# From global biodiversity commitments to local action: revenue potential and allocation dynamics of the Cali Fund

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# From Global Biodiversity Commitments to Local Action: Revenue Potential and Allocation Dynamics of the Cali Fund*

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**Abstract**

Established at CBD COP16 in 2024, the Cali Fund is the first global mechanism requiring private companies benefiting from genetic data to share 1% of their profits or 0.1% of revenues, with biodiversity-rich countries and local communities. I provide the first global firm-level estimates of the fund's revenue potential and a systematic analysis of its distributional properties on both the contribution and allocation sides under alternative design choices, using firm-level data for 21,690 eligible companies across 100 countries. Under realistic voluntary uptake, annual contributions would reach approximately \$0.9 billion, rising to \$3.6 billion under full participation. The revenue base is narrow: two sectors account for 51% of contributions under full compliance and the top 100 contributors for 27.6%. Under realistic voluntary uptake, sectoral composition shifts further, with pharmaceuticals alone accounting for nearly 50% of expected revenues under the central scenario. For most sectors the payment rule ties contributions directly to profitability, making fund revenues sensitive to economic conditions: firms clustered near the zero-profit threshold can move in and out of contribution obligations as profits fluctuate. Pharmaceuticals is the exception: most eligible firms in this sector pay on revenue regardless of profit swings, providing a stable base but making overall fund revenues heavily dependent on pharmaceutical participation. On the recipient side, the distribution of who receives how much is largely determined by the way the allocation formula is designed. Prioritising the geographic origin of genetic data channels nearly half of all resources to wealthy research economies while African States receive 6.4%. The mathematical form of the formula also matters: the formula and normalisation method together can shift allocations by up to 13 percentage points away from Western countries without changing any stated weight. With both contribution rules and allocation criteria still open for revision at COP17 in October 2026, the paper shows these choices are not distributionally neutral.

**JEL codes:** Q57; Q56; F53; C15; H41

**Keywords:** Digital sequence information; benefit-sharing; biodiversity finance; Cali Fund; multilateral mechanisms; allocation formula; firm-level data

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## List of Abbreviations

| | | | |
|---|---|---|---|
| ABS | Access and Benefit-Sharing | INSDC | Intl. Nucleotide Sequence Database Collaboration |
| AHTEG | Ad Hoc Technical Expert Group on Allocation Methodology | IPLCs | Indigenous Peoples and Local Communities |
| BHI | Biodiversity Habitat Index | KMGBF | Kunming-Montreal Global Biodiversity Framework |
| CBD | Convention on Biological Diversity | LDCs | Least Developed Countries |
| COP | Conference of the Parties | MLM | Multilateral Benefit-Sharing Mechanism |
| DSI | Digital Sequence Information | NPV | Net Present Value |
| GEF | Global Environment Facility | SIDS | Small Island Developing States |
| GBIF | Global Biodiversity Information Facility | STAR | System for Transparent Allocation of Resources |

# 1 Introduction

Advances in genome sequencing have transformed biological genetic resources into Digital Sequence Information[1] (DSI): digital representations of DNA, RNA, and protein sequences, which are becoming increasingly central to commercial innovation in pharmaceuticals, biotechnology, cosmetics, and artificial intelligence (Switzer et al., 2025; Maia and Bourgeois-Gironde, 2025; Tsioumani and Rabitz, 2025). Unlike physical genetic resources, which are excludable through national access controls under the Nagoya Protocol, DSI deposited in public databases is largely non-excludable: it can be accessed without entering into bilateral agreements with the provider country (Nawaz et al., 2021)[2]. This weakens the Access and Benefit-Sharing (ABS) framework established by the Nagoya Protocol and deprives biodiversity-rich states of direct benefits from the commercial exploitation of their natural resources (Silvestri and Roig-Cerdeño, 2025; Sett et al., 2024). At the same time, biodiversity conservation remains severely underfunded, with an estimated annual financing shortfall of approximately $700 billion compared to current flows of about $124-$143 billion, of which roughly 10% is supplied by the private sector (Deutz et al., 2020).

The Cali Fund, adopted at CBD COP16 in October 2024 (Decision 16/2 (CBD, 2024a)), is the first effort to address this gap through a multilateral mechanism intended to share private sector benefits from the use of DSI with the countries and communities that safeguard the biodiversity from which it originates. Its objective is clear: channel resources from private-sector entities that profit from DSI to biodiversity-rich developing countries and Indigenous Peoples and Local Communities (IPLCs) (CBD, 2024a). The mechanism is currently operating under indicative modalities adopted at COP16, with both the contribution rules and the allocation formula subject to revision at COP17 in October 2026. Whether the final design achieves the fund's fair and equitable sharing objective depends on a series of decisions that remain unsettled, and the empirical evidence needed to inform those decisions does not yet exist.

This paper provides the first global, bottom-up, firm-level estimate of the Cali Fund's revenue potential and a systematic analysis of its distributional properties on both sides of the mechanism. On the contribution side, it asks how large the fund is likely to be, how the burden is distributed across firms and sectors, and what the minimum rule implies for revenue stability. On the allocation side, it examines which criterion is the most consequential lever and how sensitive allocations are to the formula choice. The two components are then connected through a net transfer assessment: some countries both host large DSI-reliant industries and hold significant shares of publicly deposited sequence data, creating an inherent tension between the two sides whose resolution depends entirely on the weight placed on geographic origin.

[1] DSI remains a placeholder term without agreed definition (adh, 2020). Consistent with the CBD's AHTEG on DSI 2020 study's approach, this analysis treats publicly deposited nucleotide sequence data as the tractable operationalisation of DSI, reflecting the INSDC infrastructure that underpins 95% of public sequence databases adh (2020).

[2] Some Parties have extended national ABS legislation to cover DSI originating from their territory (e.g., Brazil, India, and Malaysia), but enforcement remains limited at the level of the public databases that aggregate global sequence data (Ljungqvist et al., 2025).

**Contribution design** Under full compliance, 21,690 eligible entities across 100 CBD Party jurisdictions generate annual contributions of $3.6 billion, falling to $929 million under realistic voluntary uptake. The revenue base is structurally concentrated: two sectors account for 51% of contributions and the top 100 firms for 27.6%. Under realistic voluntary uptake, the sectoral composition shifts materially: the pharmaceutical sector's share rises from 26.3% to 49.6% of total contributions, while information and AI falls from 25.2% to 11.1%, making the fund's revenue prospects considerably more dependent on pharmaceutical participation than the full-compliance picture suggests. The minimum rule introduces systematic heterogeneity in contribution burdens and year-to-year instability, with 17% of eligible firms changing contribution regime between the eligibility window and the 2023 reference year.

**Allocation design** The geographic origin criterion is the most consequential single lever: under DSI-only weighting, most developed economies[3] capture 47.8% of total allocations while African States receive 6.4%. The formula and normalisation method have jointly large consequences: together they can shift allocations by up to 13.3 percentage points away from Western countries without any change in stated weights.

**Net transfer** Under the additive formula with equal weights, African States and Latin America and the Caribbean are net recipients of $140 million and $90 million respectively, while WEOG and Asia-Pacific face net outflows of $322 million and $367 million. Thirty-three countries change net position sign across weight configurations (Table 27) in the Annex, with Canada being the most extreme case: it is a marginal net recipient under equal weights but the largest net recipient in the analysis under DSI-origin weighting.

The fund was created to address a specific inequity: biodiversity-rich developing countries gain little from the commercial use of genetic resources by DSI-dependent industries in wealthy economies (Silvestri and Roig-Cerdeño, 2025; Lawson et al.; Scholz et al., 2022). Both the contribution rules and the allocation formula remain open for revision at COP17, and this paper shows that the choices made on each side will jointly determine whether resources flow in the direction the fund was created to achieve. The results come at a pivotal time: unlike most multilateral environmental funds, which have been examined only after their rules were fixed, this paper analyses both sides of the mechanism while its modalities are still under negotiation.

# 2 Modalities of the Cali Fund

Decision 16/2 defines indicative rules for both contributions and allocations, which will be subject to revision at COP17 in October 2026. The core parameters for each are set out below.

## 2.1 Money-in: private sector contributions

Decision 16/2 defines eligible contributors as direct and indirect DSI users across seven sectors, without specifying what constitutes either form of use (Brink and van Hintum, 2022; Silvestri and Roig-Cerdeño, 2025). Participation does not create binding legal obligations; the decision calls on Parties to adopt national measures encouraging contributions, making the mechanism's effectiveness depend on voluntary corporate engagement (Orozco and Scholz, 2025). The indicative financial thresholds, eligible sectors, and contribution rates are set out in Box 1.

[3] Specifically, the Western European and Other States category based on the UN regional classification, see Table 15 for the full classification. Note the United States is not a CBD Party and is excluded from the analysis.

**Box 1.** Key parameters for Cali Fund private sector contributions (CBD Decision 16/2)

**Company size** Entities that exceed at least two out of three thresholds on their balance sheet dates, averaged over the preceding three years: total assets of USD 20 million, sales of USD 50 million, and profits of USD 5 million.

**DSI-dependent sectors** Sectors that may benefit directly or indirectly from the use of digital sequence information on genetic resources include pharmaceuticals; nutraceuticals; cosmetics; animal and plant breeding; biotechnology; laboratory equipment related to sequencing and DSI use (including reagents and supplies); and information, scientific, and technical services related to DSI, including artificial intelligence.

**Indicative contribution rates** Eligible entities should contribute **1% of profits or 0.1% of revenue** to the global fund.

### 2.2 Money-out: the allocation formula

Decision 16/2 calls for additional analytical work on allocation design ahead of COP17 and establishes the Ad Hoc Technical Expert Group on Allocation Methodology (AHTEG) to develop options for disbursing the funds (CBD, 2025).

Decision 16/2 sets out three indicative criteria to guide allocation:

- biodiversity richness and related ecological metrics;
- the geographical origin of the genetic resources from which DSI is obtained, where such information is available; and
- capacity needs, with particular focus on developing countries and Indigenous Peoples and Local Communities (IPLCs) (CBD, 2024a).

In addition, the Decision establishes binding distributional priorities that constrain the allocation space. At least 50% of total funding is expected to support the self-identified needs of IPLCs, while remaining resources are directed primarily to developing countries, in particular Least Developed Countries (LDCs), Small Island Developing States (SIDS), and countries with economies in transition. Eligible uses of funding include biodiversity conservation and sustainable use, implementation of national biodiversity strategies and action plans, scientific research, and capacity-building related to the generation, access, analysis, and storage of DSI (CBD, 2024a).

## 3 Related literature

### 3.1 DSI governance, benefit-sharing and multilateral finance

Given that Decision 16/2 was adopted only in October 2024, the absence of empirical analysis is unsurprising; the literature has necessarily focused on institutional design ahead of the mechanism's operationalisation (Maia and Bourgeois-Gironde, 2025; Muñoz-García et al., 2025; Blom et al., 2025a; Orozco and Scholz, 2025). Existing studies identify commercial DSI users as the relevant contributors and discuss contribution rates and eligibility thresholds, but do not offer a systematic empirical evaluation of the contributor pool's size or the total revenue the mechanism is likely to yield (Muñoz-García et al., 2025; Scholz et al., 2022). The evidence base is even weaker on the allocation side, with limited empirical guidance on how a formula should be operationalised or what distributive outcomes it would produce (de Souza de Lima et al., 2024; Muñoz-García et al., 2025).

Prior quantitative estimates exist but none applies the Decision 16/2 modalities directly. Matt Bassford et al. (2024) estimate UK contributions using a top-down approach restricted to DSI-using subsectors within biopharmaceuticals, agricultural sciences, and industrial biotechnology, yielding approximately USD 57-79 million under full compliance[4]; CBD (2024c) provide global estimates across five sectors

[4] Applying the Decision 16/2 modalities and the calibrated S3 scenario to UK firms in this study yields a central estimate of approximately USD 98 million (Section 7). The somewhat higher figure is consistent with the broader

assuming a uniform profit margin and predating Decision 16/2; and Menon Economics (2025) apply a bottom-up approach to Norwegian firms only, estimating annual contributions of $24.8 million under full compliance.[5] The present study extends this work globally across all seven sectors and 100 CBD Party jurisdictions, integrating compliance scenarios, sensitivity analyses, and a systematic treatment of the allocation dimension.

The broader multilateral environmental finance literature shows that contribution burdens and allocation outcomes depend materially on indicator choice, weights, and participation scope (Cui and Gui, 2015; Pickering et al., 2015; Egli and Stünzi, 2019; Dellink et al., 2009; Michaelowa et al., 2020; Mori et al., 2019; Persson and Remling, 2014). The most direct precedent is the GEF, which twice confronted the same allocation problem: its Resource Allocation Framework used a biodiversity benefits index alongside a performance measure (Global Environment Facility, 2005), while its successor STAR adopted an explicit multiplicative formula with LDC floors and a 10% country ceiling (Global Environment Facility, 2018). Both illustrate the core tension between biodiversity-oriented components that concentrate resources in megadiverse countries and redistributive adjustments that shift toward smaller, lower-capacity recipients. The Cali Fund faces the same challenge, with the additional complication that its contributor base is defined by private-sector DSI use rather than sovereign donor pledges (Muñoz-García et al., 2025; Maia and Bourgeois-Gironde, 2025).

## 3.2 Voluntary compliance and sector heterogeneity

The Cali Fund can be situated within the literature on voluntary environmental cooperation. In models of self-enforcing international environmental agreements, participation falls short of the cooperative optimum when actors can share in the benefits of cooperation without bearing its costs (Barrett, 1994; Carraro and Siniscalco, 1998). This logic applies directly here: contributions are voluntary, the mechanism generates diffuse public-good benefits, and enforcement relies on reputational rather than legal pressure. Firm-level participation is rarely uniform: larger, more visible, and more consumer-facing firms are more likely to join, while upstream and business-to-business sectors face weaker incentives (Tashman et al., 2022; Haddock-Fraser and Fraser, 2008; Rasche et al., 2022). Since contributions are calculated on total financials rather than DSI-attributed revenues, the effective burden also varies with DSI intensity across sectors (Scholz et al., 2022).

Voluntary schemes also display a consistent temporal pattern: participation starts low and accelerates as the signalling value of joining rises with the participant pool (Prakash and Potoski, 2012; Seok et al., 2021). The Cali Fund is at an especially early phase, asking firms to support a novel mechanism without an established peer group. Revenue estimates assuming steady-state participation will therefore overstate early-year contributions (Demir et al., 2026).

This literature supports treating participation as varying across sectors and over time, rather than as uniform and static. This perspective underpins the compliance adjustments in the contribution-flow model.

## 3.3 Multi-criteria conservation priority-setting

A final relevant strand of literature comes from conservation priority-setting, where limited budgets must be allocated across competing biological, social, and political objectives (Dujardin and Chadès, 2018). Priority rankings depend strongly on the criteria used to construct them, and multi-objective conservation planning shows formally that different objectives, weights, and decision-makers' preferences generate different trade-offs, making priority-setting a normative exercise(Moffett and Sarkar, 2006; Dujardin and Chadès, 2018). Work on global biodiversity financing shows that alternative allocation designs produce different distributive outcomes depending on whether they prioritize ecological importance, socioecological criteria, or more anthropocentric objectives (Droste et al., 2019).

Decision 16/2 scope, which extends to all seven Enclosure I sectors rather than the three DSI-using subsectors examined by Matt Bassford et al. (2024).

[5] Applying the Decision 16/2 modalities to the Norwegian subsample in this study yields an S0 estimate of $24.7 million, providing a cross-validation of the firm-level methodology against an independently constructed estimate for the same jurisdiction.

The allocation challenge raised by the Cali Fund follows a comparable logic. Measures of biodiversity value, DSI origin, and capacity needs can each generate their own ranking of potential beneficiaries, so any specific selection of weights will directly shape how resources are allocated. This paper maps outcomes over the feasible design space to show that the magnitude of distributional consequences from these design choices is large, comparable in scale to changing stated weights, and therefore cannot be treated as a purely technical matter. As far as the author is aware, such a systematic mapping has not previously been applied to a multilateral biodiversity fund.

Collectively, these strands of research highlight the main design trade-offs the Cali Fund must manage, yet they do not resolve the core empirical issues. To date, no study has simultaneously estimated the fund's revenue capacity at the firm level, analysed the distributional implications of its contribution rule, and assessed its allocation formula against alternative benchmarks while the mechanism's modalities remain open to revision.

# 4 Conceptual Framework

This section formalises the two core components of the Cali Fund mechanism: the contribution rule and the allocation formula. The two components are studied jointly because their interaction determines whether the mechanism channels resources in the direction its fair and equitable sharing objective requires. The contribution rule governs who pays and how much; the allocation rule governs who receives and how much; and the net transfer analysis combines both to assess whether resources flow in the direction the mechanism intends.

