per the model proposed by Frye and Jacobs (2012) (see Appendix 7.2).

3.3.2 Estimating the increase in RWA

The estimation of the RWA for the loans in scope of our analysis is done in line with the below formula as prescribed by the Basel framework. [25]

$$RWA = 12{,}5 . EAD . LGD . f(PD, M) \tag{16}$$

with

$$f(PD, M) = \left[N\left(\frac{1}{\sqrt{1-R}} N^{-1}(PD) + \sqrt{\frac{R}{1-R}} N^{-1}(0{,}999) \right) - PD \right] . \frac{1+(M-2{,}5)b}{1-1{,}5b},$$

where

- $$\begin{cases} b = (0{,}11852 - 0{,}05478 . ln(PD))^2 \\ R = 0{,}24 - 0{,}12 . \frac{1-e^{-50.PD}}{1-e^{-50}} \end{cases};$$

  and
- M is the effective maturity of the loan.

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[22] Basel Framework (bis.org)
[23] Definition: The counterparty's probability of default over one year, determined in accordance with Articles 160, 163, 179 and 180 of Regulation (EU) No 575/2013, 11.4.1, p.253, AnaCredit Reporting Manual Part II – Datasets and data attributes, second edition (europa.eu)
[24] The change in LGD is modelled based on the estimated change in PD, as per the model proposed in BIS Working Papers, No 113 (Altman, Resti, & Sironi, 2022). See Appendix 8.2 for more information.
[25] Basel Framework (bis.org)

The change in RWA - ΔRWA- is the increase in RWA due to the nature shock and can then be expressed as in equation (16). As for the estimation of the ΔEL, we assume an effective maturity of one year for simplification reasons, use the PD as estimated in section 3.3.1, and estimate the change in LGD using the model proposed by Frye and Jacobs (2012). Sensitivity analysis shows that the higher the choice of effective maturity (M), the higher the RWA impact (Appendix 7.4). Therefore, our assumed maturity of one year likely results in an underestimation of risk.

$$\Delta RWA_b = 12{,}5. \sum_l^{Loans\ of\ b} [\Delta f(PD_l, 1). LGD_l + \Delta LGD_l. f(PD_l, 1) + \Delta f(PD_l, 1). \Delta LGD_l]. EAD_l \quad (17)$$

where b is a bank and l is a loan in the bank's portfolio.

3.3.3 Estimating the CET1 ratio depletion

The depletion of the CET1 ratio (from here on referred to as ΔCET1 ratio) due to the asset depreciation that results from the dependence on nature and the state of nature degradation is estimated using the definition of the CET1 ratio as defined in the Basel framework.

$$CET1_b^{ratio} = \frac{CET1_b^{capital}}{RWA_b} \quad (18)$$

From the above formula, we derive $\Delta CET1_b^{ratio}$, the depletion of the CET1 ratio of bank b.

$$\Delta CET1_b^{ratio} = \frac{CET1_b^{capital} - \Delta EL_b}{RWA_b + \Delta RWA_b} - CET1_b^{ratio} \quad (19)$$

$\Delta CET1_b^{ratio}$will then serve as an indicator of the sensitivity of bank b to nature-related physical risks coming from the credit portfolio, taking into account the dependence on nature and the state of nature degradation. With this indicator, we can conclude on the relative sensitivity of different banks and countries to a particular ecosystem service (see Section 4).

3.4 The ecosystem service degradation sensitivity indicator (EDSI)

In an effort to have a better view of the risk that ES degradation poses to a bank's capital position, we propose an indicator that takes into account not only the depletion of a bank's capital position due to ES degradation but also a bank's capital "cushion" above minimum requirements (Phase 4 in Figure 2). Through considering both of these aspects, we get an indicator that approximates a sort of "distance to the breach of minimum requirements" due to ES degradation. Specifically, we estimate how much of a bank's CET1 ratio above the TSCR ratio made up of CET1 gets depleted due to a shock on ecosystem services. We use the TSCR, which includes the pillar 1 requirement and the pillar 2 requirement, as the level below which there would be a breach of minimum requirements.[26]

$$EDSI_b = \frac{\Delta CET1_b^{ratio}}{CET1_b^{ratio} - TSCR_b^{ratio}} \quad (20)$$

Aggregating to a country level, CET1 and TSCR ratios at the country level are estimated as weighted averages, weighed by RWAs of banks within each country (c).

[26] A comparison to the TSCR is also done by the EBA when analyzing the level of capital depletions when stress-testing European banks. See EBA publishes the results of its 2023 EU-wide stress test | European Banking Authority (europa.eu).

$$EDSI_c = \frac{\Delta CET1_c^{ratio}}{CET1_c^{ratio} - TSCR_c^{ratio}} \quad (21)$$

4. Results

The proposed framework is most useful for cross-bank comparison, given that it depicts a bank's credit risk profile as it relates to the sensitivity of its capital position to a shock on ecosystem services. Such bank-level analysis has also the benefit of being more actionable for central bank and supervisory authorities. Due to confidentiality reasons, however, the results are aggregated at country level. The presented aggregations could therefore hide cross-bank heterogeneity and might be not representative of the banking sector of a certain country if the results are influenced by one or a few banks with a very different risk profile than the rest of a country's banks. In the Figures below – as in the methodology presented in section 3.3 and 3.4 - countries are approximated by a theoretical bank that aggregates all the capital and risk weighted assets of the significant banks included in our sample in that country. The results presented herein must be read as a relative sensitivity of countries to a certain shock on an ecosystem service – subject to the limitations highlighted in section 5, such as the use of a better ES degradation index – and not as an absolute level of vulnerability or resilience of the banking sector of a specific country.

4.1 Results with fixed alpha of 1% per ES

Figures 4 and 5 show country-level results for methodological Option 1 presented in section 3.2.2.3, i.e. when theoretical shock – α – of 1% is applied on each ES. Given that this shock is assumed, the results must be read in relative rather than absolute terms of impact. In addition, as this shock is assumed to be the same across ES, cross-country comparison cross-ES is possible. The comparison shows that SSM countries incur, on average, more credit risk- related CET1 ratio depletion (Figure 4) and sensitivity of the EDSI indicator (Figure 5) due to shocks in the ecosystem services i. mass stabilization and erosion control, ii. climate regulation, iii. flood and storm protection, iv. surface water and v. ground water. The cross-ES comparison also points to a certain degree of consistency in the comparative sensitivity of countries: some countries are generally less sensitive across ES (e.g. France, Spain, Ireland), while some countries are generally more sensitive (e.g. Finland, Cyprus, Greece).

Figure 4: ΔCET1 ratio due to ES shock, using Vulnerability max (DS & Degr)

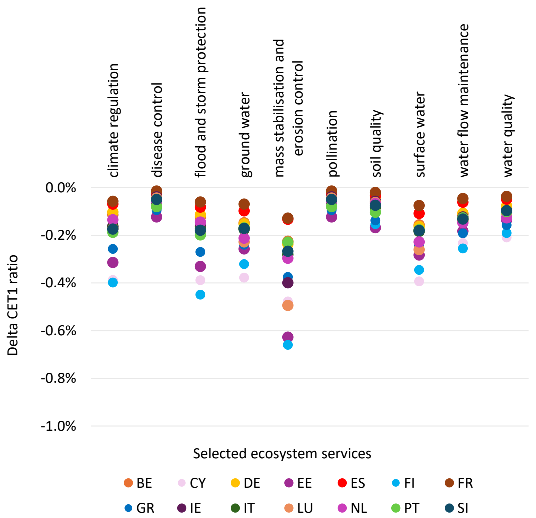
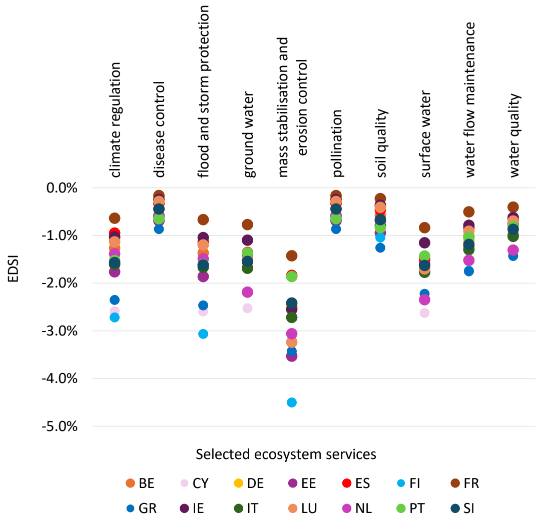


Figure 5: EDSI due to ES shock, using Vulnerability max (DS & Degr)



Given that the size of the portfolio considered in this analysis – loans to NFCs, FIs, and sovereigns – differs per bank and subsequently also per country, it is relevant to consider how much of the CET1 ratio depletion is due to the size of the portfolio as compared to total assets. Based on a linear regression analysis, we have found that only around 10% of the sensitivity of the ΔCET1 ratio is explained by the differences on the size of the portfolio in scope of our analysis as compared to total assets. The remaining 90% of the sensitivity of the ΔCET1 ratio across countries is explained by factors explicitly considered in our framework.[27] Still, it is good to note that France and Spain, that generally seem to be less sensitive across ES, have some of the lower ratios of portfolio-size-over-total-assets. Portugal, on the other hand, has a comparatively even lower ratio of portfolio-size-over-total-assets and still turns out to be relatively more impacted. Lastly, it is worth mentioning that countries' relative sensitivity to different ES varies. For example, Luxembourg is the 3rd most sensitive country to a shock on ES mass stabilization and erosion control and only the 11th most sensitive to a shock on ES disease control (Figure 4).

The estimation of the EDSI allows us to compare how much closer to a capital breach the shocks in different ES bring different banks (Figure 5). As an example, an EDSI of -3% for the Netherlands due to a shock on ES mass stabilization and erosion control means that the resulting depletion of the CET1 ratio would eat away 3% of its CET1 capital buffer above the TSCR filled with CET1. Another 97% of the CET1 buffer above the TSCR with CET1 would be remaining before the Netherlands, i.e. the "representative Dutch bank", breaches its minimum requirement of TSCR filled with CET1. When comparing Figure 4 to Figure 5, we see that Greece's relative position worsens compared to Estonia, indicating that Greece has a lower level of CET1 capital above the TSCR requirement than Estonia. Since capital buffers above the TSCR (e.g. macroprudential buffers or Pillar 2 Guidance) are not included in the EDSI, as they are not considered a minimum requirement, this shift in position could

[27] The R^2 of the linear regression of ΔCET1 ratio on the ratio of loans outstanding-to-total assets is around 10%, with ES pollination having the highest R^2 of 34% and ES ventilation having the second-highest R^2 of 26%.

partly be due to Greece having lower capital buffers than Estonia. For example, Estonia set its countercyclical capital buffer at 1.5% in December 2023, while Greece's was set at 0%.

4.2 Results with fixed depreciation rate of 1% per ES at the aggregated SSM level

Figures 6a, 6b and 7a, 7b show the country-level results for methodological Option 2 presented in section 3.2.2.3, i.e. when the shock on each ES - (α_{ES}) - is derived from an assumed 1% depreciation rate per ES at the aggregated euro area level. Given this assumed depreciation rate, the results must be read in relative terms across countries rather than as absolute impacts. In addition, given the potentially different backward-estimated shock on each ES, only a comparison across countries within the same ES is possible as opposed to a cross-ES comparison for Option 2. To understand why a comparison of capital depletion across ES is not possible, it is helpful to illustrate through an example: a much smaller shock on the ES surface water – on which many large economic sectors are highly dependent on – would lead to the same 1% depreciation as a much larger shock on the ES pollination – on which not many large economic sectors are highly dependent on.

Figure 6a: ΔCET1 ratio, using DS max

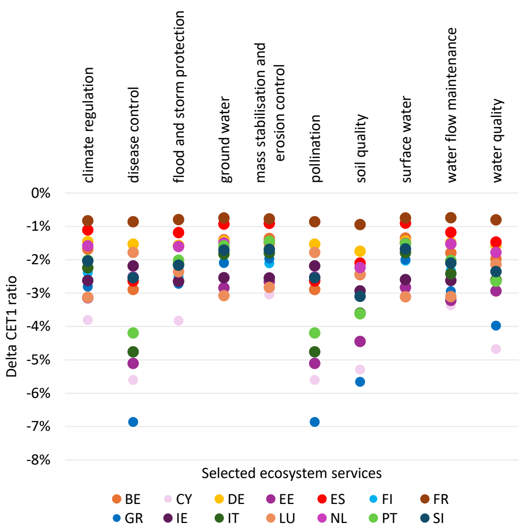


Figure 6b: ΔCET1 ratio, using Vulnerability max (DS & Degr)