## 4.1 Contribution rule

The Cali Fund is conceptually a benefit-sharing transfer rather than a corrective tax. The use of DSI does not directly harm biodiversity, and contribution rates are not determined by the magnitude of any externality. The primary issue addressed by this mechanism is the underprovision of biodiversity conservation as a global public good. Source countries incur the costs of conservation, while DSI users obtain commercial benefits without contributing to these expenses. The Cali Fund advances the third objective of the CBD by allocating a portion of commercial returns from DSI users to the countries and communities responsible for conserving the biodiversity from which DSI is derived.

Let $\mathcal{F}$ denote the set of eligible firms indexed by $f$. Each firm is characterised by operating revenue $R_f > 0$ and profit after tax $\pi_f$, with profit margin $m_f = \pi_f / R_f$.

Under Decision 16/2, firms contribute the lower of a revenue-based and a profit-based levy:

$$C_f = \min\left(\tau_R R_f,\ \tau_\pi \max(0, \pi_f)\right), \tag{1}$$

where $\tau_R = 0.001$ and $\tau_\pi = 0.01$. The effective contribution rate as a share of revenue is:

$$\tau_f = \frac{C_f}{R_f} = \begin{cases} 0 & \text{if } m_f \leq 0, \\ \tau_\pi \cdot m_f & \text{if } 0 < m_f \leq m^*, \\ \tau_R & \text{if } m_f > m^*, \end{cases} \tag{2}$$

where $m^* = \tau_R / \tau_\pi = 0.1$ is the indifference margin. Below $m^*$ the effective rate rises with profitability; above it the rate is flat, so two firms with identical revenues but margins of 11% and 50% pay exactly the same amount. Total fund revenue under full compliance is $F = \sum_{f \in \mathcal{F}} C_f$.

In practice, participation is voluntary and heterogeneous across firms. Each firm participates with probability $p_f \in [0, 1]$, which depends on:

- a sector-level baseline participation rate $\alpha$, reflecting the propensity of firms in that sector to engage voluntarily with the mechanism. This is shaped by reputational exposure to consumers and investors, prior institutional engagement with ABS-related frameworks including the Nagoya

Protocol, and established norms of participation in voluntary environmental and sustainability schemes, all of which vary substantially across the Enclosure I sectors;

- an ownership multiplier $\gamma$, reflecting the stronger propensity of publicly listed firms to participate relative to unlisted entities. Listed firms face greater investor scrutiny, more extensive ESG disclosure requirements, and higher reputational exposure, all of which increase the cost of non-participation in a publicly visible voluntary mechanism; and
- a DSI intensity parameter $\omega$, reflecting uncertainty about the degree to which commercial activity in a given sector draws on DSI. Where DSI use is well-evidenced and central to innovation, $\omega$ is calibrated high; where use is indirect, incidental, or poorly documented, $\omega$ is calibrated lower, reducing the probability that firms in that sector engage with a mechanism premised on DSI use.

The participation probability $p_f$ reflects voluntary decisions not to participate, but does not account for strategic restructuring in reaction to the mechanism. To partially reduce this risk, eligibility is defined at the granular subsidiary level (see Section 5.1.2).

These combine as:

$$p_f = \min(\alpha \cdot \gamma \cdot \omega,\ 1). \tag{3}$$

Under Decision 16/2, the contribution base is defined on total entity financials rather than on revenues or profits attributable to DSI-related activity specifically, and no firm-level DSI attribution mechanism is established. As a result, once a firm decides to participate, the amount it pays is determined solely by the minimum rule applied to its total revenue or profit, irrespective of how central DSI is to its commercial operations. The DSI intensity parameter $\omega$ therefore does not scale the contribution of participating firms; it enters the participation probability directly, capturing the likelihood that a firm engages with a mechanism premised on DSI use. Because $\omega$ cannot be directly observed at the firm level, it is calibrated from indirect evidence on sectoral DSI use patterns (Section 5.1.3). Realised fund revenue is then:

$$F = \sum_{f \in \mathcal{F}} X_f \cdot C_f, \tag{4}$$

where $X_f \in \{0, 1\}$ is the participation indicator, equal to 1 with probability $p_f$ and 0 otherwise. The calibration of $\alpha$, $\gamma$, and $\omega$ is described in Section 5.1.3.

Annual contribution flows are projected forward to assess the cumulative revenue the mechanism would generate over a relevant policy horizon. The net present value (NPV) of contributions discounts future flows to a common reference year, allowing comparison across scenarios with different participation trajectories and aggregating annual revenue into a single summary measure. NPV is defined as:

$$\mathrm{NPV} = \sum_{t=0}^{T-1} \frac{c_t \cdot F}{(1+r)^t}, \tag{5}$$

where $F$ is the annual revenue estimate under the relevant scenario, $r$ is the discount rate, $T$ is the projection horizon, and $c_t \in [0, 1]$ is a time-varying scalar that scales aggregate revenue to reflect that participation builds up over time rather than starting at its mature-state level. Under full compliance and steady-state participation, $c_t = 1$ for all $t$; the S4 maturation trajectory, in which $c_t$ rises linearly from 0.10 in $t = 0$ to 1.00 at $t = T - 1$, is described in Section 5.1.3. The reference discount rate is $r = 0.03$, with sensitivity to rates within two percentage points reported in Table 20. The projection horizon runs from 2026 to 2035.

## 4.2 Allocation rule

Let $\mathcal{N}$ denote the set of eligible recipient countries indexed by $i$. Allocation is based on three criteria specified in Decision 16/2: biodiversity value ($B_i$), geographic origin of genetic resources ($G_i$), and capacity needs ($N_i$), each expressed as each country's proportional share of the cross-country total, so that $\sum_i B_i = \sum_i G_i = \sum_i N_i = 1$[6]. A share $\delta \geq 0.5$ of total revenue is allocated to IPLCs. The remaining share $(1-\delta)F$ is distributed across countries according to allocation shares $s_i$, with $\sum_i s_i = 1$. The analytical scope of this paper is restricted to the country-level share $(1-\delta)F$: the AHTEG on Allocation Methodology is mandated to develop options for the distribution of this component, while the modalities governing the IPLC pool $\delta F$ are subject to separate CBD deliberations. The allocation formula examined here concerns only the country-level pool.

Decision 16/2 specifies the three criteria but neither the formula for combining them nor the weights to be assigned. Two functional forms are evaluated, reflecting substantively distinct approaches to aggregation.

**Additive formulation**

$$s_i^A = \frac{w_B B_i + w_G G_i + w_N N_i}{\sum_{j \in \mathcal{N}} (w_B B_j + w_G G_j + w_N N_j)}, \tag{6}$$

where $w_B$, $w_G$, and $w_N$ are non-negative weights summing to one. This form allows strong performance on one criterion to compensate for weakness on another.

**Multiplicative formulation**

$$s_i^M = \frac{B_i^{w_B} \cdot G_i^{w_G} \cdot N_i^{w_N}}{\sum_{j \in \mathcal{N}} B_j^{w_B} \cdot G_j^{w_G} \cdot N_j^{w_N}}. \tag{7}$$

This form follows the structure used in the GEF STAR system. A near-zero score on any single criterion reduces the overall allocation substantially regardless of performance elsewhere, limiting cross-criterion compensation. Decision 16/2 prescribes neither form; the analysis evaluates both under the same weight configurations to assess whether conclusions are robust to this prior design choice.

## 4.3 Criterion trade-offs and the allocation design space

The three criteria set out in Decision 16/2 map onto different ethical positions. Giving priority to biodiversity value ($B_i$) embodies an efficiency rationale: resources are directed to places where biodiversity is most highly concentrated. Giving priority to geographic origin ($G_i$) embodies a historical justice rationale: benefits are returned to the countries that are the source of DSI. Giving priority to capacity needs ($N_i$) embodies a redistributive equity rationale: resources are directed to countries that are least able to finance conservation on their own. Since the allocation pool is fixed, the mechanism is zero-sum, and this paper maps outcomes across the feasible design space to show how weight configurations shift distributions across countries, regions, and income groups.

## 4.4 Net transfers

The contribution and allocation rules jointly determine the net position of each country within the mechanism. Country $i$'s aggregate contribution obligation is the sum of contributions from firms within its jurisdiction:

$$\mathcal{C}_i = \sum_{f \in \mathcal{F}_i} C_f, \tag{8}$$

where $\mathcal{F}_i$ denotes the set of eligible firms registered in country $i$. This is a jurisdictional rather than an incidence measure: the ultimate economic burden may be passed on to consumers or shareholders in

[6] In the empirical implementation (Section 5.2), each indicator is rescaled to [0,1] using min-max normalisation prior to entering the formula; the proportional representation here describes the general case.

other jurisdictions, but the jurisdictional position is the relevant unit for assessing which countries face contribution obligations and which receive allocations under the mechanism's governance structure. Country $i$'s net transfer is:

$$T_i = (1 - \delta) \cdot s_i \cdot F - \mathcal{C}_i, \tag{9}$$

where $s_i$ is the allocation share under the chosen formula and weight configuration, applied to the country-level pool $(1 - \delta)F$ as described in Section 5.2. A positive value indicates that country $i$ receives more than its registered firms contribute; a negative value indicates the reverse. Countries that simultaneously host large DSI-dependent industries and score highly on allocation criteria face an inherent tension between the two sides, and their net transfer status can flip sign as weight configurations shift the allocation share.

# 5 Methodology

This section outlines the empirical implementation of the conceptual framework introduced in Section 4.

## 5.1 Contribution flows

The contribution-flow analysis proceeds in three stages: Stage 1 determines eligible entities and calculates firm-level contributions; Stage 2 aggregates these into revenue estimates under five compliance scenarios; and Stage 3 evaluates sensitivity to alternative methodological choices and data assumptions.

### 5.1.1 Policy parameters and eligibility criteria

The core modalities established in Decision 16/2 are translated into analytical parameters that determine the scope of Stage 1. These parameters cover eligible sectors, entity thresholds, contribution rates, financial indicators, and geographical and temporal boundaries. They remain fixed throughout Stages 1 and 2; modifications to selected parameters are examined in Stage 3.

Table 1 summarises the core modelling parameters and assumptions.

Table 1: Summary of core modelling parameters and assumptions

| **Parameter** | **Value(s) and assumptions** |
|---|---|
| Sectors | Enclosure I sectors*: pharmaceuticals, nutraceuticals, cosmetics, animal and plant breeding, biotechnology, laboratory equipment, and IT services[a]. Translated into ISIC, NACE Rev.2, and NAICS industrial classifications. |
| Financial indicators | Contribution base: profit after tax and operating revenue. Eligibility threshold: total assets, profit, and revenue. All indicators matched to IFRS definitions (Table 9) and converted to USD using IMF exchange rates (UN operational rates where IMF rates are unavailable). |
| Eligible entities | All commercial entities (listed and unlisted) operating in at least one Enclosure I sector that exceed at least two of the following three thresholds, averaged over the preceding three years: total assets $\geq$ USD 20 million; sales $\geq$ USD 50 million; profit $\geq$ USD 5 million. |
| Contribution rates | The lower of: 0.1% of revenue or 1% of profit, reflecting the expectation that entities minimise their contribution. |
| Geographical scope | CBD Parties with available firm-level data. |
| Temporal scope | 2021-2023 for the three-year threshold averaging; 2023 as the contribution base year. Stage 3 robustness testing extends the window to 2018-2024. |

*Notes:* Parameters are based on Decision 16/2 modalities and jointly define the scope of Stage 1 input generation. [a] Sector names are abbreviated; see Box 1 for full names. *The term refers to the seven sectors enumerated in Enclosure I of CBD Decision 16/2 and reproduced in Box 1. *Source:* CBD Decision 16/2 and author's assumptions.

#### 5.1.2 Stage 1: Firm-level input generation

Stage 1 determines the set of eligible entities and calculates the corresponding annual contribution for each firm under the Decision 16/2 rules.

**Eligible entity identification** The eligible entity population is identified as a sample rather than a full census, as no single database covers all firms across all CBD Party jurisdictions. The identification involves four consecutive steps: data harmonisation, sector and geography filtering, validation of firm-level data coverage against official statistics, and application of the 2-of-3 financial eligibility thresholds[7].

For entities that are part of multinational corporate groups, eligibility is determined at the level of the individual subsidiary rather than the consolidated group level. This is in line with the sector-based logic of Decision 16/2 and the expectation that firms would limit contributions to entities most directly involved in DSI-related commercial activities. In practice, this means giving precedence to unconsolidated accounts[8] in Orbis (Section 6). Firms identified as holding companies on the basis of secondary industry codes and zero revenues are additionally excluded to avoid double-counting (Annex B.2.2). Alternative approaches are examined in Stage 3 (Section 5.1.4).

Geographical coverage is uneven by necessity. For EU member states and selected OECD countries[9] samples are validated against official statistics. For the remaining CBD Parties, all entities satisfying the eligibility conditions are included, providing a conservative lower-bound estimate, in line with the methodology of Bajgar et al. (2019).

**Firm-level contribution computation** For each eligible entity, the annual contribution ($C_f$) is derived by applying Equation 1 to the entity's 2023 financials. The smaller of 1% of profit and 0.1% of revenue is used, consistent with the expectation that entities minimise their payment. Loss-making firms are assigned a profit-based contribution of zero.

**Minimum rule analysis** For each eligible entity, the effective contribution rate is computed from Equation 2. The margin distribution is examined within each Enclosure I sector relative to $m^* = 0.10$. Two counterfactual levy designs are computed: a pure revenue levy at $\tau_R = 0.001$ applied to all eligible entities, and a pure profit levy at $\tau_\pi = 0.01$ applied to profitable firms only. The gap between the minimum rule aggregate and each counterfactual measures the burden shift attributable to the minimum rule within each sector.

#### 5.1.3 Stage 2: Revenue estimation and scenario analysis

Stage 2 combines the firm-level contribution inputs $\{C_f\}$ from Stage 1 into revenue estimates across five scenarios. The full-compliance scenario S0 provides an upper bound. Scenarios S1-S4 rely on a Monte Carlo simulation that sequentially switches on three adjustment dimensions: sector-level compliance heterogeneity ($\alpha$), ownership heterogeneity ($\gamma$), and DSI intensity ($\omega$). A fourth dimension, the temporal profile of participation, is added in S4. Table 2 outlines the design of these scenarios. S3 is the central scenario for annual revenue analysis and static NPV projections; S4 is the central scenario for NPV projections incorporating the maturation trajectory.

[7] See Annex B for more details on each step

[8] Unconsolidated accounts report the financial results of a single legal entity alone. For corporate groups, an unconsolidated account can be filed separately by the parent company and each of its subsidiaries. Unlike consolidated accounts, unconsolidated accounts do not capture the financial results of the entire corporate group.

[9] The OECD Structural Business Statistics database (SDBS) (OECD, 2026) provides turnover data at the required level of granularity only for a small sample of non-EU countries, with many gaps in the data over time.

Table 2: Revenue estimation scenarios

| Scenario | Sector participation ($p_s$) | Ownership multiplier ($\gamma_o$) | DSI intensity ($\omega_s$) | Time path |
|---|---|---|---|---|
| S0: Full compliance | $=1$ | $=1$ | $=1$ | Static |
| S1: Sector heterogeneity | Calibrated | $=1$ | $=1$ | Static |
| S2: Sector and firm heterogeneity | Calibrated | Calibrated | $=1$ | Static |
| S3: Sector, firm, and DSI heterogeneity | Calibrated | Calibrated | Calibrated | Static |
| S4: Maturation | Calibrated, dynamic | Calibrated | Calibrated | Dynamic |

*Note:* S3 is the central scenario for annual revenue analysis; S4 is the central scenario for NPV projections. Calibrated denotes that the parameter takes its literature-based value from Tables 11, 12, and 13; $=1$ denotes no adjustment is applied. All Monte Carlo scenarios run 10,000 simulation draws; results are reported as mean and 5th–95th percentile interval alongside the S0 upper bound from Table 8.

S3 is designated the central scenario because it propagates uncertainty across all three behavioural dimensions simultaneously: sector participation ($\alpha$), ownership ($\gamma$), and DSI intensity ($\omega$), each drawn stochastically from calibrated distributions. In S3, $\omega$ enters the participation probability as $p_f = \min(\alpha \cdot \gamma \cdot \omega, 1)$, reflecting that DSI intensity shapes whether firms engage with the mechanism at all rather than simply scaling the contributions of those that do. The DSI intensity parameters in S3 rest on indirect proxy evidence rather than direct observation of firm-level DSI use, and the supporting literature is considerably thinner than for the participation and ownership dimensions. Sensitivity of results to these parameters is examined in Panel B of Table 20. S4 applies a time-varying compliance scalar to the S3 participation rates, reflecting that voluntary schemes consistently show slow early uptake before converging to their steady-state levels (Prakash and Potoski, 2012; Seok et al., 2021; Demir et al., 2026). Participation in the initial period (year 1) is set to 10% of each sector's S3 mature-state rate, rising linearly to the full S3 rate by the end of the projection horizon. S4 quantifies the cumulative NPV cost of slow early uptake relative to the static S3 baseline.