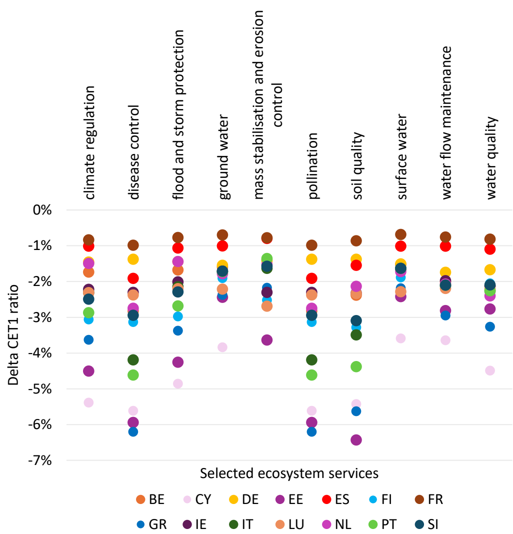


Figure 7a: EDSI, using DS max

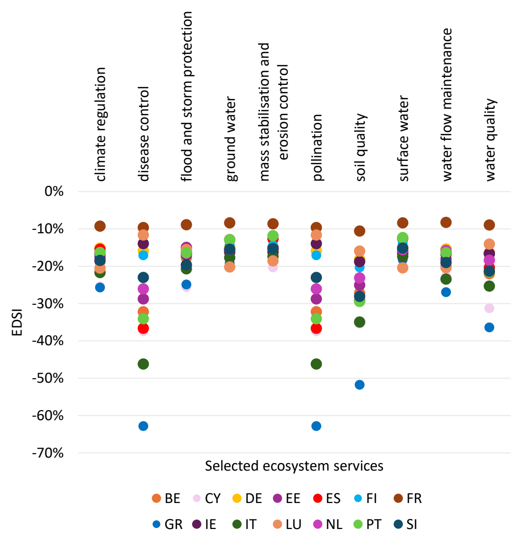
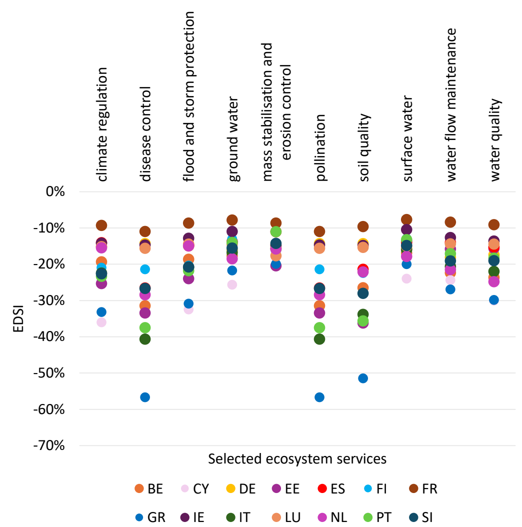


Figure 7b: EDSI, using Vulnerability max (DS & Degr)



Figures 6a and 6b show the CET1 ratio depletion due to a 1% depreciation rate at the aggregated SSM level for each ES. The difference between these figures is that in 6a the impact is only due to dependence on nature, while in 6b the impact is due to both dependence on nature and the extent of nature degradation, which we call the Vulnerability to nature degradation. From Figure 6a and b we can draw two conclusions. First, adding the extent of ES degradation for different countries accentuates the differences in the countries' capital depletion per ES. This is apparent in a much wider dispersion of ΔCET1 ratios across countries for each particular ES when comparing Figure 6a and 6b. Regardless of this wider dispersion, we do notice that across figures 6a and 6b, the depletion of the CET1 ratio is more heterogeneous within some ES. This heterogeneity reflects differences in the breakdown of economic sectors across countries. As an example, for the ES ground water, on which many and similar economic sectors across countries are dependent, the ΔCET1 ratio across countries is less dispersed than for ES pollination. Second, we observe that adding nature degradation as a driver of financial losses – in addition to dependency on nature – sometimes changes countries' relative sensitivity to a particular ES. For example, moving from Figure 6a to 6b we observe that the relative position of Greece improves when the extent of the degradation of its ecosystem services is taken into account, pointing to other countries having comparatively more degraded ES than Greece. Lastly, similarly to the results in section 4.1, we observe some consistency in the comparative sensitivity of countries to a shock across ES: some countries are generally less sensitive across ES (e.g. France, Spain), while other countries are generally more sensitive (e.g. Greece, Cyprus, Estonia) (Figure 6b).

The estimation of the EDSI allows us to compare how much closer to a capital breach the shocks in different ecosystem services bring different banks (Figure 7a,7b). Figures 7a and 7b show the EDSI due to a 1% depreciation rate at the aggregated SSM level for each ES. The difference between these two figures is that in 7a the impact is only due to dependence on nature, while in 7b the impact is due to both dependence on nature and extent of nature degradation (Vulnerability to nature degradation). The conclusions drawn in Figure 6 a and b can also be drawn for these figures. Specifically, we can see that when the EDSI indicator considers Vulnerability to nature degradation, Greece turns out to be one of the most sensitive countries while France and Ireland turn out to be least sensitive (Figure 7b). In addition, when comparing Figure 6b to Figure 7b, we find that – similarly to the comparison between Figure 4 and 5 – the relative position of countries within a particular ES changes. For example, when moving from Figure 6b to 7b, the relative position of Greece compared to Estonia worsens for ES climate regulation. This points to a potentially lower level of CET1 capital above the TSCR requirement for Greece compared to Estonia. As also mentioned in section 4.1, this difference might be due to other non-minimum requirements, such as macroprudential buffers, which are not considered in the EDSI.

5. Discussion

Our analysis faces methodological limitations that match the state of maturity of the research field of nature-related financial risk. First, there are two main limitations related to the use of the DS. One is that the DS does not have a geographical component, meaning that every economic sector is assumed to have the same dependence on nature across all regions of the world. This might not be true do to different reasons, including possible differences in technological advancement among countries. Second, the DS is at a sub-sectoral level and not more granular. This means that differences in the dependence of a certain firm on a particular ecosystem service - which can be due to different business models, sustainable practices, etc., - are not taken into account. As an example, using the DS as-is and not enriching it with firm-level information would mean that a firm that uses water in a more efficient manner would still experience the same change in PD as a firm that uses water less efficiently in the same sector, ceteris paribus. By knowing their customers and taking into account customer-specific information - such as sustainable practices, easiness of switching suppliers, etc. - banks could sometimes effectively manage their risks by re-directing their portfolios towards firms with more nature-friendly/efficient use of natural resources within the same sector.

Two other notable limitations are the lack of firm-specific supply chain geolocational information and the lack of a perfect mapping between the ES included in the ENCORE database and other databases that measure the extent of ES degradation across regions. Due to the lack of geolocational data for the supply chain of firms to which a bank lends, an input-output table such as EXIOBASE has been used. Such table gives a geographically explicit overview of flows of production, consumption, and investment within countries and flows of international trade in goods and services between countries. However, firm-specific supply chains might not always resemble the flows of input-output tables. In addition, there is also a lack of geolocational data for the direct/primary process; in this study we use the location of the firm that is listed as a debtor in AnaCredit. This is of course an imperfect proxy, as the debtor location in AnaCredit does not have to correspond to the location of where the primary activities are undertaken. Lastly, in order to better approximate the Vulnerability to ES degradation, it is important to have a precise mapping of the ES included in ENCORE – from which we retrieve dependencies – and ES included in other databases that measure the extent of nature degradation across countries. For this report, we use the ND-Gain index as a proxy for the extent of nature degradation in different countries given its global coverage. Another index that better corresponds to the degree of ES degradation and/or has more ES granularity would be better suited for such an analysis.

Our analysis is also faced with the difficulty of modelling the non-linearities of nature. The many components of nature evolve non-linearly and are subject to tipping points. Given the difficulties involved in modelling such natural phenomena, this study has followed the simpler approach of assuming nature degradation and its impact on firms is linear. This has been done by estimating asset depreciation due to nature degradation by the simple multiplication between the dependence score (ranging between 0 and 1) and the index of nature degradation (ranging between 0 and 1).

6. Conclusion

This paper proposes a new framework for translating shocks to nature – ecosystem services – to credit-related capital depletion for banks, bypassing at the moment the need for better linkages between nature and macroeconomic models. The link from nature to credit-related losses is done through the introduction of a nature degradation-induced asset depreciation to the balance sheet of a bank's debtors, which increases the probability of default of these debtors. The additional asset depreciation rate due to the degradation of ecosystem services is expressed as a product of i. a shock on ecosystem services on which a debtor/firm depends, ii. the dependence of the firm on ecosystem services (as approximated by the dependence on ecosystem services of the economic sector in which the firm operates), and iii. the extent of nature degradation in the countries where the firm and its supply chain are located.

We find that going beyond dependencies on nature, which is where most research is currently focusing on, and taking a further step of introducing the extent of nature degradation into financial risk estimations adds a needed - and currently missing - layer of risk. Our results show that taking into account the extent of nature degradation adds more differentiation in the capital impacts of banks and countries, and results in a better proxy of financial risk.

This framework, and more specifically the EDSI indicator, enables cross-bank and cross-country comparison: it can be useful to central banks and supervisory authorities as a way of prioritizing the banks that are most sensitive to the degradation of a particular ecosystem service, e.g. when an imminent threat to an ecosystem service becomes apparent. Given that the EDSI also takes into account the cushion of capital that a bank has on top of its minimum requirements, it would also inform supervisors of the "distance to the breach of minimum requirements" upon the calibration of a shock on nature (section 3.4). Alternatively to the EDSI, the central bank and supervisory authority can compare the "simple" CET1 ratio depletion of different banks due to a shock in an ecosystem service (section 3.3). While the presented results are aggregated at country level, the same estimations can be used to present the results at bank level. In that way, banks could be compared to others in the same country or peer group (e.g. based on business model, size, etc.).

To bring the EDSI - or the ΔCET1 ratio indicator - a step further, additional research is needed to calibrate the link between a shock on ecosystem services and the loss of productivity of economic sectors dependent on those ecosystem services. Such calibration would allow the framework to be used for stress-testing the capital position of banks and other financial institutions and for reading the capital impacts in absolute terms. In this paper, due to the lack of such calibration, we have assumed theoretical shocks on nature and have therefore produced results that can only be read in relative terms, i.e. a comparison across countries and banks, rather than absolute results that would give a definite answer as to the capital impact of a shock on nature. Beyond calibration, we encourage further work on improving the dependence scores on ES (e.g. by adding to them a geographical component).

This paper's main contribution is to introduce a flexible framework for assessing nature-related financial risks in a field where there is as of yet no straightforward and broadly accepted approach. While the current paper focuses on physical risk- related credit losses for European banks through the loans they have extended, the framework is flexible to be more widely applicable with few modifications. We highlight a few next steps as most promising. A first next step would be to integrate market risk related to bond and equity holdings. Second, the same methodology could be applied to estimate the sensitivity of insurers' capital positions to nature degradation, while exploring the applicability to pension funds. Another important extension of this work would be the implementation of multi-dimensional shocks, integrating i. physical and transitional risks and ii. the interaction between nature and climate. Importantly, this methodology could become usable as a fully fledged risk assessment and/or stress test upon calibrating nature-related shocks and their consequent impact on firms' productivity using nature-to-economy modelling frameworks.

7. Appendix

7.1 Sensitivity of the ΔCET1 ratio to the definition of the Vulnerability score

Given that this study does not focus on the calibration of shocks to nature but rather assumes them, this section presents two types of sensitivities related to our methodological choices when backwards-estimating the shock on nature – alpha – based on an assumed aggregated depreciation rate of 1% at the SSM level per ES (Option 2 presented in section 3.2.2.3). The first source of sensitivity under analysis relates to the definition of the Vulnerability index, which is once done considering only the dependence score – *DS* in columns 4 and 5 of Table 2 – and once done considering the extent of nature degradation in addition to the dependence score – *Vuln* in columns 2 and 3 of Table 2. The second type of sensitivity under analysis regards the method of weighing the direct and indirect scores that make up the DS and Vulnerability indexes: columns 2 and 4 present an equal weighing between the direct and indirect components, while columns 3 and 5 present the maximum of the direct and indirect scores (Table 2). For a detailed description of the direct and indirect components please refer to section 3.2.2.2.

Table 2: Reverse-calibrated alpha assuming a 1% aggregated depreciation rate at the SSM level per ES

Ecosystem Services	Vuln with 0.5*Direct + 0.5*Indirect	Vuln with max(direct, indirect)	DS with 0.5*Direct + 0.5*Indirect	DS with max(direct, indirect)
Animal-based energy	103.6	58.7	45.0	24.2
Bio-remediation	26.7	17.0	6.4	3.9
Buffering and attenuation of mass flows	53.6	30.8	38.1	20.1
Climate regulation	20.2	12.4	5.3	3.1
Dilution by atmosphere and ecosystems	50.9	30.7	14.1	8.2
Disease control	77.9	44.4	37.8	20.2
Fibres and other materials	42.1	24.3	15.8	8.6
Filtration	37.0	24.4	9.6	5.8
Flood and storm protection	17.4	11.3	4.7	2.9
Genetic materials	96.8	55.3	42.7	23.0
Ground water	14.2	9.2	3.1	1.9
Maintain nursery habitats	123.1	66.7	88.9	44.6
Mass stabilisation and erosion control	6.0	5.5	2.3	2.1
Mediation of sensory impacts	29.6	18.4	6.8	4.0
Pest control	57.4	33.8	27.3	14.8
Pollination	77.9	44.4	37.8	20.2
Soil quality	52.3	30.9	19.8	10.7
Surface water	13.1	8.4	2.9	1.7
Ventilation	78.0	47.3	26.2	14.9
Water flow maintenance	22.5	14.2	6.1	3.6
Water quality	29.2	18.2	9.6	5.7

Note: The gray cells are those for which the simplified formula used for calculating alpha is not appropriate, given that alpha is not close to 0. The gray cells are those for which alpha >30%.

The results presented in Table 2 are the reverse-calibrated alpha shock parameters. When a small alpha corresponds to an ES, it means that a minor shock on that ES can have a significant impact (of 1% at the aggregated SSM level for that ES). From the above table we can conclude that a small shock (alpha of less than 10%) on ES mass stabilization and erosion control or ES surface water has the same impact as a much bigger shock (alpha of more than 44%) on ES genetic materials. The gray alphas in Table 2 should be disregarded, as the simplification that we have used in equation (11) is only valid for small alphas.[28] A more precise, i.e. less simplified, analysis could provide exact results without relying on this simplification.

The primary methodological approach chosen in this study corresponds to column 3 of Table 2 and the dotted orange curves in Figures 8 and 9, as these correspond to a Vulnerability index that is the highest of the direct and indirect vulnerabilities – *Vuln_max* - (section 3.2.2.2). In Figures 8 and 9, we first rank banks based on their ΔCET1 ratio using as reference the methodological option used in the main body of this report, as represented by the orange curve. Then, keeping this order of the banks, we build other alternative curves to show the sensitivity of the ΔCET1 ratio to other possible methodological choices. A spike or dip in the curves of these methodological alternatives shows that banks would be ordered differently in terms of impact when using the alternative definition. This is relevant for our analysis, as it would mean that the relative sensitivity of banks and countries could change under methodological choices different from the ones we have chosen in the main report. Specifically, a peak (dip) in the alternative curves means that a bank would have been ordered more to the right (left), corresponding to a smaller (bigger) ΔCET1 ratio.