**Monte Carlo calibration (S1–S4)** Although the voluntary cooperation literature motivates the expectation of participation heterogeneity (Barrett, 1994; Carraro and Siniscalco, 1998), the paper does not attempt to derive participation conditions from coalition stability models; no comparable mechanism exists to validate such predictions empirically. Participation rates are instead calibrated from the empirical literature on voluntary scheme membership, which captures the sector- and firm-level heterogeneity that theory predicts (Tashman et al., 2022; Haddock-Fraser and Fraser, 2008; Rasche et al., 2022).

For each simulation draw, three parameters are drawn stochastically. The sector-specific participation rate $\alpha$ is the baseline: it is a probability in its own right, bounded to $[0, 1]$, and drawn from a Beta distribution:

$$\alpha \sim \text{Beta}(a,\ b), \quad a = \alpha \cdot 10, \quad b = (1-\alpha) \cdot 10, \tag{10}$$

where the mean of the distribution equals the central calibration value from Table 3 and the concentration parameter of 10 determines the spread of draws around the mean. Interquartile ranges differ across sectors despite the shared concentration because the Beta distribution's spread depends on the mean. For sectors with central values near 0 or 1 the spread is compressed against the boundary and yields narrower absolute IQRs than for sectors with central values near 0.5, which allow more symmetric spread.

The ownership multiplier $\gamma$ and, in S3 and S4, the DSI intensity parameter $\omega$ both operate as adjustments to $\alpha$ rather than as probabilities in their own right: the $[0, 1]$ constraint on the participation probability is imposed by the $\min(\cdot,\ 1)$ operator in Equation 3. They differ, however, in the direction of adjustment, which determines the appropriate distribution for each. $\gamma$ can shift participation either upward (listed firms, $\mu = 1.30$) or downward (unlisted firms, $\mu = 0.85$) relative to the sector baseline, so a Normal distribution with symmetric uncertainty around the calibrated mean is appropriate. A standard deviation of 0.10 is used, reflecting that the ownership effect on voluntary scheme participation is the best-evidenced of the three dimensions, with a narrower implied IQR of 0.14 for both ownership types relative to the sector-level ranges for $\alpha$ and $\omega$:

$$\gamma \sim \text{Normal}(\mu,\ 0.10), \tag{11}$$

where one draw is taken for each ownership type per simulation, applied uniformly across all sectors. By contrast, $\omega$ can only reduce participation relative to the sector baseline: a draw above 1 would imply that a sector's DSI use intensity exceeds full reliance on DSI-derived inputs, which lacks substantive interpretation[10]. The Beta distribution is therefore appropriate for $\omega$ for the same reason it is used for $\alpha$:

$$\omega \sim \text{Beta}(a,\ b), \quad a = \omega \cdot 5, \quad b = (1-\omega)\cdot 5, \tag{12}$$

with a concentration parameter of 5 rather than 10, reflecting that DSI intensity evidence is thinner and more indirect than the voluntary scheme membership literature underpinning $\alpha$[11]. For S1 and S2, $\omega = 1$ and no draw is taken.

All three parameters enter the participation probability jointly as $p_f = \min(\alpha{\cdot}\gamma{\cdot}\omega,\ 1)$. Full justification and sources for all three parameters are provided in Tables 11–13 in the Annex. The resulting P5–P95 intervals reflect uncertainty across all three parameters jointly and do not capture true uncertainty about DSI contribution behaviour, because no data on firm-level participation in a DSI mechanism exist to validate the calibration values.

Table 3: Calibration parameters for Monte Carlo scenarios

| Sector / type | $\alpha$ (participation) mean [P25–P75] | $\omega$ (DSI intensity) mean [P25–P75] | $\gamma$ (ownership) mean [P25–P75] |
|---|---|---|---|
| Cosmetics | 0.60 [0.50–0.71] | 0.35 [0.20–0.48] | |
| Pharmaceuticals | 0.50 [0.39–0.61] | 0.90 [0.86–0.99] | |
| Nutraceuticals | 0.40 [0.29–0.50] | 0.45 [0.29–0.60] | |
| Biotechnology | 0.35 [0.24–0.45] | 0.90 [0.86–0.99] | |
| Laboratory equipment | 0.20 [0.11–0.27] | 0.55 [0.40–0.71] | |
| Animal & plant breeding | 0.20 [0.11–0.27] | 0.80 [0.71–0.93] | |
| Information and AI | 0.15 [0.07–0.21] | 0.75 [0.64–0.89] | |
| Listed firms | | | 1.30 [1.23–1.37] |
| Unlisted firms | | | 0.85 [0.78–0.92] |

*Note:* Mean denotes the central calibration value; P25 and P75 denote the 25th and 75th percentiles of the draw distribution. $\alpha$ is drawn each simulation from $\text{Beta}(a,b)$ with $a = \alpha \cdot 10$ and $b = (1-\alpha)\cdot 10$. $\omega$ is drawn from $\text{Beta}(a,b)$ with $a = \omega \cdot 5$ and $b = (1-\omega)\cdot 5$, reflecting a lower concentration parameter than for $\alpha$, consistent with weaker evidence on sectoral DSI use intensity; for S1 and S2: $\omega$=1. $\gamma$ is drawn from $\text{Normal}(\mu, 0.10)$ with one draw for listed and one for unlisted firms per simulation, applied across all sectors. All three parameters enter the participation probability jointly as $p_f = \min(\alpha \cdot \gamma \cdot \omega,\ 1)$. Full justification and sources are provided in Tables 11–13 in the Annex.

#### 5.1.4 Stage 3: Sensitivity testing

Stage 3 evaluates how sensitive S0 and the central scenario S3 are to methodological choices and data assumptions. Each test varies one parameter at a time while holding all others fixed:

- **Contribution year and averaging window:** alternative three-year windows from 2018 onward;

[10] A sector's participation rate cannot exceed 100% of firms, and DSI use intensity cannot exceed full reliance on DSI-derived inputs. The Beta distribution respects both constraints by construction.

[11] Both concentration parameters are modelling judgements rather than data-derived estimates. The three parameters are drawn independently across sectors, abstracting from common shocks to voluntary scheme participation that would positively correlate draws across sectors and widen the reported P5-P95 intervals. No empirical basis exists for estimating an inter-sector covariance matrix for a mechanism of this kind. Sensitivity to the central calibration values is examined in Panel B of Table 20 via uniform ±0.10 shifts in each parameter mean.

- **Contribution rates:** 25%, 50%, 75%, and 125% of indicative values;
- **Contribution base:** profit-only and revenue-only alternatives;
- **Discount rate:** NPV estimates at rates within two percentage points of the 3% reference rate;
- **Extreme observations:** winsorisation at the 95th and 99th percentiles within each sector; and,
- **Eligibility thresholds:** revisions of ±25%, ±50%, and ±100% applied to individual thresholds and all three simultaneously; downward revisions computed from the full in-scope firm population to capture firms that become eligible under lower thresholds.

Sensitivity to the Monte Carlo calibration is additionally examined by varying $\alpha$, $\gamma$, and $\omega$ by $\pm 0.10$ for each sector and re-running S1-S3 simulations. Further detail is provided in the Annex.

## 5.2 Allocation flows

The allocation analysis takes the S3 central scenario annual revenue estimate as given and evaluates how alternative formulas and weight configurations distribute resources across eligible recipient countries.

### 5.2.1 Indicator selection

The allocation analysis uses one publicly available indicator per criterion, consistent with established practice in comparable biodiversity finance settings, to illustrate the distributional effects of Decision 16/2's three criteria rather than to predict the specific measurement choices to be agreed at COP17.

Biodiversity value is proxied by the Biodiversity Habitat Index (BHI), geographic origin by INSDC sequence counts, and capacity needs by the inverse UN Scale of Assessment. Each indicator is described in Section 6.2.

### 5.2.2 Allocation scenarios

To map the full allocation design space, both formulas are evaluated across all possible combinations of $w_B$, $w_G$, and $w_N$ that sum to one, producing 10,302 combinations in total, providing the basis for Figure 4. Four weight configurations are then examined in detail as special cases (Table 4), spanning the boundaries of the feasible space and providing interior reference points. For the multiplicative formula, a small floor value is added to each indicator to prevent zero allocations where data are missing.

Min-max rescaling to $[0, 1]$ is applied to all three indicators as the baseline normalisation. Two alternatives are reported in Table 26 in the Annex as sensitivity checks: proportional normalisation, where each indicator is expressed as each country's share of the cross-country total ($\sum_i B_i = \sum_i G_i = \sum_i N_i = 1$), and a log transformation of $G_i$ prior to proportional scaling, replacing the raw count with $\log(1 + G_i)$.

Table 4: Weight configurations for allocation scenario analysis

| **Scenario** | **Description** | $\mathbf{w_B}$ | $\mathbf{w_G}$ | $\mathbf{w_N}$ |
|---|---|---|---|---|
| Equal weights | Balanced across all three criteria | 1/3 | 1/3 | 1/3 |
| Biodiversity-maximising | Prioritises conservation impact | 1 | 0 | 0 |
| Geographic origin | Prioritises historical justice | 0 | 1 | 0 |
| Capacity needs | Prioritises development equity | 0 | 0 | 1 |

*Note:* Corner solutions define the boundaries of the feasible allocation space. Equal weights carry no normative status and are included solely as an interior reference point. Each configuration is evaluated under both the additive and multiplicative formula.

## 5.3 Net transfer analysis

For each country, the net transfer $T_i$ is calculated following Equation 9, using the aggregate contribution from the S3 central scenario, together with the allocation shares derived for each of the eight formula-weight combinations. The outcomes are summarised by CBD regional group and by World Bank income group. Countries whose net position changes sign across configurations are explicitly highlighted.

# 6 Data

## 6.1 Contribution flows

The analysis draws on two main types of data for contribution flow estimation: firm-level financial data used in the primary estimation, and country-sector aggregates used for validation.

**Firm-level financial data (bottom-up)** The primary source is Orbis (Moody's Analytics) Moody's Analytics (2025), the most widely used global commercial database for firm-level financial information, covering over 600 million publicly listed and private entities across more than 100 countries OECD (2020). It provides the balance sheet and income statement data required to apply the Decision 16/2 eligibility thresholds and to compute contributions at the entity level. Orbis is used both for nationally representative samples, where coverage is validated against official statistics, and for non-representative country samples as conservative lower bounds, in order to maximise coverage of CBD Parties.

Table 5 reports summary statistics for the 21,690 eligible entities. The median eligible firm has annual revenues of $95 million and a profit margin of 6.6%, well below the indifference threshold $m^* = 0.10$, meaning the majority of eligible firms are profit-base payers under the minimum rule. Pharmaceuticals is the only sector in which the median firm's margin (10.4%) exceeds $m^*$, and it also has the highest share of listed firms (23.8%), consistent with the sector's concentration in large, publicly traded multinationals. Animal and plant breeding has the lowest median margin (5.2%) and the widest interquartile range (0.5% to 17.8%), reflecting its heterogeneity across crop, livestock, and aquaculture sub-sectors. The interquartile range of revenue across all sectors extends from USD 57 million at P25 (just above the USD 50 million eligibility threshold) to USD 202 million at P75, reflecting the right-skewed distribution of firm sizes.

Table 5: Summary statistics for eligible entities by Enclosure I sector

| Sector | $n$ | Med. rev. ($mn) | Revenue IQR (P25–P75, $mn) | Med. assets ($mn) | Med. profit ($mn) | Med. margin | Margin IQR (P25–P75) |
|---|---|---|---|---|---|---|---|
| Information and AI | 5,217 | 96 | 58–202 | 95 | 6.4 | 6.0% | 1.4%–15.7% |
| Animal & plant breeding | 4,256 | 83 | 47–170 | 97 | 4.6 | 5.2% | 0.5%–17.8% |
| Biotechnology | 3,709 | 96 | 56–217 | 120 | 5.7 | 5.9% | 0.9%–15.4% |
| Pharmaceuticals | 3,401 | 105 | 59–246 | 165 | 10.2 | 10.4% | 3.6%–21.2% |
| Laboratory equipment | 2,846 | 93 | 57–179 | 114 | 7.4 | 7.9% | 2.8%–16.9% |
| Nutraceuticals | 1,513 | 104 | 64–218 | 91 | 5.0 | 4.2% | 1.1%–10.1% |
| Cosmetics | 748 | 100 | 66–214 | 97 | 7.4 | 6.0% | 2.6%–12.4% |
| *All sectors* | *21,690* | *95* | *57–202* | *111* | *6.5* | *6.6%* | *1.5%–16.7%* |

*Notes:* All figures in nominal USD millions, reference year 2023. Revenue IQR reports the 25th–75th percentile range of operating revenue within each sector. Profit margin $m_f = \pi_f / R_f$ computed from 2023 financials; Margin IQR reports the 25th–75th percentile range. Median profit is reported directly and does not equal the product of median revenue and median margin, as the median of a ratio differs from the ratio of medians. The narrow gap between the eligibility threshold ($50mn) and the P25 of revenue across all sectors ($57mn) indicates that a substantial share of eligible firms sit close to the threshold floor. Pharmaceuticals is the only sector in which the median firm's margin (10.4%) exceeds $m^* = 0.10$, and it also has the highest median total assets ($165mn) and the widest revenue IQR ($59mn–$246mn), consistent with the sector's concentration in large, publicly traded multinationals. Loss-making firms ($\pi_f \leq 0$) contribute zero; their share ranges from 11.5% (cosmetics) to 21.2% (animal & plant breeding). Of the 21,690 eligible firms, 14.5% are publicly listed, ranging from 10.7% (animal & plant breeding) to 23.8% (pharmaceuticals). The full P10–P90 distribution of revenue, total assets, and profit by sector is reported in Table **??** in the Annex.
*Source:* Author's calculations based on Orbis (Moody's Analytics).

Despite its extensive coverage, Orbis has well-documented limitations. Coverage is most reliable for EU and selected OECD economies and deteriorates for developing countries, particularly in Sub-Saharan Africa and East Asia (OECD, 2020; Kalemli-Özcan et al., 2024). This is also observed in the final sample used in the analysis: of the 196 CBD Parties, 100 have at least one eligible firm in Orbis, with coverage gaps concentrated in Africa and Asia-Pacific (See Table 17 and Figure 9 in Annex C). For validated country samples, estimates are broadly representative of the eligible population; for remaining CBD Parties, they are conservative lower bounds that cannot be extrapolated to the full eligible firm population. A risk of double-counting arises where consolidated accounts are retained in the absence of unconsolidated equivalents. Firms reporting only consolidated accounts account for 6.2% of the eligible sample and contribute up to 16.1% of S0 contributions, providing an upper bound on the potential bias (Table 21 in Annex C). These constraints are discussed in detail in Annex B.

**Sectoral aggregates (top-down)** Firm-level aggregates are benchmarked against Eurostat Structural Business Statistics Eurostat (2025) for EU-27 countries and OECD Structural and Demographic Business Statistics OECD (2026) for OECD members. Equivalent sources with broader global coverage could not be identified. All sectors meet or exceed the 60-90% adequacy range from Kalemli-Özcan et al. (2024), with manufacturing divisions clustering between 81% and 96% and services divisions between 73% and 109%. Full validation results are reported in Figure 9 and Table 19 in the Annex.

**Macroeconomic and supporting data** Exchange rates, deflators, and national accounts aggregates are obtained from the IMF IMF (2026) and the UN Statistics Division UNSD (2026a,b). The specific steps are described in Annex B.

## 6.2 Allocation flows

The allocation analysis draws on one publicly available indicator per criterion. Table 6 summarises the source, construction, and primary limitation of each.

Table 6: Allocation indicators by criterion

| Criterion | Indicator | Construction | Primary limitation |
|---|---|---|---|
| Biodiversity value ($B_i$) | BHI, CSIRO (Ware et al., 2026) | Species diversity projected to persist under current habitat condition, connectivity, and compositional heterogeneity; KMGBF component indicator; aggregated to country level. | Reflects habitat condition rather than conservation effort; alternative biodiversity measures would produce meaningfully different country rankings. |
| Geographic origin ($G_i$) | INSDC sequence counts, EMBL-EBI via GBIF (European Bioinformatics Institute (EMBL-EBI), 2025c,b,a) | Country-level counts of distinct organism-collection events; human sequences excluded and duplicates removed. | Only 15% of INSDC sequences carry a country tag (Scholz et al., 2021); coverage favours countries with stronger research infrastructure. As INSDC accounts for 95% of public nucleotide databases, this disparity is structural. |
| Capacity needs ($N_i$) | Inverse UN Scale of Assessment 2025–2027 (UN DGACM, 2024; Oldham, 2026) | Inverse of each country's UN Scale of Assessment rate ($N_i = 1/\text{rate}$). Preferred over inverse GDP per capita because the underlying UN Scale formula is based on GNI but adjusted for low per capita income, external debt burden, and an LDC ceiling of 0.01%. | 28 countries share the minimum assessment rate of 0.001%, preventing differentiation within the lowest-income group. |

*Note:* All indicators rescaled to $[0, 1]$ using min-max normalisation prior to entering the allocation formula. Sensitivity to alternative normalisations is reported in Table 26.

Table 7 reports summary statistics for each indicator prior to normalisation. The three criteria differ substantially in their cross-country dispersion. INSDC sequence counts are highly concentrated, with Canada alone accounting for 29% of all country-tagged sequences and a coefficient of variation of 4.38. The inverse UN Scale is also skewed, with 28 countries sharing the minimum assessment rate. BHI varies far less across countries (CV = 0.09), which limits its discriminatory power in the formula relative to the other two criteria.

Table 7: Summary statistics for allocation indicators (pre-normalisation, 191 CBD Parties)

| Indicator | Mean | SD | Min | P25 | Median | Max |
|---|---|---|---|---|---|---|
| BHI 2024 ($B_i$, index 0–1) | 0.698 | 0.066 | 0.547 | 0.650 | 0.688 | 0.879 |
| INSDC sequences ($G_i$, count) | 27,740 | 121,520 | 0 | 1,271 | 3,517 | 1,546,592 |
| Inverse UN Scale ($N_i$, 1/rate) | 227.1 | 338.8 | 0.1 | 6.5 | 71.4 | 1,000.0 |

*Notes:* Statistics computed prior to normalisation. BHI maximum is Suriname; minimum is Bangladesh. INSDC maximum is Canada (1.5 million sequences, 29% of the country-tagged total); minimum is Namibia (0 tagged sequences). Inverse UN Scale minimum is Belize and 27 other countries sharing the minimum assessment rate of 0.001%; maximum is China (assessment rate 20.0%). The coefficient of variation is 0.09 for BHI, 4.38 for INSDC sequences, and 1.49 for the inverse UN Scale, illustrating that BHI varies far less across countries than the other two criteria.

# 7 Results

## 7.1 Contribution flows

Under full compliance, the 21,690 eligible entities across 100 CBD Party jurisdictions generate annual contributions of $3,646 million (Table 8). The central S3 estimate of $929 million represents 25.5% of this upper bound. Sector-level participation heterogeneity is the dominant source of reduction: S1 alone brings contributions to $1,162 million, the ownership multiplier in S2 adds $41 million, and the DSI intensity adjustment in S3 subtracts a further $274 million. At a 3% discount rate, the S3 static NPV reaches $8.2 billion to 2035; under the S4 maturation path the cumulative total falls to $4.3 billion, a $3.9 billion cost of slow early uptake that makes S4 the more policy-relevant baseline[12].

Table 8: Estimated Cali Fund contributions: annual and NPV projections under alternative compliance scenarios

| | Annual (central estimates) | | | | NPV at 3% ($bn) | |
|---|---|---|---|---|---|---|
| **Scenario** | **Mean ($mn)** | **P5** | **P95** | **% of S0** | **To 2030** | **To 2035** |
| S0 Full compliance | 3,646 | — | — | 100.0 | 17.2 | 32.0 |
| S1 Sector heterogeneity | 1,162 | 810 | 1,533 | 31.9 | 5.5 | 10.2 |
| S2 Sector and ownership | 1,203 | 830 | 1,602 | 33.0 | 5.7 | 10.6 |
| S3 Sector, ownership, and DSI intensity | 929 | 591 | 1,296 | 25.5 | 4.4 | 8.2 |
| S4 Gradual uptake (S3 + maturation) | — | — | — | — | 1.3 | 4.3 |

*Notes:* P5 and P95 reflect uncertainty in sector-level participation rates across 10,000 Monte Carlo draws. NPV for S1–S3 assumes static participation ($c_t = 1$); S4 applies a maturation scalar rising linearly from 10% in 2026 to 100% by 2035, applied to the S3 central estimate (Section 5.1.3). S3 is the central scenario for annual revenue analysis; S4 is the central scenario for NPV projections. Discount rate sensitivity is reported in Table 20. Reference year 2023.
*Source:* Author's calculations.

The full eligible sample estimate (S0) of $3,646 million holds up well across alternative averaging windows, ranging from $2,986 million to $3,927 million. The lower bound is driven by the pandemic-affected 2020 base year rather than any structural feature of the eligible population. The minimum rule proves to be a significant design choice: switching to either a pure revenue or profit levy roughly doubles the estimated contributions, while winsorisation reveals that a small number of very large firms account for a disproportionate share of the total, with the 95th percentile cap alone reducing the aggregate by 44%. Among the Monte Carlo calibration parameters, sector-level participation rates are the most consequential, with the S3 central estimate ranging from $646 million to $1,215 million under a uniform 0.10 shift in $\alpha$; the ownership and DSI intensity adjustments produce narrower ranges of $838–$1,018 million and $810–$1,043 million respectively. Full sensitivity results are reported in Table 20.

[12]The S4 estimate should be interpreted with caution. The maturation trajectory is a simplifying assumption: given the novelty of the mechanism, there is no empirical basis for predicting when participation will reach its steady-state level, and the linear ramp from 10% to 100% over the projection horizon is one of many plausible paths. If contributions remain near zero in the first several years, the NPV cost of slow uptake would be substantially larger than the $3.9 billion reported here. The S4 figure is therefore best read as a lower bound on the maturation cost rather than a point estimate.

Threshold sensitivity results are reported in Table 23. The findings reflect the high concentration of contributions at the top of the financial distribution. Doubling all three thresholds simultaneously removes 43.5% of eligible firms from scope but reduces S0 contributions by only 7.4%, because newly excluded firms sit near the lower boundary of the distribution and contribute little relative to the large firms that dominate the aggregate. The reverse holds for downward revisions: halving all thresholds adds 14,317 firms, a 66.0% increase in the eligible population, but raises contributions by only 5.5%, for the same structural reason. Threshold design therefore has large implications for the scope and inclusivity of the mechanism but limited implications for its revenue, a distinction that is directly relevant to the choice between a narrow high-revenue instrument and a broader norm-setting one at COP17.

For the full eligible sample, contributions are concentrated in two sectors: pharmaceuticals ($960 million) and information and AI services ($919 million) together account for 51% of the full-compliance total despite representing 40% of eligible firms (Figure 1). This reflects both firm size and the operation of the minimum rule: the top 100 firms account for 27.6% of total contributions, with the top 10 alone accounting for 8.6%[13] (total concentration Figure 10, and within-sector concentration Figure 11). As a result, the fund's revenue base is structurally dependent on the participation of a small number of identifiable firms.

Under the central scenario (S3), the sectoral composition shifts materially relative to the full-compliance baseline (see Table 22 for the underlying participating revenue base by sector). The pharmaceutical sector's share rises from 26.3% to 49.6% of total contributions, reflecting its relatively high participation rate ($\alpha = 0.50$), high DSI intensity ($\omega = 0.90$), and the stability of revenue-base payers within the sector. In contrast, the information and AI sector's share falls from 25.2% to 11.1%, consistent with its low participation calibration ($\alpha = 0.15$), the diffuse nature of its DSI use, and a moderate DSI intensity adjustment ($\omega = 0.75$). Sectoral shares under S1–S3 are reported in Table 24.

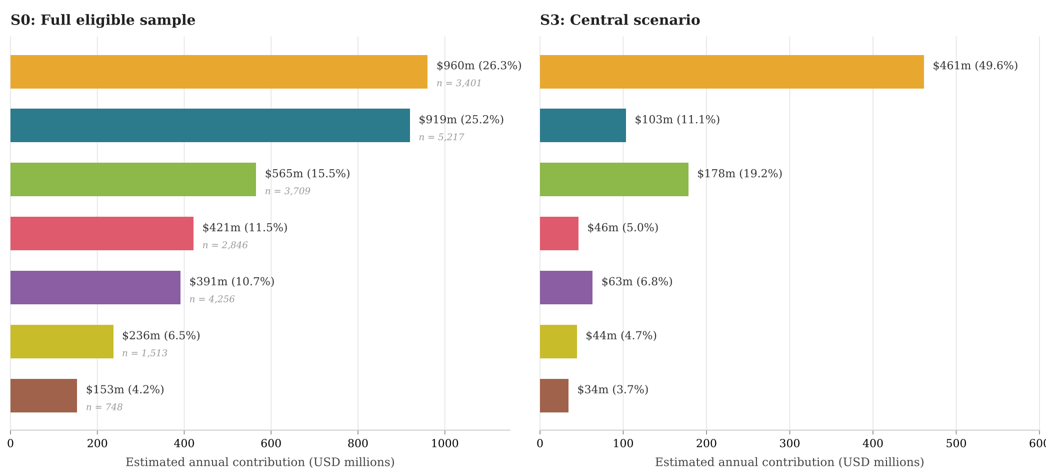



Figure 1: Estimated annual contributions by Enclosure I sector under the full eligible sample (S0, left panel) and central scenario (S3, right panel)

*Notes:* S0 contributions estimated under $C_f = \min(0.001 \times R_f, 0.01 \times \max(0, \pi_f))$, reference year 2023. S3 central estimates are means of 10,000 Monte Carlo draws under calibrated sector participation ($\alpha$), ownership ($\gamma$), and DSI intensity ($\omega$) parameters (Table 3). $n$ denotes eligible entities per sector.
*Source:* Author's calculations based on Orbis (Moody's Analytics).

The top 10 CBD Party jurisdictions collectively account for 73.7% of estimated S0 contributions (Table 25). This figure should be considered in light of two offsetting data limitations. First, contributions from Switzerland and Canada are likely materially understated due to incomplete unconsolidated account coverage for large multinationals headquartered in these jurisdictions. Second, Ireland's $205

[13] Restricting the sample to unconsolidated accounts only (U1/U2, $n$ = 20,335) reduces the top-100 concentration share from 27.6% to 25.7% and the top-10 share is unchanged at 8.6%, confirming that the structural finding is not driven by the inclusion of consolidated-account firms (C1).

million S0 estimate primarily reflects the concentration of multinational registered activity for tax purposes, rather than a genuine commercial presence of that scale, which partially compensates for the understatement elsewhere. The United States, as the largest single source of DSI-dependent commercial activity globally, is excluded as a non-Party to the CBD. Consequently, the true geographic concentration of the contribution base is broader than the S0 figures indicate.

The minimum rule creates systematic heterogeneity across sectors. Pharmaceuticals is the only sector in which the median firm is a revenue-base payer (median $m_f = 0.12$; margin distributions by sector are shown in Figure 12 in the Annex); in every other sector the median firm sits below $m^* = 0.10$ and pays on profit. Figure 2 shows that 60.5% of total contributions are revenue-binding overall, but this masks a sharp sectoral divide. Revising $\tau_R$ therefore targets a concentrated population of high-margin firms, while revising $\tau_\pi$ redistributes the burden toward the majority of eligible firms in breeding, nutraceuticals, and cosmetics. The rate choice at COP17 determines which sectors bear the adjustment, not just how much the fund raises.

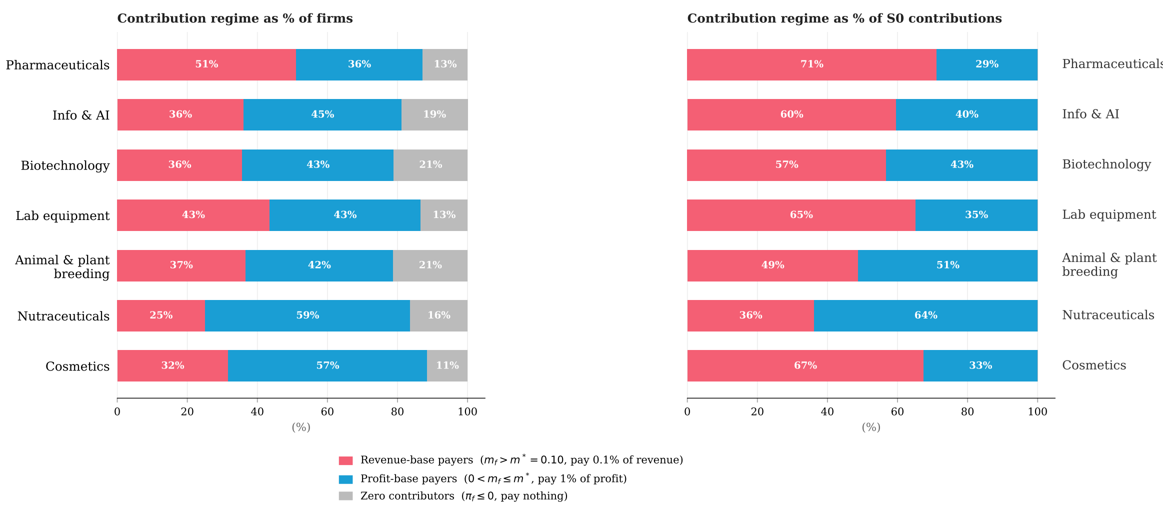



Figure 2: Contribution regime decomposition by sector (full eligible sample, S0)

*Notes:* Each bar shows the share of firms (left) and the share of total S0 contributions (right) attributable to each contribution regime. Regimes are determined from 2023 reference-year financials: *revenue-base payers* (coral) have $m_f > m^* = 0.10$ and pay $\tau_R R_f = 0.1\%$ of revenue; *profit-base payers* (blue) have $0 < m_f \leq m^*$ and pay $\tau_\pi \pi_f = 1\%$ of profit; *zero contributors* (grey) have $\pi_f \leq 0$ and pay nothing. Sectors ordered by total S0 contribution, highest to lowest. Reference year 2023.

A further consequence of the minimum rule is year-to-year instability in contribution revenues. Seventeen per cent of eligible firms changed contribution regime between the three-year averaging window and the 2023 reference year; the distribution of these firms along the margin axis is shown in Figure 13 in the Annex. The dominant source is profit volatility near zero: firms that dropped to zero were clustered just above the zero margin during the averaging period and fell into loss in 2023. By contrast, the revenue-base region above $m^*$ is highly stable. Contribution revenues are therefore most volatile among firms closest to the minimum viable margin, not among the large payers that dominate the aggregate. This rate should be treated as period-specific rather than a stable structural feature, as 2023 may not be representative of a typical year[14].

## 7.2 Allocation flows

The geographic origin criterion is the most consequential single lever, as illustrated in Figure 3. Under DSI-only weighting, Western European and Other States capture 47.8% of total allocations while

[14] The 2023 reference year aligns with the first full post-COVID recovery period for many industries, which may have increased the volatility of profits around zero compared with a more typical year. As a result, the switching rate should be viewed as an estimate specific to the current period rather than as a stable structural parameter. Monitoring this rate over several reference years as the fund becomes operational would enhance the robustness of the analysis.

African States receive just 6.4%, reflecting the concentration of INSDC sequences in a small number of high-income research economies. The capacity needs criterion reverses this: African States receive 41.2% and WEOG falls to 2.5%. The biodiversity criterion produces a more moderate redistribution, broadly tracking where intact habitat is concentrated, with Africa (27.8%), Asia-Pacific (26.0%), and Latin America (19.0%) as the primary beneficiaries. Equal weights sit between these extremes, directing 25.6% to high-income countries overall under the baseline min-max normalisation. Figure 4 places the two criteria in direct comparison. Varying $w_G$ from 0 to 1 shifts WEOG's allocation share by approximately 40 percentage points, making it by far the most consequential lever for North-South distribution. Varying $w_B$ across the same range produces a maximum swing of around 12 percentage points, but this movement is spread across groups rather than concentrated in the North-South direction. The biodiversity criterion is not irrelevant, but it does not materially alter the direction of North-South resource flows under any weight configuration. Under the current indicators, the dominant trade-off at COP17 is therefore between $w_G$ and $w_N$.