Figure 8: The sensitivity of the ΔCET1 ratio when using Vuln_max versus DS_max, for ES ground water

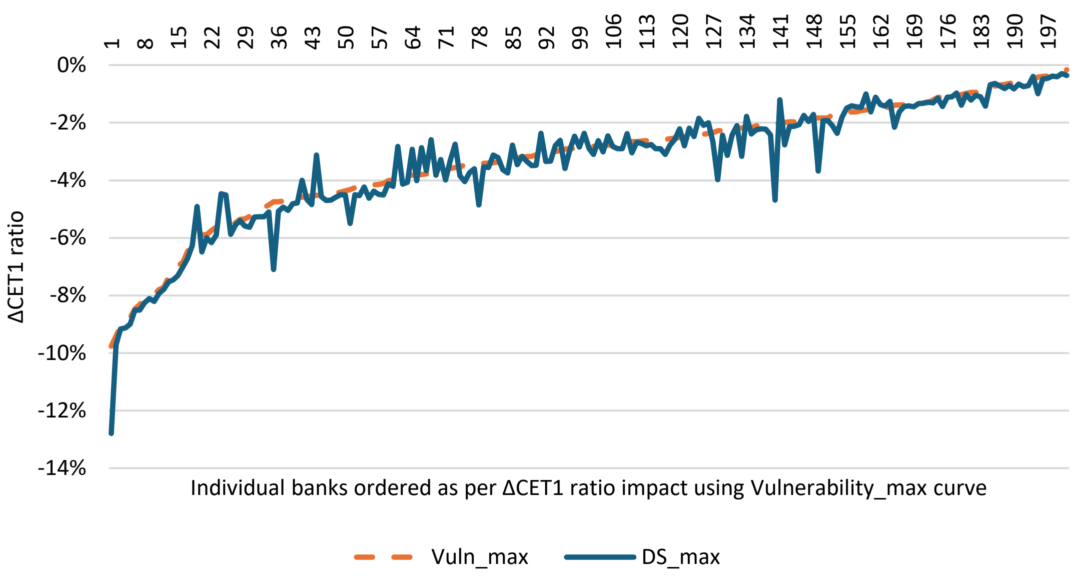


Figure 8 shows the ΔCET1 ratio when using *Vuln_max* versus *DS_max* (see section 3.2.2.2). As the blue curve, which depicts the ΔCET1 ratio for *DS_max*, shows substantial peaks and dips, we can conclude

[28] This can also be seen by the production of some alphas >100%, which are not theoretically possible.

that including nature degradation in credit risk assessments adds more differentiation across banks and enhances the realism of the evaluation.

Figure 9: The sensitivity of the Δ CET1 ratio when using Vuln_max versus other aggregation functions, for ES: ground water

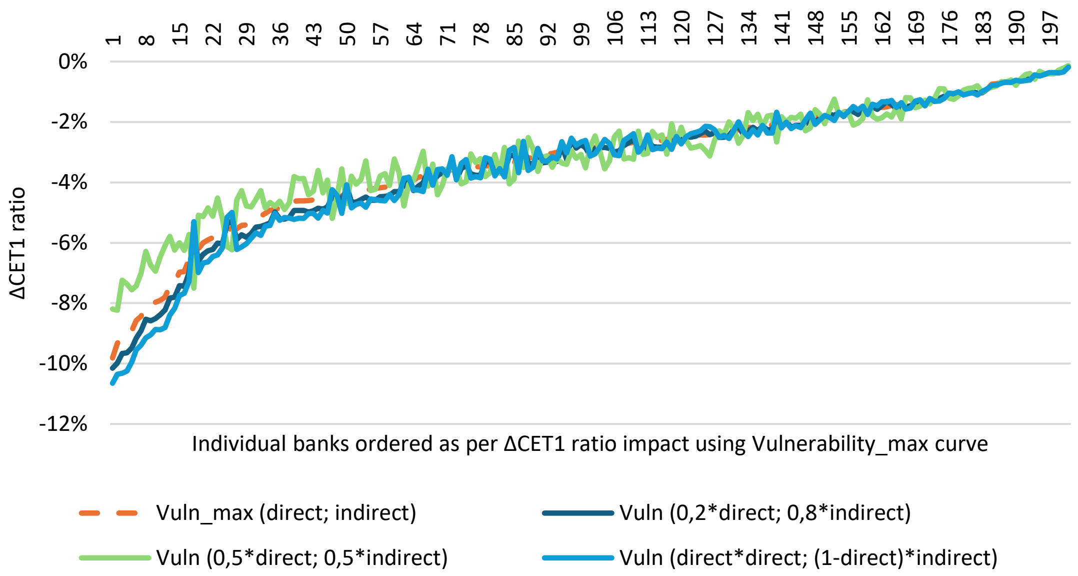


Figure 9 shows the ΔCET1 ratio when using *Vuln_max* versus vulnerability when using different aggregation functions:

- Vuln (0,20*direct; 0,8*indirect) means that the Vulnerability index is a weighted average of 20% of direct vulnerability and 80% of indirect vulnerability;
- Vuln (0,50*direct; 0,5*indirect) means that the Vulnerability index is a weighted average of 50% of direct vulnerability and 50% of indirect vulnerability;
- Vuln (direct*direct; (1-direct)*indirect) means that the Vulnerability index uses as weights the direct index and the (1-direct) index, as in the ECB OS on Nature physical risks (2023).

The assumption regarding the aggregation of direct and indirect vulnerabilities is made to bypass the lack of detailed information on firms' supply chains. The observation of peaks and dips across the alternative three aggregation functions – excluding *Vuln_max* that is the reference aggregation method -, indicates that the method of aggregating these vulnerabilities does influence the ranking of banks in terms of ΔCET1 ratio impact. This suggests that further data and research on this aspect would be beneficial. However, relative to the ΔCET1 ratio sensitivity of other factors presented throughout the Appendix this appendix, the aggregation method is comparatively less sensitive. Therefore, more detailed examinations of aggregation methods can be done a later stage unless it is possible to provide company-specific information.

7.2 Sensitivity of the ΔCET1 ratio to different calibration points used in LGD modelling

The novelty of this paper is a proposed framework that integrates vulnerability to nature degradation into the PDs of banks' counterparties, which subsequently impacts banks' EL and RWAs and ultimately their capital ratios. Given that our focus has been on PDs, we have chosen to model the variation of

LGDs based on our estimated variation of PDs using a model proposed by Frye and Jacobs (2012). The modelling of LGDs is, next to PDs, crucial for the estimation of credit risk related expected losses and RWAs for banks. In this section we check the sensitivity of the ΔCET1 ratio to two different calibration points used by Frye and Jacobs.