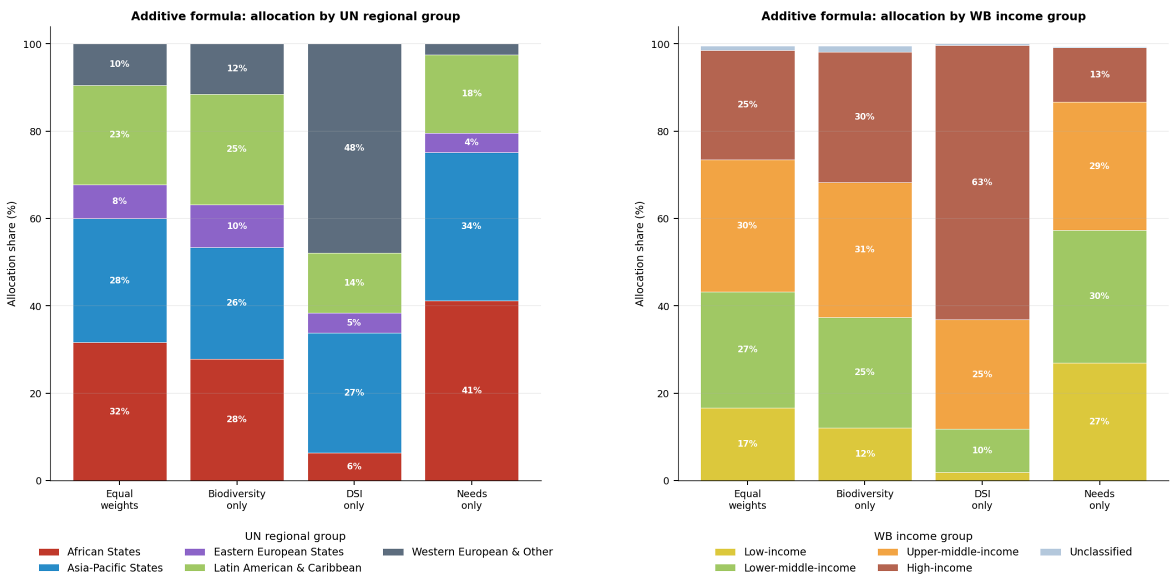



Figure 3: Allocation shares under the additive formula across four weight configurations: equal weights ($w_B = w_G = w_N = 1/3$), biodiversity-only, DSI-only, and needs-only. Indicators: BHI ($B_i$), inverse UN Scale ($N_i$), INSDC counts ($G_i$). 191 CBD Parties (see Table 15 for exclusions). Additive formula, min-max normalisation.

*Source:* Author's calculations.

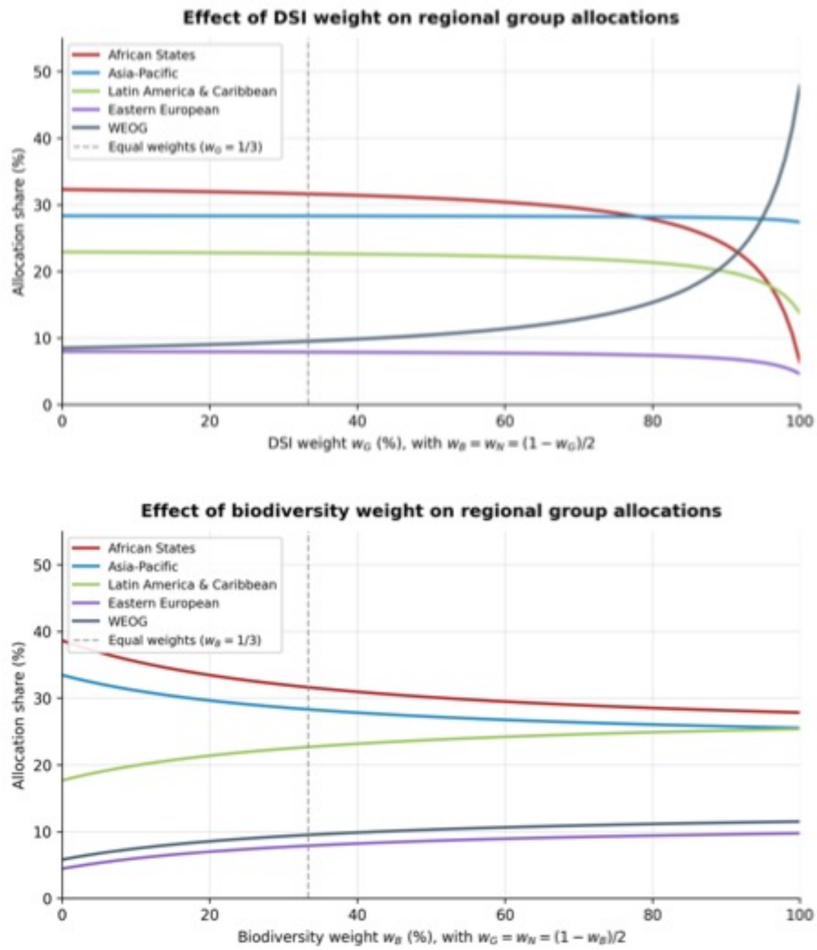



Figure 4: Allocation shares as a function of $w_G$ (upper) and $w_B$ (lower), remaining weights equal at $(1-w)/2$. Indicators: BHI ($B_i$), inverse UN Scale ($N_i$), INSDC counts ($G_i$). 191 CBD Parties. Additive formula, min-max normalisation.

*Source:* Author's calculations.

The formula choice interacts with the normalisation method in a substantial way (Figure 5). Under proportional normalisation, switching from additive to multiplicative at equal weights reduces WEOG's share from 21.3% to 8.0% and raises African States from 25.1% to 35.3%, a shift of 13.3 percentage points. Under min-max normalisation (the baseline used throughout the paper) the same switch produces a shift of only 1.9 percentage points (WEOG: 9.5% to 7.6%; African States: 31.6% to 35.5%). The difference arises because proportional normalisation preserves the extreme concentration of INSDC sequences, giving high-income research economies a near-zero relative score on capacity needs, which the multiplicative formula then penalises heavily. Min-max normalisation compresses that concentration, and the two formulas converge. Taken together, the normalisation method and formula choice can jointly shift allocations by up to 13 percentage points, comparable in scale to moving from equal weights to DSI-only weighting.

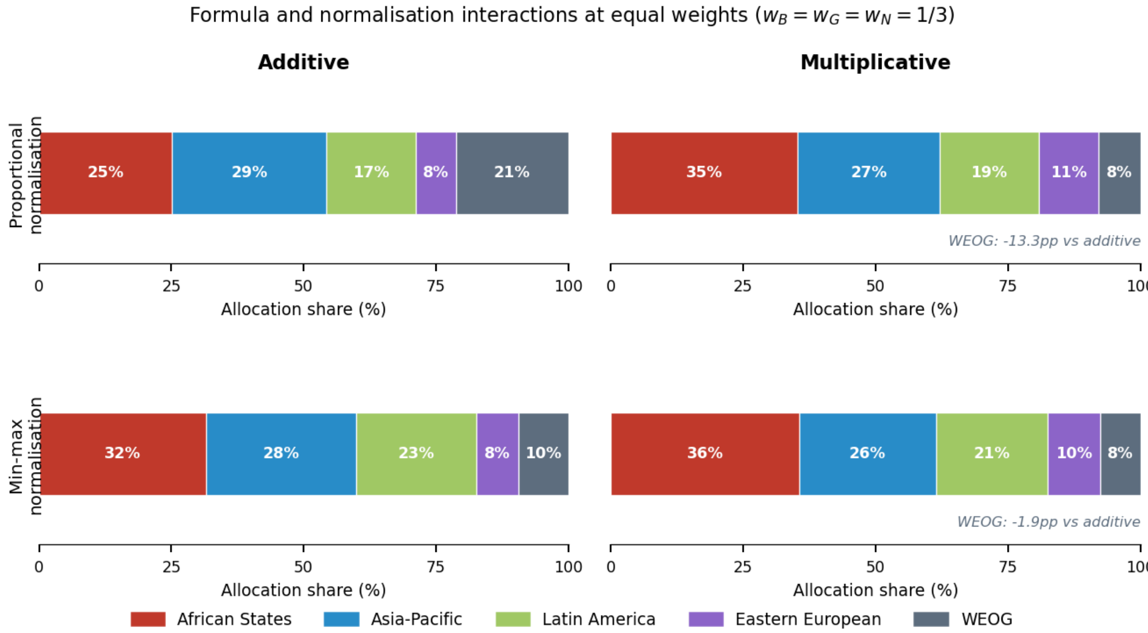



Figure 5: Allocation shares under the additive and multiplicative formulas at equal weights ($w_B = w_G = w_N = 1/3$), by normalisation method

*Notes:* Each panel shows the five CBD regional group allocation shares at equal weights. *Proportional*: each indicator expressed as each country's share of the cross-country total. *Min-max*: each indicator rescaled to $[0, 1]$ prior to entering the formula; this is the baseline normalisation used in the paper. Annotated shifts compare multiplicative to additive within each normalisation. Same sample and indicators as Figure 4.
*Source:* Author's calculations.

### 7.3 Net transfer analysis

The net transfer analysis uses the S3 central scenario as the contribution baseline. Country-level contribution obligations are compared against country-level allocations under the additive equal-weights formula with min-max normalisation. Consistent with the analytical scope set out in Section 5.2, the comparison is restricted to the country-level pool $(1 - \delta)F_{S3}$ = \$464 million; the IPLC pool is not analysed.

Under the additive formula with equal weights, the redistributive pattern broadly aligns with the fund's fair and equitable sharing objective (Figure 6). African States contribute \$7 million but receive \$147 million, a net gain of \$140 million. This positive net transfer largely reflects the genuine absence of large DSI-reliant firms meeting the Decision 16/2 eligibility thresholds across most of the region (Table 17). However, incomplete Orbis coverage for Sub-Saharan Africa may additionally understate contribution obligations where eligible firms do exist (OECD, 2020; Kalemli-Özcan et al., 2024), making the figure an upper bound on the true redistributive gain. The magnitude of this overstatement cannot be quantified without better firm-level and sector-level data for the region. Latin America and the Caribbean gains \$90 million on contributions of \$15 million. The two large net contributor groups are WEOG (net outflow of \$322 million) and Asia-Pacific (net outflow of \$367 million), the latter driven by China alone accounting for \$268 million, followed by the United Kingdom, Japan, India, and Germany (Figure 7). The largest net recipients are small island states and least-developed countries with no eligible firms, each receiving approximately \$6 million. By income group, high-income countries contribute 54% of the total but receive only 25% of the country-level pool, while low-income countries face no contribution obligations but receive 21% of allocations (Figure 8).

Thirty-three countries change net position sign across the four weight configurations. Canada is the most striking case: a marginal net recipient under equal weights (+\$2.2 million) but the largest net recipient in the analysis under DSI-origin weighting (+\$131 million), reflecting its dominant share of publicly deposited sequence data. This result should be interpreted with caution, however, as Canadian firm-level contribution data are likely incomplete in Orbis, meaning Canada's contribution obligations are probably understated. Brazil shows the inverse pattern, moving from net contributor under most configurations to a net recipient of \$6.9 million under DSI-origin weighting.

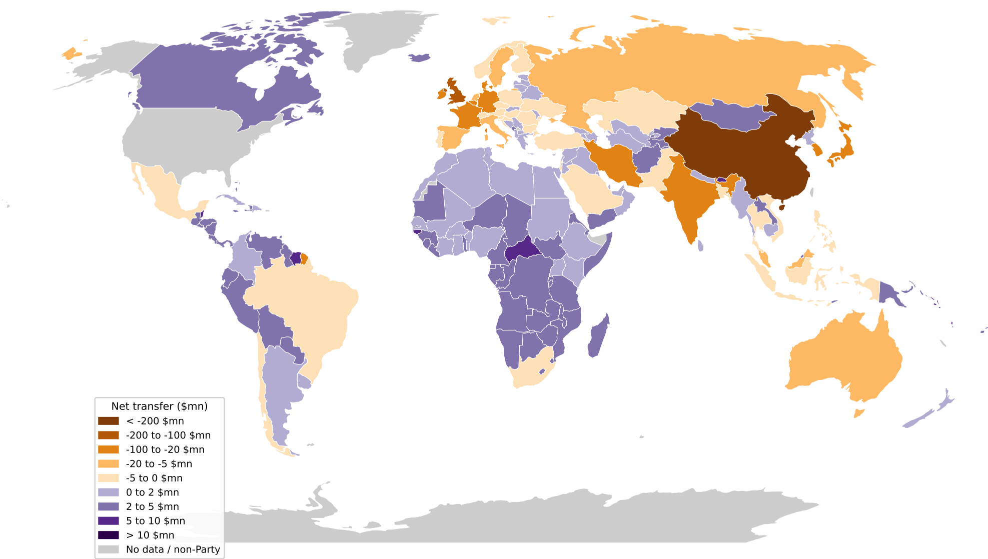



Figure 6: Net transfer by country under the additive formula with equal weights ($w_B = w_G = w_N = 1/3$)

*Notes:* Net transfer $T_i = (1 - \delta) \cdot s_i \cdot F_{S3} - \mathcal{C}_{i,S3}$, where $\delta = 0.5$ is the IPLC floor, $s_i$ is the allocation share under the additive equal-weights formula with min–max normalisation, $F_{S3} = \$929$mn is the S3 central annual estimate, and $\mathcal{C}_{i,S3}$ is country $i$'s expected contribution under S3 participation rates. The map reflects the country-level allocation pool only ($(1 - \delta)F_{S3} = \$464$mn); the IPLC pool is not analysed (see Section 5.2). Grey indicates the United States (non-CBD Party) or countries with insufficient data. Canada's net transfer estimate (+\$2mn) should be interpreted with caution as Orbis firm-level coverage for Canada is incomplete and contribution obligations are likely understated (see discussion).
*Source:* Author's calculations.

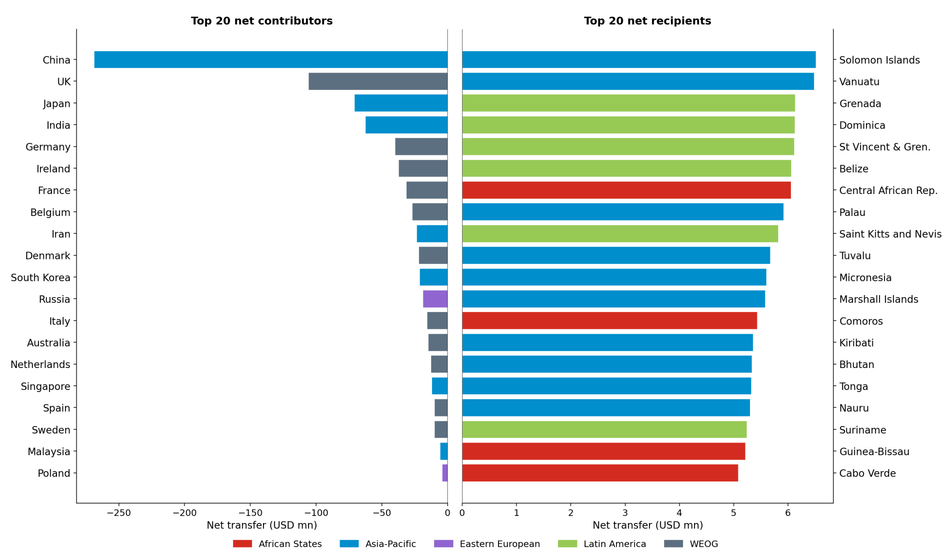



Figure 7: Top 20 net contributors and net recipients under the additive formula with equal weights

*Notes:* Countries ranked by net transfer $T_i$ under the additive equal-weights formula. Bars coloured by CBD regional group. S3 central scenario; $\delta = 0.5$. The IPLC pool is excluded; see Section 5.2.
*Source:* Author's calculations.

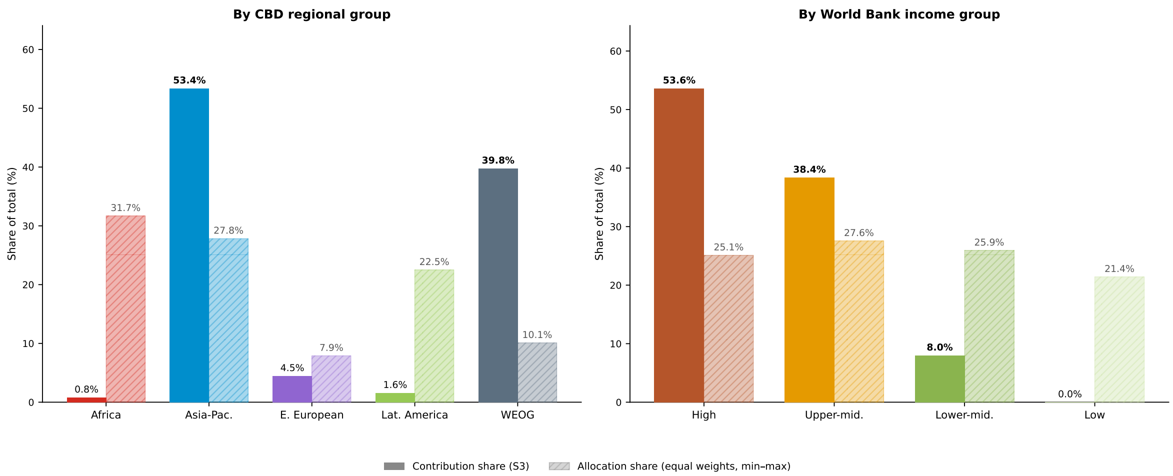



Figure 8: Contribution and allocation shares by World Bank income group and CBD regional group under the additive formula with equal weights

*Notes:* Solid bars show each group's share of total S3 contributions; hatched bars show each group's share of the country-level allocation pool ($(1-\delta)F_{S3} = \$464$mn). The IPLC pool is not analysed (see Section 5.2). Additive formula, equal weights. Unclassified countries (Ethiopia, Venezuela) omitted.
*Source:* Author's calculations.

# 8 Discussion

## 8.1 Contribution design: concentration, instability, and the rate choice

The Cali Fund's revenue base concentration creates an asymmetric risk. With the top 100 firms accounting for 27.6% of estimated contributions and two sectors for 51%, the fund's viability depends on the voluntary engagement of a small and identifiable group. Large, prominent firms face stronger reputational pressures and closer investor oversight than smaller ones (Tashman et al., 2022; Rasche et al., 2022; Lee, 2009), so concentration may partly reflect self-selection toward the most likely payers. The risk is nonetheless one-sided: if participation among the top contributors falls short, the revenue gap is large and there is no compensatory mechanism. The S3 sectoral breakdown illustrates this concentration risk. Under realistic participation and DSI intensity assumptions, pharmaceuticals account for approximately half of expected revenues, compared with just over a quarter under full compliance. This reflects the sector's relatively high participation rate, high DSI intensity calibration, and the dominance of revenue-base payers whose contributions are insensitive to short-term profit fluctuations. The fund's revenue risk is therefore focused not only on the largest contributors overall, but specifically on large pharmaceutical firms whose voluntary engagement is the single most consequential factor in reaching the central estimate.

Decision 16/2 proposes certificates as one tool to encourage participation and urges Parties to adopt national measures, but leaves both largely undefined Blom et al. (2025b); Orozco and Scholz (2025). Concentration creates vulnerability, but it also means targeted engagement strategies are feasible in a way they would not be for a diffuse contributor base.

The minimum rule creates a structural instability that deserves attention at COP17. Firms whose average margin over the eligibility window sits just above zero can drop out of payment obligations entirely if their profitability falls in the contribution year, while firms in the revenue-base region above $m^*$ are highly stable. This creates a governance problem: firms near the zero-margin threshold can move in and out of obligations without any change in their underlying commercial activity, making contribution liabilities sensitive to short-term profit fluctuations rather than to DSI use. Rate revision at COP17 will not resolve this, but the choice of rate matters for the composition of the contributor pool. Raising $\tau_R$ raises $m^*$, contracting the stable revenue-base population and shifting more firms onto the profit base, which reintroduces the instability the revenue-base regime was avoiding. Raising $\tau_\pi$ lowers $m^*$, expanding the stable revenue-base population, though it increases the burden on firms already paying on profit. Only asymmetric changes to the two rates move the benchmark margin and thus affect which firms pay on revenue versus profit; proportional shifts in both rates simply scale all contributions by the same factor without altering the composition of the contributing firms (Figure 14). Beyond rates, the choice between profit and revenue as the primary base has implications for avoidance risk: profit is more vulnerable to transfer pricing and intra-group arrangements than revenue, which is generally harder to reallocate across jurisdictions (Cobham and Janský, 2018; Tørsløv et al., 2023). This problem is not limited to the rate design. Where contributions are measured at the jurisdiction of registration rather than economic activity, the contributor base is distorted by tax-motivated profit and revenue routing: Ireland's $205 million estimate in Table 25 reflects this directly. The mechanism's reliance on jurisdictional rather than source-based measurement creates a possible structural misalignment between who appears to pay and where DSI-dependent activity actually occurs. Those are empirical questions the COP should consider when evaluating the relative merits of the two bases and DSI use attribution to contributing firms.

## 8.2 Allocation design: criteria, weights, and their distributional implications

The allocation outcomes highlight a core tension within the geographic origin criterion. Its underlying justification is historical justice: benefits should be directed back to countries whose biodiversity underpins commercially valuable DSI. Yet in its current form, the criterion effectively captures sequencing capacity rather than actual biodiversity contribution. Log-normalising the INSDC indicator reduces WEOG's share under DSI-only weighting from 47.8% to 16.0% (Table 26 in the Annex). This is a measurement argument rather than a sensitivity test: the log-normalised result may be the more defensible representation of geographic origin, and the AHTEG should consider it when selecting an indicator ahead of COP17. Placing heavy emphasis on this criterion thus risks channeling benefits to the wrong countries for the wrong reasons, and this issue cannot be resolved merely by recalibrating the weights. The AHTEG must therefore explicitly consider, before COP17, whether the current indicator is appropriate for its intended purpose or whether a different proxy is required, although INSDC's new origin data obligations (INSDC, 2023) should progressively enhance data coverage.

The choice of formula interacts with the normalisation method to amplify or dampen this effect. Under proportional normalisation, moving from an additive to a multiplicative scheme reallocates 13.3 percentage points away from WEOG without any change in stated weights; under the baseline min-max normalisation the same switch produces only a 1.9 percentage point shift, because min-max compresses the extreme concentration of INSDC sequences that the multiplicative formula would otherwise penalise. Jointly, the two choices span up to 13 percentage points, a range comparable to moving between major weight configurations. The normalisation method and formula choice are therefore not neutral prior decisions: they determine how much the formula matters, and should be made explicit in the AHTEG's technical recommendations.

The picture differs for the biodiversity criterion. The BHI shows limited variation across countries (CV = 0.09), and changing $w_B$ mainly reallocates resources between WEOG and Eastern European States, rather than between developed and developing country blocs. Under all weight configurations, the biodiversity criterion has little impact on the overall North–South allocation pattern. This is partly because the BHI varies so little across countries, and partly because static habitat measures reflect ecological conditions rather than the level of conservation effort (Bollarapu et al., 2024; Strange et al., 2024). As a result, the AHTEG's selection of a biodiversity metric may ultimately matter more than this analysis indicates (Heink and Kowarik, 2010; Hillebrand et al., 2025).

## 8.3 Net transfers and the fair and equitable sharing objective

The net transfer analysis is the most direct test of whether resources flow in the direction Decision 16/2 intends. The measure compares jurisdictional contribution obligations against allocation shares rather than transfers between the same actors, since firms pay in while governments and IPLCs receive out; and 50% of fund revenue goes to IPLCs before any country-level distribution. Under equal weights, the pattern broadly aligns with the fund's redistributive objective, as shown in Figures 6 and 8.

The aggregate figures hide important within-region variation. The Asia-Pacific net outflow is largely a

China story, driven by its large pharmaceutical and IT sectors and high UN Scale assessment rate. The WEOG picture is more structurally interesting. Ireland is well-documented as a jurisdiction where multinationals concentrate registered activity for tax purposes (Tobin and Walsh, 2013), meaning its contribution obligations may partly reflect registration patterns rather than genuine commercial presence. This points to a general problem: the countries that appear as large contributors may not be those where the economic activity and the biodiversity use actually occurs.

The 33 countries that change net position sign across weight configurations (Table 27) reveal the political economy of the COP17 negotiations. They cluster into high-income research economies that score well on geographic origin but poorly on capacity needs, of which Canada is the extreme case, and middle-income countries with both biodiversity claims and some industrial presence, of which Brazil is the clearest example. Canada also benefits from the raw rather than log-normalised INSDC indicator, meaning the stakes at COP17 run to indicator design as much as to the weights. As noted in Section 7, Canada's contribution obligations are likely understated in Orbis, so the net transfer swing should be read as an upper bound on the true redistributive gain under DSI-origin weighting. For the second group, the formula choices determine whether they are net beneficiaries or net contributors. The formula is not a technical instrument: it is a distributive choice that will produce winners and losers among the negotiating parties themselves.

The structural tension between the contribution and allocation sides also deserves explicit attention. The countries with the greatest leverage over the fund's revenue base are the same high-income research economies that would benefit most from high $w_G$ weighting. Whether this represents a stabilising feature of the mechanism or a structural bias against its redistributive purpose depends on how much weight one places on fund revenue versus fund direction, a normative question this paper cannot resolve but makes visible.

The results also point toward what a well-designed mechanism would need. On the contribution side, a stable revenue base requires either replacing the profit floor with a pure revenue levy or introducing a minimum contribution for firms that cross the eligibility threshold. On the allocation side, a formula that genuinely delivers the fund's objective would need an origin indicator that tracks biodiversity provision rather than sequencing infrastructure, a biodiversity indicator with sufficient cross-country variance to be distributionally meaningful, and an aggregation structure that prevents any single criterion from dominating. The multiplicative formula at equal weights produces more redistributive outcomes than the additive formula under either normalisation, but the magnitude of the advantage depends almost entirely on the normalisation choice: 13.3 percentage points under proportional, 1.9 percentage points under min-max. The normalisation method is therefore the more consequential prior decision, and one the AHTEG should address explicitly before turning to the formula choice.

# 9 Conclusion

The Cali Fund offers a genuinely new model for biodiversity finance: instead of depending on government commitments, it calls on private companies that profit from genetic resources to support the countries and communities that conserve the biodiversity on which those resources depend. With full compliance, annual contributions could total \$3.6 billion, decreasing to approximately \$0.9 billion under more realistic voluntary participation and DSI intensity assumptions, with two industries and a small number of firms providing most of the funding.

The findings point to significant sensitivity on both dimensions. On the contribution side, the minimum rule introduces structural instability and the choice of revenue versus profit as the primary base affects avoidance risks. On the allocation side, the geographic origin criterion effectively proxies sequencing infrastructure rather than biodiversity provision, and the formula and normalisation method together can shift allocations by up to 13 percentage points without modifying any stated weight. The modalities adopted at COP16 are a starting point, not a finished design, and the results should be read as informing rather than pre-empting the decisions ahead. The analysis shows that decisions presented as technical, such as the choice of formula, the method of normalisation, and the weighting scheme, have distributional impacts substantial enough to determine whether resources are directed toward the goals for which the fund was established. The design choices still open at COP17 will materially shape who pays, who benefits, and by how much.

# 10 Annex

# A Classification and variable mapping for contribution flows

## A.1 Financial indicators

Decision 16/2 refers to profit and revenue as the contribution bases, and total assets as one of the eligibility threshold benchmarks, but does not define any of the three indicators. This study adopts definitions from the International Financial Reporting Standards (IFRS) issued by the IFRS Foundation. Where data sources use different terminology, or where national accounts are used for validation, the mapping to these definitions is described in Section B.2.1. Table 9 provides definitions for each indicator.

Table 9: Financial indicators from Decision 16/2

| **Decision 16/2 indicator** | **Firm-level variable** | **IFRS definition** | **IFRS reference** |
|---|---|---|---|
| Profit | Profit (loss) after tax | The total of income less expenses, excluding the components of other comprehensive income. | IAS 1.7 |
| Revenue | Operating revenue | Income arising in the course of an entity's ordinary activities. | IFRS 15.A |
| Total assets | Balance sheet total | Sum of current and non-current assets.* | IFRS 5.A |

*Notes:* *IFRS does not define 'total assets' explicitly; the term refers to the sum of IFRS-defined current and non-current assets. *Sources:* IFRS Foundation (2024, 2025a,b).

## A.2 Orbis consolidation codes

Table 10: Orbis consolidation codes

| **Code** | **Type** | **Description** |
|---|---|---|
| C1 | Consolidated | Consolidated accounts of companies for which unconsolidated accounts are not available. |
| C2 | Consolidated | Consolidated accounts of companies for which unconsolidated accounts are also available. |
| U1 | Unconsolidated | Unconsolidated accounts of companies for which consolidated accounts are not available. |
| U2 | Unconsolidated | Unconsolidated accounts of companies for which consolidated accounts are also available. |
| LF | Limited financials | Accounts with limited financial information. |

Source: OECD (2020)

## A.3 Literature-informed calibration of contribution flow modelling

Table 11: Central sector-specific participation assumptions ($\alpha$)

| **Sector** | $\alpha$ | **Justification** | **Sources** |
|---|---|---|---|
| Cosmetics | 0.60 | Consumer-facing and brand-sensitive, with biodiversity sourcing and natural-ingredient narratives that are visible to stakeholders, making reputational incentives under a public biodiversity fund relatively strong. Higher than pharmaceuticals because reputational pressure operates directly through consumer purchase decisions. | Haddock-Fraser and Fraser (2008); Tashman et al. (2022); Haddock-Fraser and Tourelle (2010); Escobedo and Lojenga (2013); Grădinaru et al. (2022) |
| Pharmaceuticals | 0.50 | Large, visible firms likely to show moderate to high participation under a voluntary biodiversity scheme: the sector is accustomed to ABS-related scrutiny, and relatively mature in reporting, but its reputational incentives are mediated more through policy and stakeholder channels than through direct consumer pressure. | Demir and Min (2019); Haddock-Fraser and Fraser (2008); Fabbri et al. (2020); Dejan N. Zec (2023); Sarkis et al. (2010); Michiels et al. (2022) |
| Biotechnology | 0.35 | Biotechnology is most accurately viewed as a mixed, intermediate case: exposure to ABS and Nagoya-related issues can be significant in biopharma and adjacent uses, but awareness, public scrutiny, and reputational pressure vary widely between subsectors, particularly beyond the most publicly visible companies. | Kang et al. (2015); Sarah A. Laird; Karabin et al. (2021); Dyczkowska and Dyczkowski (2020) |
| Nutraceuticals | 0.40 | Nutraceutical and botanical health-product firms can face reputational pressure because consumers value natural-origin, provenance, and certification claims, but fragmented regulation and complex supply chains make sector-wide participation uneven. | Stamboulakis and Sanderson (2020); Cho and Choi (2019); Komala et al. (2023); Delisi et al. (2021); Hobbs (2002) |
| Laboratory equipment | 0.20 | Primarily providers of sequencing equipment, consumables, and research tools situated upstream in the value chain, rather than principal downstream users of genetic resources and DSI, and therefore subject to relatively low public reputational visibility and limited historical role in ABS discussions. | Satam et al. (2023); Haddock-Fraser and Fraser (2008) |
| Animal & plant breeding | 0.20 | High use of plant genetic resources and related information has not translated into strong monetary benefit-sharing under dedicated multilateral frameworks (e.g. the Plant Treaty), while traceability and transaction costs make breeding-related contribution tracking difficult; on the animal side, comparable ABS engagement appears much more limited. | Rabitz (2017); Wynberg et al. (2021); von Wettberg and Khoury (2020); Michiels et al. (2022) |
| Information and AI | 0.15 | May derive substantial value from DSI, but use is diffuse and dematerialised, and is typically monetised through downstream data, analytics, or service models rather than visible biodiversity-facing products. | Lawson et al. (2025, 2019); Sherkow et al. (2022); Nawaz et al. (2021) |

*Note:* These are rounded, literature-informed calibration values rather than direct estimates of observed contribution behaviour.

Table 12: Ownership-based participation multipliers ($\gamma$)

| **Firm type** | $\gamma$ | **Justification** | **Sources** |
|---|---|---|---|
| Listed | 1.30 | Stronger investor scrutiny, greater disclosure pressure, and higher reputational risk make listed firms more likely to join and remain engaged in voluntary schemes. | Luo et al. (2012); Rasche et al. (2022); Lee (2009) |
| Unlisted | 0.85 | Weaker public scrutiny and less frequent CSR-related disclosure. May still engage where customer or supply-chain pressure is strong, but average participation is lower. | Rasche et al. (2022); Lee (2009) |

*Note:* The adjusted participation probability for firm $f$ is $p_f = \min(\alpha \cdot \gamma \cdot \omega, 1)$, where $\alpha$ is the sector baseline rate, $\gamma$ is the ownership multiplier, and $\omega$ is the DSI intensity parameter (Table 13). These are calibration assumptions informed by adjacent literature, not direct estimates of DSI contribution behaviour.