According to Frye and Jacobs, for a firm *i* , ΔLGD_i can be approximated based on the variation in PD_i as follows:

$$N^{-1}[PD_i.LDG_i] - N^{-1}[PD_i] = \frac{N^{-1}[PD^{calib}.LGD^{calib}] - N^{-1}[PD^{calib}]}{\sqrt{1-\rho}} \tag{22}$$

with

- PD^{calib} is the average annual default rate of a calibration data set.
- LGD^{calib} is calculated based on the average annual loss rate and PD^{calib} from the same calibration data set.
- ρ is a correlation term between the modeled default risk and systemic risk

The formula can be used to recalculate the LDG as follows.

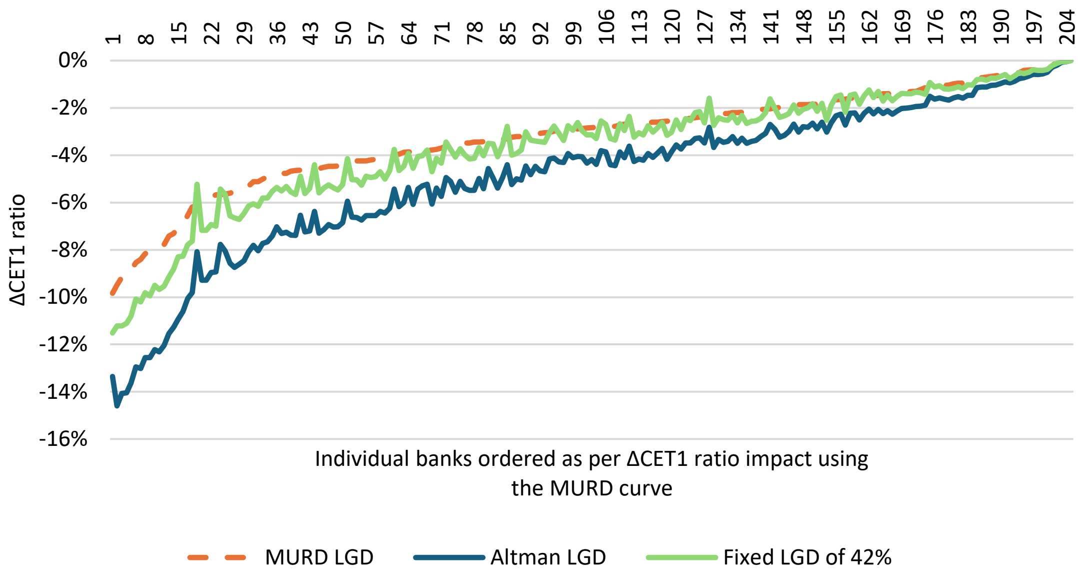
$$LGD_i = \frac{N\left[\frac{N^{-1}[PD^{calib}LGD^{calib}] + \sqrt{1-\rho}.N^{-1}[PD_i] - N^{-1}[PD^{calib}]}{\sqrt{1-\rho}}\right]}{PD_i} \tag{23}$$

We can ultimately express the variation of LGD_i in terms of the variation of PD_i.

$$\Delta LGD_i = LGD_i^{PD\ new} - LGD_i^{PD\ old} \tag{24}$$

This necessitates a calibration point [PD^{calib}; LGD^{calib}] and a correlation term between the modeled default and systemic risk, in accordance with the Vasicek approach used by Frye and Jacobs. The Frye and Jacobs paper refers to two calibration points: [PD=4,59% ; LGD=65,2% ; ρ =10%] from Altman and Karlin and [PD=4,54% ; LDG=42,8% ; ρ =10%] from Moody's Ultimate Recovery Database (MURD) (Frye & Jacobs, LGD Risk Resolved, 2019). In this paper we have used the calibration of MURD. The below Figure shows the sensitivity of ΔCET1 ratio when using two other calibrations: the calibration used by Altman and Karin, and a fixed LGD of 42%. While the Altman calibration results in a more pronounced depletion of the CET1 ratio compared to the MURD calibration, it does not significantly affect the raking of banks by ΔCET1 ratio. When comparing the MURD calibration to the fixed LGD calibration, we notice very little difference in terms of both shock amplitude and raking of the banks. These results suggest that while the calibration choice for the LGD model is worth considering, it does not produce a critical sensitivity in the model.

Figure 10: The sensitivity of the ΔCET1 ratio when using the MURD LGD calibrations versus the Altman and static LGD fixed at 42%, for ES ground water



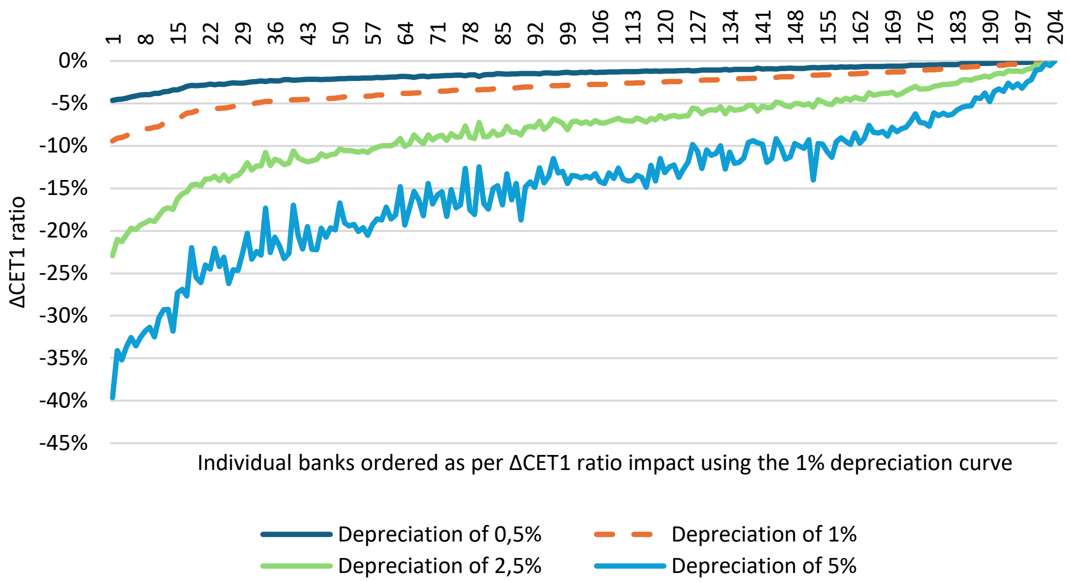
7.3 Sensitivity of the ΔCET1 ratio to different magnitudes of the aggregated asset depreciation shocks

Given that we lack external data on asset depreciation due to nature degradation, this paper uses an assumed aggregated asset depreciation rate of 1% at the SSM level per ES (see Option 2 in section 3.2.2.3). Therefore, in this section we conduct a sensitivity analysis to grasp to what extent the magnitude of the depreciation shock impacts the depletion of the CET1 ratio.

Figure 11 ranks banks from the most to the least affected, in terms of ΔCET1 ratio, based on the assumed 1% aggregated depreciation rate (see orange curve).[29] The other curves show the ΔCET1 ratios for alternative magnitudes of depreciation rates. We observe that for asset depreciation shocks of up to 2.5% the rankings of banks remain consistent, i.e. the curves are smooth. However, larger asset depreciation shocks give rise to noticeable peaks and dips in the curve, suggesting the need to re-evaluate the rankings. These results suggest that for economically “reasonable", i.e. not extreme, shocks the overall rankings remain largely consistent. However, increasing the level of the depreciation shock increases discrimination between banks and points to non-linearities of impact. This latter point highlights the necessity of avoiding linear extrapolation between smaller and larger shocks, especially in stress testing.

[29] The figure excludes a few outlier banks with extremely high ΔCET1 ratio.

Figure 11: The sensitivity of the ΔCET1 ratio when using different depreciation rates, for ES ground water

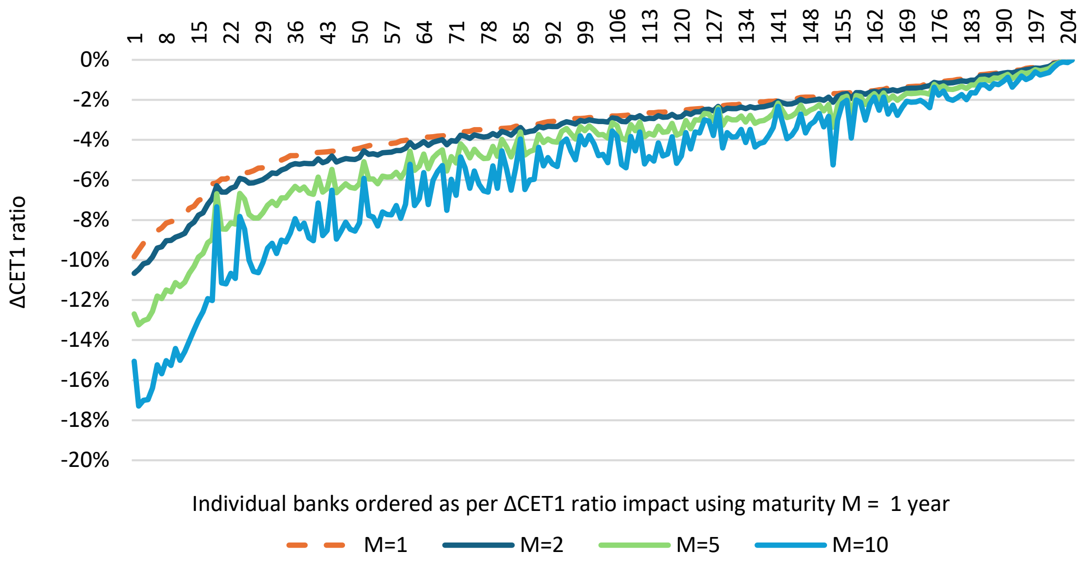


7.4 Sensitivity of the ΔCET1 ratio to different values of M

When using the RWA formula that the Basel framework prescribes for estimating the RWA of the loans in scope of our analysis, we lack data on the effective maturity of the loans (M). We therefore use an approximation of one year for M as in equation (16). Our analysis shows that the ΔCET1 ratio is sensitive to the choice of M: the higher the M, the higher the ΔCET1 ratio (Figure 12). This is logical, considering that loans with higher maturities typically give rise to higher credit risk. From Figure 12 we can see that for average maturities between 1 and 5 years the depletion of the CET1 ratio is around 20% higher, while the relative order of losses between banks remains fairly consistent.[30] For longer maturities, such as 10 years, the impact is greater and there is a noticeable difference in the ranking of banks. Therefore, we can conclude that the effective maturity of the loans is a key driver of results, especially when banks' loan portfolios differ significantly in their maturities.

[30] The figure excludes a few outlier banks with extremely high ΔCET1 ratio.

Figure 12: The sensitivity of the ΔCET1 ratio when using different values of M, for ES ground water



7.5 Sensitivity of the ΔCET1 ratio to mapping between ES from ENCORE and vulnerabilities from ND-GAIN

For this study, we have had to map the 21 ES of ENCORE into the six nature categories of the ND_GAIN vulnerability index. To do this, we have adopted a simplified approach of mapping into the ND_GAIN "water" category all water-related ES of ENCORE, and mapping into the ND_GAIN "ecosystems" category the remaining ENCORE ES (column 2, Table 3). To shed more light onto the impact of using different mapping approaches, in the below table we also present an alternative mapping whereby all ENCORE ES are mapped into the same ND_GAIN Vulnerability index category "ecosystems" (column 3, Table 3).

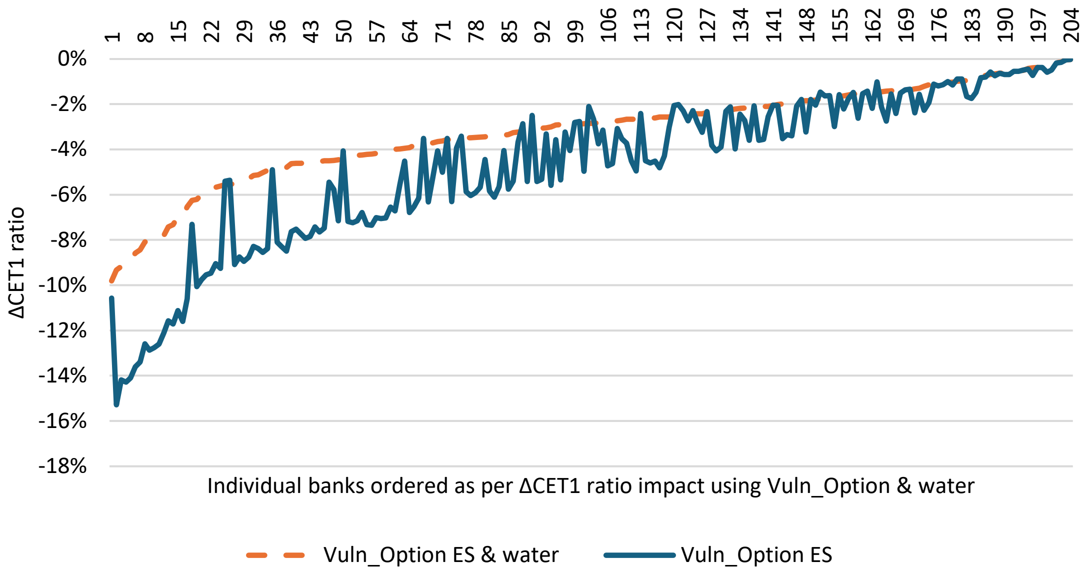
Table 3: Two alternative approaches of mapping ENCORE ES to ND_GAIN Vulnerability nature categories

Ecosystem Services	**ND-GAIN Vuln. Option_ES & water**	**ND-GAIN Vuln. Option_ES**
Animal-based energy	ecosystems	ecosystems
Bio-remediation	ecosystems	ecosystems
Buffering and attenuation of mass flows	water	ecosystems
Climate regulation	ecosystems	ecosystems
Dilution by atmosphere and ecosystems	ecosystems	ecosystems
Disease control	ecosystems	ecosystems
Fibres and other materials	ecosystems	ecosystems
Filtration	water	ecosystems
Flood and storm protection	ecosystems	ecosystems
Genetic materials	ecosystems	ecosystems
Ground water	water	ecosystems
Maintain nursery habitats	ecosystems	ecosystems
Mass stabilisation and erosion control	water	ecosystems

Mediation of sensory impacts	ecosystems	ecosystems
Pest control	ecosystems	ecosystems
Pollination	ecosystems	ecosystems
Soil quality	ecosystems	ecosystems
Surface water	water	ecosystems
Ventilation	ecosystems	ecosystems
Water flow maintenance	water	ecosystems
Water quality	water	ecosystems

We find that the mapping choice between the ENCORE ES and an index of nature degradation (in our case the two alternative mappings to the ND_GAIN vulnerability index) produces significant sensitivity in the CET1 ratio impact. Specifically, we see that when compared to our reference methodological option – *Vuln_Option ES & water* – the alternative mapping significantly alters the ranking of banks' capital impacts. This finding underscores the critical importance of choosing a detailed and comprehensive mapping of dependency indices to indices of nature degradation, and of testing alternative mapping approaches to ensure an accurate interpretation of the results.