Table 13: DSI intensity multipliers ($\omega$) used in S3

| **Sector** | $\omega$ | **Justification** | **Sources** |
|---|---|---|---|
| Biotechnology | 0.9 | Strong commercial sequence-use evidence, especially from patent and database citation studies and other sequence-defined innovation indicators | Bousfield et al. (2016); Oldham et al. (2013); Jefferson et al. (2015); Zhivkoplias et al. (2024); Dunshirn and Zhivkoplias (2024) |
| Pharmaceuticals | 0.9* | Strong proxy evidence that public sequence data and biological databases are widely used in pharmaceutical research and downstream patenting, though direct sector-level measures of public DSI use are lacking. | Bousfield et al. (2016); Oldham et al. (2013); Jefferson et al. (2015) |
| Animal & plant breeding | 0.80 | DSI use appears substantial on the plant side of this merged category, but weaker and less well documented on the animal side, which supports a relatively high but not maximum multiplier. | Petrillo et al. (2015); Brink and van Hintum (2022); von Wettberg and Khoury (2020); Martyniuk and Haska (2021) |
| Information and AI | 0.75 | Public DSI appears materially important for bioinformatics and other data-intensive services, but the evidence is indirect, and commercial uses are not well reflected in sector-level metrics. Because of this mix of apparent importance and measurement uncertainty, the sector is given a high, though not top-tier multiplier. | Drysdale et al. (2020); Lawson et al. (2025) |
| Laboratory equipment | 0.55 | Lab equipment suppliers benefit from DSI indirectly, through sequencing demand rather than direct sequence utilisation, with consumables accounting for 68-72% of complete genome sequencing costs. On this basis, the sector is assigned a moderate but clearly sub-top-tier multiplier. | Schwarze et al. (2020); van Nimwegen et al. (2016) |
| Nutraceuticals | 0.45 | Commercial use of biological resources is predominantly extract-based rather than sequence-based. Patent activity is narrow and compound-focused rather than genomic and regulatory frameworks require minimal genetic characterisation at product development stage. Systematic DSI use implausible for most products. | Oldham et al. (2013); Komala et al. (2023); Cho and Choi (2019) |
| Cosmetics | 0.35 | Dominant extract-based pipeline requires no genetic sequence information. An emerging subsector using plant cell cultures and GMO fermentation for cosmetic ingredients plausibly involves DSI use. Low multiplier reflecting marginal, subsector-specific engagement. | Bourgaud et al. (2025); Oldham et al. (2013) |

*Note:* Multiplier values are expert-judgment estimates informed by evidence of DSI use intensity; supporting citations establish the empirical basis for sectoral rankings rather than precise calibration. *Decision 16/2 exempts entities not relying on DSI from contribution obligations. For conventional small-molecule generics, developed through bioequivalence testing and physicochemical reverse engineering, this exemption is technically well-founded: their development involves no sequence-based analysis at any stage (Kathpalia H et al., 2025; Ranjan, 2025). Biosimilars are different. As biological products, they require sequence-based structural characterisation to demonstrate similarity to a reference biologic, which means DSI use is embedded in the development process (Ranjan, 2025). Among the largest eligible generic manufacturers headquartered in CBD Party jurisdictions Pharma Boardroom (2025), biosimilar revenues are substantial, to cite a few: Sandoz reported biosimilar revenues of 30% of net sales in 2025, (Sandoz, 2025), while Teva, which describes itself as holding the second-largest biosimilar portfolio in the industry, is on track to double biosimilar revenues by 2027 (Teva, 2026). Since Orbis does not allow the eligible pharmaceutical population to be partitioned by sub-sector, $\omega$ necessarily reflects the average DSI intensity across all eligible firms in a given sector. Given that innovative pharmaceutical companies dominate the eligible population by revenue, and that the largest generics manufacturers in the sample have substantial biosimilar operations, $\omega = 0.9$ remains the most appropriate approximation available.

## A.4 Decision 16/2 sector mapping

The NACE classification adopted from Oldham (2025) is already narrowed to sectors most directly mapped to DSI-relevant activity. Even so, NACE granularity at the 3- and 4-digit level does not separate firms with directly DSI-based activity from those in adjacent segments of the same broader category. This is most visible in animal and plant breeding (covering seed and livestock breeders alongside agricultural commodity producers and food processors), information and AI (covering bioinformatics alongside general IT services), and laboratory equipment (covering sequencing instruments alongside general scientific and industrial equipment). The resulting eligible population is therefore broader than the scope used in prior DSI studies. CBD (2024b), for example, restrict the pharmaceutical category to manufacturers of finished pharmaceutical preparations (NACE 21.2), whereas this analysis includes both NACE 21.1 (manufacture of basic pharmaceutical products, including active pharmaceutical ingredients and excipients) and NACE 21.2. Comparable distinctions apply across other sectors. Manual verification of DSI dependence at the firm level is not feasible for a population of over 21,000 entities, and Orbis industry code assignments are known to produce classification errors, particularly for conglomerates and firms operating across multiple segments (OECD, 2020). The sector-differentiated participation rates ($\alpha$) and DSI intensity parameters ($\omega$) in S1–S3 partially correct for this by assigning lower values to sectors where classification is broadest and DSI use most heterogeneous, but do not eliminate the underlying misclassification risk.

Table 14: DSI sector classification mapping: ISIC Rev.4/5, NACE Rev.2, and NAICS

| Sector | ISIC class | NACE class | NAICS code |
|---|---|---|---|
| Pharmaceuticals | 21 (Class 2100) | 21.1–21.2 | 3254 |
| Cosmetics | 20 (Class 2023) | 20.41–20.42 | 3256 |
| Nutraceuticals | 10 (Class 1079) | 10.89 | 311999* |
| Biotechnology | 20 (Class 2011); 71 (Class 7120); 72 (Class 7210) | 20.11–20.14; 71.2; 72.1 | 325199*; 5417 |
| Animal & plant breeding | 01 (Groups 11–15) | 01.1–01.5 | 1111–1129 |
| | 01 (Group 16) | 01.6 | 1151–1153 |
| | 02 (Groups 21–24) | 02.1–02.4 | 1131–1133 |
| | 03 (Groups 31–33) | 03.1–03.2 | 1141, 1125 |
| | 20 (Class 2012) | 20.15 | 3253 |
| | 20 (Class 2021) | 20.20 | 3253 |
| Laboratory equipment | 26 (Class 2651) | 26.51 | 334513, 334514, 334516* |
| | 23 (Class 2310) | 23.1 | 3272 |
| | 32 (Class 3250) | 32.5 | 3391 |
| Information and AI | 62 (Class 6219) | 62.0 | 5415 |
| | 63 (Class 6310) | 63.1 | 518210*; 519290* |

*Notes:* Sector names abbreviated; see Box 1 for full names. *Matched at 6-digit NAICS level; 4-digit codes 3251, 3119, 3345, and 5191 excluded as too broad. NACE 20.15 and 32.99 excluded to avoid double-counting and over-broad coverage respectively. For NAICS IT services, both 519130 (2017 vintage) and 519290 (2022 vintage) are matched to ensure full Orbis coverage regardless of NAICS vintage recorded. Classification to ISIC follows Oldham (2025), classification to NACE Menon Economics (2025), and classification to NAICS done by the author.

### A.5 CBD regional group classification

Table 15: CBD regional group classification

| Regional group | Notes |
|---|---|
| African States | 55 member states. |
| Asia-Pacific States | 53 member states. |
| Eastern European States | 28 member states (CBD definition); includes five Central Asian states (Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, Uzbekistan) classified under Asia-Pacific by the UN. |
| Latin American and Caribbean States | 33 member states. |
| Western European and Other States | 29 member states plus observers. Includes Israel (full member since 2004) and Türkiye (also in Asia-Pacific). United States participates as observer but is not a CBD Party and is excluded from the analysis. |

*Source:* UN Department for General Assembly and Conference Management (UN Department for General Assembly and Conference Management) and CBD Secretariat. Full membership lists available from the CBD Secretariat.

### A.6 World Bank income group classification

Table 16: World Bank income group classification, FY2026

| Income group | GNI p.c. | Notes |
|---|---|---|
| Low-income | ≤$1,135 | 25 CBD Parties. |
| Lower-middle-income | $1,136–$4,495 | 50 CBD Parties. |
| Upper-middle-income | $4,496–$13,935 | 54 CBD Parties. |
| High-income | ≥$13,936 | 87 entries in World Bank classification; non-sovereign territories and dependencies not party to the CBD are excluded from the analysis. The United States is the only UN member state not a Party to the CBD and is excluded from the analytical scope. |
| Unclassified | — | Ethiopia (temporarily unclassified FY2026) and Venezuela (unclassified since FY2021); both are CBD Parties and included in the analysis where data are available but omitted from income group breakdowns. |

*Notes:* GNI per capita thresholds use the Atlas method, based on 2024 data. Full country lists available at World Bank (2026).

## B Technical Methodology

This annex sets out additional details for the contribution flow estimation discussed in Sections 5.1.2 and 5.1.4. It describes the four sub-steps of Stage 1 (entity identification), the sensitivity parameters evaluated in Stage 3, and additional methodological notes.

### B.1 Orbis data limitations

Orbis is the most extensive available database of cross-country firm-level financial information. Several well-documented constraints are relevant to this analysis.

**Uneven geographic coverage** Orbis data are most reliable for European and selected OECD economies, while coverage deteriorates markedly for developing economies, particularly in East Asia, Latin America, and Sub-Saharan Africa OECD (2020); Dall'Olio et al. (2022); Kalemli-Özcan et al. (2024). Coverage is also mixed within some European countries, with German and French firms being under-represented relative to other EU economies OECD (2010a). In its raw form, the database is not nationally representative Kalemli-Özcan et al. (2024), and the firm-level estimates are therefore more reliable for EU-27 and a limited number of well-covered OECD countries than for the full set of CBD Parties.

**Firm size bias** Firms in Orbis tend to be larger, older, and more productive than the average, even within the same size categories, and show less productivity variation in the lower half of the distribution OECD (2020). The database is more representative for sectors dominated by large firms, such as pharmaceuticals. Given that this analysis focuses on entities exceeding the Decision 16/2 financial thresholds - a population skewed toward larger firms - this bias is unlikely to materially affect the results.

**Missing data and reporting gaps** Financial data are unavailable for every firm and every year, particularly for profit. There is an average reporting delay of approximately two years, and coverage of specific balance sheet items varies by country and firm type OECD (2010a); Kalemli-Özcan et al. (2024). Occasional errors, duplication, and gaps have also been documented Arndt (2023). These gaps affect both the application of the 2-of-3 thresholds and the determination of contribution bases. The treatment of missing data is described in the Annex Section B.2.1.

**Consolidated vs. unconsolidated accounts.** Orbis provides broader coverage of consolidated accounts (covering the entire corporate group including subsidiaries) than unconsolidated accounts (covering a single entity), with particularly poor unconsolidated coverage for the US and many developing economies. For multinationals, this complicates the attribution of financial activity to specific countries and sectors. The approach taken to address this is described in Annex Box B.2.1.

## B.2 Stage 1: Identifying eligible entities

### B.2.1 Data harmonisation

The raw Orbis data are prepared for analysis through three sequential procedures.

**Panel construction and cleaning** The raw firm-level data are first compiled into a panel following the OECD cleaning methodology OECD (2020), and the approach set out in Kalemli-Özcan et al. (2024). The method concentrates on the three financial indicators required for the analysis: profit after tax, operating revenue, and total assets (as defined in Table 1). It entails combining several database vintages to maximise temporal coverage, mapping financial observations to specific calendar years, removing duplicates, and discarding observations that contain missing, inconsistent, or implausible financial information. Observations for which a single year revenue differs by a factor of ten or more from both neighbouring years are replaced with missing values, since such isolated spikes are likely to arise from data entry errors rather than from actual shifts in financial performance. The remaining large year-on-year variations are preserved in the sample, because they cannot be reliably separated from legitimate financial events without checking individual accounts; their impact on aggregate contribution estimates is constrained via sector-level winsorisation in the sensitivity analysis (Section 5.1.4).

Firms are restricted to those with an active operational status in Orbis, retaining entities classified as active, active (dormant), or active (reorganisation). Dissolved, inactive, and unknown-status entities are excluded to avoid inflating the eligible population with firms no longer conducting commercial activities.

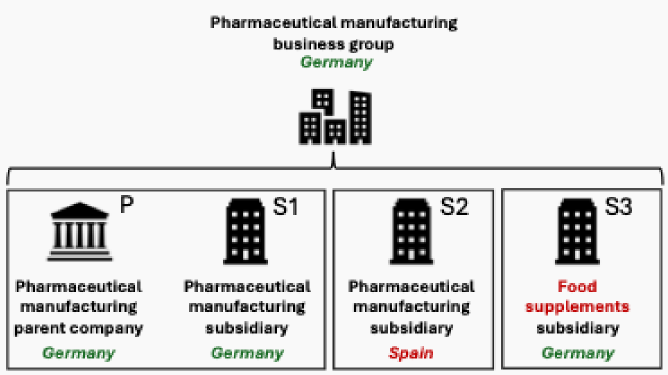
**Missing contribution base values** Where operating revenue or profit after tax is unavailable for 2023, the most recent available value within the reference window is substituted (2022 in the first instance, 2021 where 2022 is also absent). Given that 2022 was a post-COVID recovery year with elevated revenues in several Enclosure I sectors, substitution from that year may marginally inflate contribution estimates for affected firms; the contribution year sensitivity test in Section 5.1.4 provides a partial bound on this effect. Where profit data are unavailable for the reference year after substitution, the profit-based contribution is set to zero, which under the minimum rule results in a total contribution of zero for that firm. This affects 326 firms (1.5% of the eligible population); applying the revenue levy to these firms instead would add approximately $103 million to the S0 estimate, providing an upper bound on the downward bias introduced by this assumption.

**Accounts selection** To prevent double-counting of firm-level financial information, the analysis prioritises unconsolidated accounts throughout, following the approach by OECD (2020); Tarsia (2023). Where unconsolidated accounts exist for a given firm alongside consolidated ones (consolidation code C2), the consolidated accounts are removed. Consolidated accounts (C1) are also dropped in cases where unconsolidated accounts for the same firm identifier are directly observed in the data. Where duplicate accounts persist after these steps, those carrying consolidation code U2 are retained and the remaining duplicates discarded. Any residual duplicate account types with limited financial coverage, identified by consolidation code LF, are also dropped as the final step. A full description of the Orbis consolidation codes used in this procedure is provided in Table 10 in Annex A. Effectively, for entities that are part of multinational corporate groups, financial information is assigned by the industry and country in which they operate, rather than at the consolidated group level. The methodology and justification for this approach are described in Box 2.

**Box 2: Firm-level data treatment for multinational corporate groups**

Multinational corporations typically comprise a parent company and multiple subsidiaries operating across various industries and countries. Box B.2.1 illustrates an example of such a structure. This study determines Cali Fund eligibility at the level of individual subsidiaries rather than a consolidated corporate group. Most large multinationals would likely exceed the 2-of-3 thresholds at the group level, making the entire group eligible. Operating at subsidiary level enables a more focused application: only entities in DSI-relevant sectors would be in scope, while subsidiaries in unrelated lines of business would not. This aligns with the sector-based rationale of Decision 16/2 and with the realistic expectation that companies would prefer to limit contributions to entities most directly linked to DSI use.

In practice, this corresponds to using unconsolidated accounts available in Orbis, since a comprehensive ownership analysis disaggregating consolidated group accounts into individual subsidiary contributions falls outside the scope of this study. The sample therefore approximates subsidiary-level coverage but may incompletely reflect the activities of corporate groups where unconsolidated statements are missing or incomplete.




Illustrative example of a multinational corporate group structure

*Notes:* This figure illustrates the structure of a multinational corporate group and how subsidiary-level scoping applies in the context of the Cali Fund. The example group operates primarily in pharmaceutical manufacturing and is registered in Germany, comprising a parent company and three subsidiaries. Subsidiary S1 operates in the same industry and country as the parent. Subsidiary S2 operates in the same industry but in a different country (Spain). Subsidiary S3 operates in a different sector (food supplements). Under a single-entity-level approach, only entities operating in DSI-relevant sectors would fall within scope, regardless of the broader group's activities.

*Source:* Author's illustration based on Bajgar et al. (2019).

In Orbis, the majority of observations are unconsolidated accounts that do not have a corresponding consolidated version (U1). When both account types are available for the same company, unconsolidated accounts are prioritised to prevent double-counting at the group level. Firms that report only consolidated accounts (C1) remain in the sample, since excluding them would disproportionately eliminate large multinational companies i.e. exactly those most likely to meet the Decision 16/2 thresholds.

This introduces a limited but non-trivial risk of double-counting, since subsidiaries of C1 firms may also appear as separate entries in the data which use different identifiers and cannot be easily matched to their parents. Where double-counting occurs, it biases contribution flow estimates upward. This risk is most pronounced for large multinational groups, for which consolidated accounts are more common and unconsolidated coverage is weakest. The upward bias from C1 inclusion and the downward bias from incomplete Orbis coverage work in opposing directions; the net effect is uncertain and should be borne in mind when interpreting the results.

The magnitude of this upper bound is reported in Table 21. The eligible sample retains 1,355 firms reporting only consolidated accounts (C1), where no unconsolidated equivalent is available in Orbis. To assess the sensitivity of key findings to this choice, results were recomputed on the unconsolidated-only subsample ($n$ = 20,335; S0 = \$3,058 million). Concentration metrics are robust: the top-10 contribution share is unchanged at 8.6% and the top-100 share falls by 1.9 percentage points, from 27.6% to 25.7%. Sector shares shift by at most 1.1 percentage points and median profit margins are unchanged across all sectors. The revenue-binding contribution share falls from 59.3% to 57.6%. The country most affected is the United Kingdom, whose S0 estimate falls from \$353.5 million to \$169.5 million when restricted to unconsolidated accounts, consistent with the concentration of C1 consolidated accounts among multinationals registered there; this should be borne in mind alongside the Switzerland and Canada caveats in Table 25. All other qualitative findings are unaffected by C1 inclusion.

**Currency conversion** Following Kalemli-Özcan et al. (2024), financial data are extracted in original national currency rather than using Orbis's internal USD conversion, and converted to nominal USD using IMF market exchange rates for each respective year IMF (2026). Where IMF rates are unavailable, UN operational rates are used instead UN Treasury (2026). This approach follows the UN National Accounts Main Aggregates Database methodology UNSD.