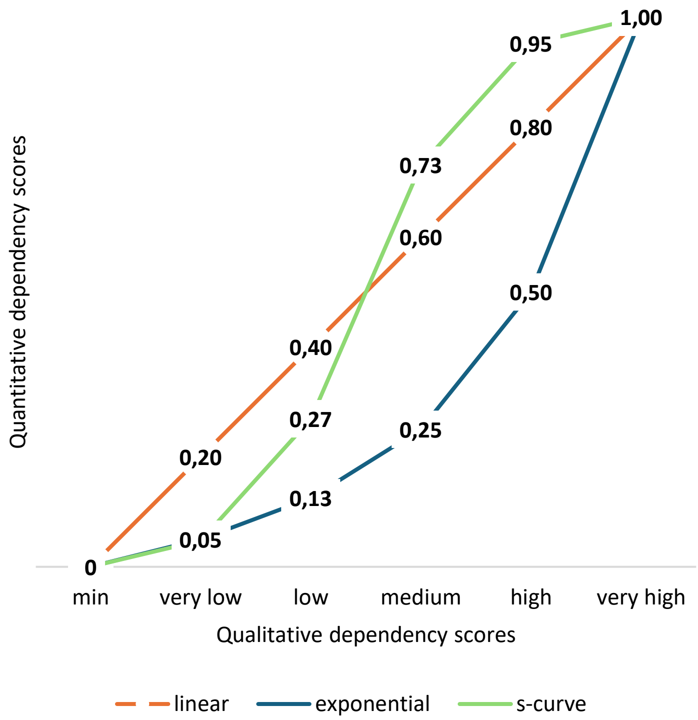
Figure 13: The sensitivity of the ΔCET1 ratio to mapping choices between ENCORE and ND-GAIN, for ES ground water



7.6 Sensitivity of the ΔCET1 ratio to different quantification methods for ENCORE's dependency scales

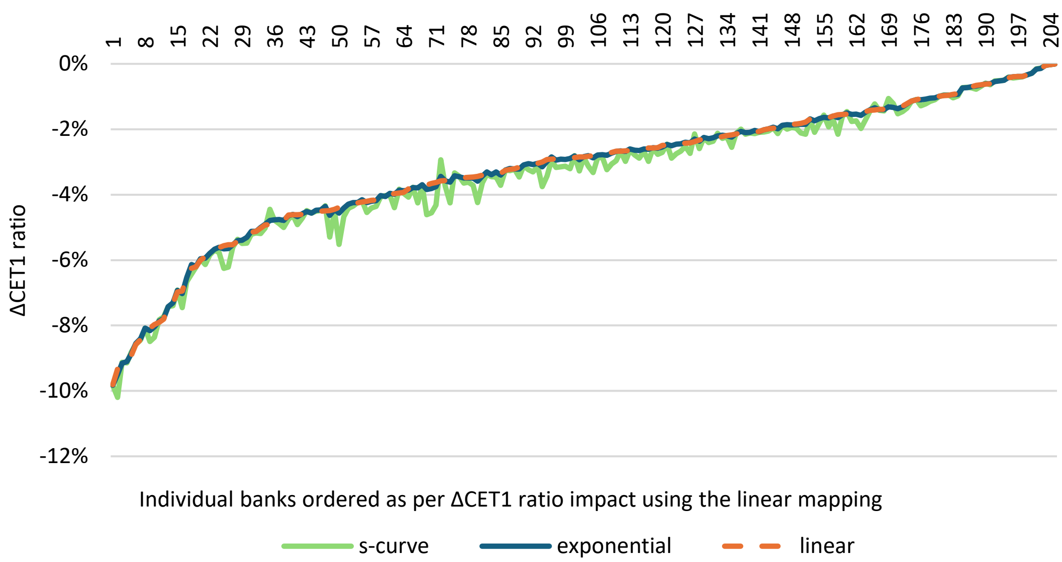
The ENCORE database grades the dependency of an industrial processes - which is later converted to an economic sector - and ecosystems services. This qualitative link uses a scale composed of 5 grades: Very Low – Low – Medium – High and Very High. In order to quantify such dependency, the scale is translated into an index between 0 and 1, where 0 corresponds to very little dependency and 1 corresponds to full dependency of a process on an ES. This numerical scale is not defined, leaving open different possibilities. In this section we show the sensitivity of the scale to three classic quantification functions: linear (which is our reference method used in the chosen methodology of this paper), exponential and S-curve. To do so, we first define a numerical correspondence table (Figure 14).

Figure 14: Qualitative-to-quantitative equivalences for ENCORE's dependency scale, for ES ground water



Following the same process to analyse ΔCET1 ratio sensitivities, we notice that the shape of the qualitative-quantitative mapping plays a secondary role compared to other modeling choices (Figure 15). The choice of the simpler and more intuitive linear scale does not seem to hide major sensitivities. It is recommended to use this in combination with a sensitivity check, to ensure that the results are also comparable when looking at each bank individually.

Figure 15: The sensitivity of the ΔCET1 ratio when using different quantification grids to quantify ENCORE's qualitative dependency scale, for ES ground water



7.7 Glossary

Abbreviation	Term
CET1	Common Equity Tier 1
DS	Dependence Score
DS direct	Direct Dependence Score
DTD	Distance to Default
EAD	Exposure at Default
EDSI	Ecosystem Service Degradation Sensitivity Indicator
EL	Expected Losses
ES	Ecosystem Service
GICS	Global Industry Classification Standard
IRB	Internal Ratings-Based
KMV	Kealhofer-Merton-Vasicek Model
LGD	Loss Given Default
NACE	Nomenclature of Economic Activities (EU industry classification)
ND-GAIN	Notre Dame Global Adaptation Initiative
OS	Occasional Study
PD	Probability of Default
PIT PD	Point-in-Time Probability of Default
RWA	Risk-Weighted Assets
SA	Standardized Approach
SREP	Supervisory Review and Evaluation Process
SSM	Single Supervisory Mechanism
TSCR	Total SREP Capital Requirement
TTC PD	Through-the-Cycle Probability of Default
Vuln	Vulnerability of a Firm to Nature (ES) Degradation

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