Because the Decision 16/2 eligibility thresholds are denominated in USD, firms reporting in volatile local currencies may cross thresholds purely due to exchange rate movements rather than genuine changes in their financial position. The three-year averaging rule reduces this problem for countries experiencing sustained depreciation or significant volatility, though it does not eliminate it entirely. This is an intrinsic limitation of applying USD-denominated thresholds to a global firm population.

### B.2.2 Sector and geography filters

**Sector filtering** Firm-level sector assignment uses the NACE Rev.2 classification at the 3- and 4-digit level, based on the ISIC-NACE Rev.2 conversion in Menon Economics (2025) and the author's NAICS matching, both consolidated in Table 14. The reference scenario includes all eligible sectoral activities classified in Orbis as the primary, core activity of each firm. A sensitivity test expanding eligibility to secondary activities is reported in Section 5.1.4.

Firms reporting NACE Rev.2 code 6420 (Activities of holding companies) or NAICS codes 551111 / 551112 (Offices of holding companies) as a secondary industry code and reporting zero operating revenue in the reference year are excluded from the sample. The secondary code alone is not sufficient for exclusion, as several large operating companies in DSI-relevant sectors carry a holding classification among multiple secondary codes reflecting the breadth of their corporate activities rather than their primary economic function. The additional criterion of zero reference-year revenue identifies entities whose financial activity consists entirely of intra-group transfers, such as dividends and capital gains from subsidiaries, rather than genuine commercial operations linked to DSI use. Including such firms would risk double-counting financial data already recorded for their subsidiaries elsewhere in the sample.

Entities reporting zero or missing operating revenue in all three years of the reference period (2021-2023) are additionally excluded. Sustained absence of revenue is inconsistent with genuine commercial activity and indicative of dormant or holding structures that may have passed the sector screen due to misclassified industry codes.

**Geography filtering** For multinational corporate groups, the geography filter is applied at the subsidiary level rather than the parent level, consistent with the approach described in the main text. Subsidiaries registered in non-Party jurisdictions are excluded even if the parent is based in a CBD Party state; the reverse also applies.

The geographical coverage is structured in two tiers. The first tier covers EU and other selected countries for which Orbis provides nationally representative samples that can be validated against official Eurostat statistics. The second tier extends coverage to remaining CBD Parties by retaining all available Orbis entities meeting the eligibility criteria, treating these estimates as conservative lower bounds. Unlike analyses of market concentration or productivity distributions, where non-representative samples produce biased results (Kalemli-Özcan et al., 2024), estimating a lower bound on contribution flows does not require national representativeness: even a partial sample of eligible firms provides a credible minimum estimate for a given country. Extrapolation to the full eligible population is not attempted, as the absence of benchmark data for these countries means the coverage ratio of the Orbis sample cannot be established. A comparable extension of Orbis coverage to non-representative economies has precedent in Bajgar et al. (2019), who retained data for 100 economies to maximise subsidiary coverage.

### B.2.3 Validation of firm-level data coverage

**Sectoral coverage validation** Prior to applying the 2-of-3 eligibility thresholds, the coverage of EU and selected European country samples is evaluated by comparing total annual firm-level revenue against Eurostat SBS net turnover at the country-sector-year level, following the first stage of the validation framework in Kalemli-Özcan et al. (2024) and extending the scope to all Enclosure I sectors.[15] Coverage ratios are calculated for each country-sector cell at the NACE Rev.2 class or group level corresponding to the Enclosure I sector mapping, ensuring that ratios reflect the specific in-scope activities rather than broader division-level aggregates. If coverage falls within the 60-90% interval commonly reported for European manufacturing in prior work (Kalemli-Özcan et al., 2024), the sample is treated as sufficiently representative. Year-specific coverage ratios are also used to select the three consecutive years with the most stable coverage across countries and sectors, which serve as the common reference window for implementing the 2-of-3 threshold rule. Country-level results are reported in Table 19 (Annex C).

This validation step is restricted to the Eurostat SBS sample. OECD SDBS benchmark data for non-EU countries are only available at the broader NACE division level, which cannot be matched to the Enclosure I sector mapping without conflating in-scope and out-of-scope activities; country-level results for these economies are therefore not reported in Table 19.

**Size distribution validation** As an additional plausibility check on whether the eligible entity sample adequately captures the large firms most likely to meet the Decision 16/2 financial thresholds, the Orbis sample is filtered to firms with at least 250 employees and aggregated at the sector-country level. This restricted sample is compared with OECD SDBS benchmark revenue for enterprises with 250 or more employees (size class S_GE250), following the second validation step in Kalemli-Özcan et al. (2024). The 250-employee cutoff is used solely to align with the size class available in OECD SDBS; it does not map directly onto the Decision 16/2 financial thresholds, which are defined in terms of assets, sales, and profit rather than employee counts. In practice, however, firms satisfying those financial criteria are expected to consist predominantly of large enterprises, making this a reasonable proxy for the eligible population. Results are reported in Figure 9 (Section 6).

The validation exercise is subject to several limitations. Eurostat SBS does not provide structural business statistics for agricultural activities, so the animal and plant breeding sector cannot be validated against official reference values; Orbis-based estimates for this sector are therefore classified as unvalidated lower bounds. Several Enclosure I sectors correspond to more than one NACE division in the benchmark dataset; where benchmark data are missing for at least one division of such a multi-division sector, the aggregate country-sector cell is coded as missing rather than calculated from the available subset. Firm-level operating revenue and national accounts turnover are not identically de-

[15] The authors of the original study looked only at the manufacturing sector.

fined: operating revenue includes non-sales income and stock changes that turnover measures exclude (OECD, 2010b; Eurostat, 2026), though in practice this gap is minor since net sales dominate operating revenue for most firms. Services sectors are also less consistently covered in national statistics than manufacturing, restricting the validation exercise to manufacturing sectors for some countries (Kalemli-Özcan et al., 2024).

# C Supplementary results

Table 17: Orbis coverage: from CBD Parties to eligible entities

| **Step** | **Countries** | **Notes** |
|---|---|---|
| All CBD Parties (excl. United States) | 196 | |
| With Orbis coverage | 124 | 72 parties with no coverage: AD, AF, AO, BF, BI, BN, BT, BZ, CF, CK; CM, CU, CV, DJ, DM, DO, ER, FM, GA, GD; GM, GN, GQ, GT, GW, HN, HT, KH, KI, KM; KP, LC, LR, LS, LY, MC, MG, ML, MM, MR; MV, MZ, NE, NI, NR, NU, PW, SB, SC, SD; SL, SM, SN, SO, SR, SS, ST, SV, TD, TG; TJ, TK, TL, TM, TO, TV, VC, VU, WF, WS; YE |
| With Enclosure I in-scope firms | 115 | 9 in Orbis but no in-scope firms: AZ, BB, BJ, CR, GY, KN, MH, RW, VE |
| With at least one eligible firm | 100 | 15 have in-scope firms below thresholds: CD, ET, GH, IQ, KG, LA, LB, LI, ME, MN, MW, PG, PY, SY, TZ |

*Notes:* Eligibility based on 2-of-3 thresholds: total assets $\geq$ USD 20 million, annual sales $\geq$ USD 50 million, profit after tax $\geq$ USD 5 million, averaged over 2021-2023. United States excluded as a non-Party to the CBD.

Table 18: Distribution of eligible entity financials by Enclosure I sector (three-year average 2021–2023, USD millions)

| **Sector** | **P10** | **P25** | **Median** | **P75** | **P90** |
|---|---|---|---|---|---|
| *Panel A: Revenue* | | | | | |
| Information and AI | 33.1 | 57.7 | 90.0 | 192.1 | 498.0 |
| Animal & plant breeding | 21.1 | 52.1 | 83.4 | 168.0 | 402.2 |
| Biotechnology | 37.4 | 59.7 | 99.5 | 227.8 | 544.1 |
| Pharmaceuticals | 38.3 | 58.9 | 105.3 | 245.7 | 653.3 |
| Laboratory equipment | 36.4 | 57.5 | 92.2 | 177.2 | 397.8 |
| Nutraceuticals | 51.2 | 63.0 | 98.6 | 211.8 | 534.3 |
| Cosmetics | 51.8 | 65.0 | 93.7 | 199.9 | 452.2 |
| *All sectors* | *34.0* | *57.8* | *93.5* | *200.4* | *500.7* |
| *Panel B: Total assets* | | | | | |
| Information and AI | 29.2 | 45.0 | 91.3 | 237.8 | 678.5 |
| Animal & plant breeding | 32.3 | 50.8 | 97.5 | 233.1 | 596.4 |
| Biotechnology | 36.7 | 58.1 | 119.6 | 304.0 | 827.1 |
| Pharmaceuticals | 47.0 | 76.7 | 160.5 | 418.2 | 1,176.6 |
| Laboratory equipment | 38.0 | 57.8 | 110.9 | 251.5 | 634.5 |
| Nutraceuticals | 31.9 | 50.1 | 89.8 | 207.7 | 605.9 |
| Cosmetics | 35.1 | 50.2 | 92.7 | 192.8 | 470.4 |
| *All sectors* | *34.2* | *54.2* | *109.4* | *271.9* | *751.7* |
| *Panel C: Profit after tax* | | | | | |
| Information and AI | −5.8 | 1.9 | 6.4 | 14.8 | 40.2 |
| Animal & plant breeding | −1.1 | 1.6 | 6.3 | 13.7 | 34.8 |
| Biotechnology | −2.1 | 2.4 | 7.1 | 18.4 | 58.7 |
| Pharmaceuticals | −0.3 | 5.0 | 10.2 | 29.0 | 88.0 |
| Laboratory equipment | −0.1 | 3.5 | 7.6 | 17.1 | 47.3 |
| Nutraceuticals | −1.1 | 1.4 | 5.4 | 12.4 | 35.2 |
| Cosmetics | 0.0 | 2.5 | 6.8 | 13.9 | 41.9 |
| *All sectors* | *−1.7* | *2.3* | *7.0* | *16.9* | *49.6* |

*Notes:* Sample restricted to firms meeting at least two of the three Decision 16/2 financial thresholds (total assets USD 20 million, sales USD 50 million, profit USD 5 million) in any Enclosure I sector ($n$ = 21,690). Financial values are three-year averages over the period 2021–2023, expressed in nominal USD millions. *Source:* Author's calculations based on Orbis (Moody's Analytics).

Country-level coverage ratios estimated at the Enclosure I sector level, rather than the broader ISIC divisions shown in Figure 9, are reported in Table 19 (Annex C). These sector-level estimates cover all firms regardless of size, as benchmark data disaggregated by firm size are not available at the four-digit NACE classification level required for the Enclosure I sector mapping.

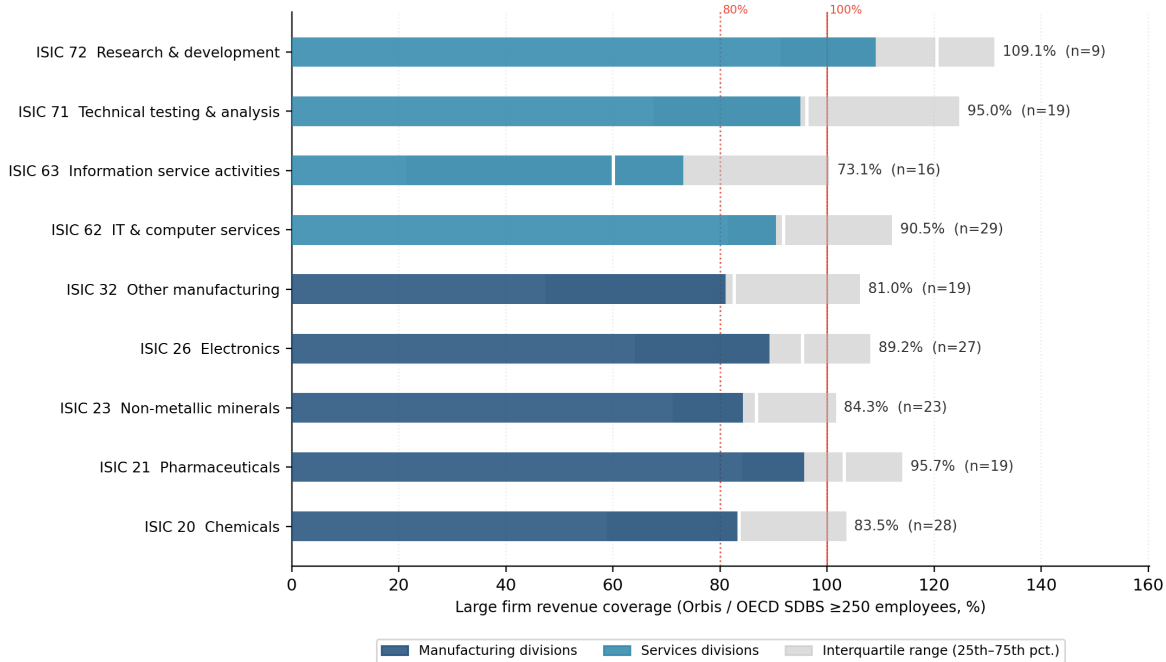



Figure 9: Large firm revenue coverage ratios by ISIC division, validated sample (2021-2023) average

*Notes*: Coverage ratio = Orbis aggregate revenue for firms with 250 or more employees / OECD Structural Business Statistics benchmark revenue for enterprises with 250 or more employees (size class S_GE250), averaged over 2021-2023. Bars show the unweighted mean across countries; grey bands show the interquartile range (25th-75th percentile); the white tick marks the median. 15.6% of country-division cells are excluded prior to computing summary statistics as coverage ratios exceed 200%, reflecting either multinational profit-shifting through holding structures (notably Ireland and the Netherlands) or near-zero benchmark denominators in R&D divisions where few large enterprises are recorded in OECD SDBS; in both cases Orbis captures more large-firm revenue than the enterprise survey benchmark. OECD SDBS figures are in national currency, converted to USD using IMF annual average exchange rates; Orbis revenue is in USD. Costa Rica is excluded due to implausibly large benchmark values. Animal and plant breeding (ISIC 01-03) is not shown as OECD SDBS coverage for that division is limited to three countries after excluding Costa Rica. Sample comprises 34 countries: 24 EU member states (Austria, Belgium, Bulgaria, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden), six non-EU countries reporting under Eurostat (Bosnia and Herzegovina, Iceland, North Macedonia, Norway, Serbia, Switzerland), and four additional OECD members (Brazil, Israel, Japan, Korea).

*Source:* Author's calculations based on Orbis (Moody's Analytics) and OECD SDBS.

| Country | ISO | Animal & Plant Breed. | Biotech. | Cosmetics | Info. & AI | Lab. Equip. | Pharma. |
|---|---|---|---|---|---|---|---|
| ***Eastern Europe*** | | | | | | | |
| Albania | AL | — | — | — | — | — | 83.3 |
| Bosnia and Herzegovina | BA | — | — | 336.8 | 51.8 | — | — |
| Bulgaria | BG | 86.8 | — | 95.4 | 93.5 | 196.7 | — |
| Croatia | HR | 127.4 | 68.3 | 87.6 | 94.0 | — | 160.2 |
| Czechia | CZ | 106.4 | 30.0 | 64.5 | 19.3 | 72.8 | 99.5 |
| Estonia | EE | 63.5 | — | 99.3 | 107.3 | 92.4 | 103.6 |
| Hungary | HU | — | 54.4 | 189.5 | 112.5 | 46.2 | 83.6 |
| Latvia | LV | 88.3 | — | 104.3 | 93.6 | — | 55.9 |
| Lithuania | LT | 56.9 | — | 87.2 | 88.7 | — | — |
| North Macedonia | MK | — | 103.9 | 107.1 | 91.5 | 65.7 | — |
| Poland | PL | — | 78.6 | 80.0 | 75.7 | 83.3 | 107.6 |
| Romania | RO | 99.5 | 79.0 | 50.5 | 96.5 | 77.6 | 60.6† |
| Serbia | RS | 100.4 | 46.2 | 102.3 | 126.6 | — | 108.4 |
| Slovakia | SK | — | — | 109.7 | 94.0 | 91.8 | 136.5 |
| Slovenia | SI | — | — | 117.0 | 95.4 | — | 94.9† |
| ***Western Europe and Others*** | | | | | | | |
| Austria | AT | 54.9 | — | 69.8 | 32.7 | 91.5 | 174.9 |
| Belgium | BE | 58.6 | 102.1 | 132.8 | 75.8 | 130.5 | 145.8† |
| Cyprus | CY | — | — | 14.3 | 7.4† | 27.4 | — |
| Denmark | DK | — | — | 40.9 | 46.4 | — | 115.5 |
| Finland | FI | 120.3 | 52.8 | 98.1 | 117.7 | 105.0† | 119.3 |
| France | FR | 60.1 | — | 68.5 | 82.0 | 70.9 | 96.0 |
| Germany | DE | 34.2 | 18.3 | 34.5 | 44.0 | 44.8 | 81.6 |
| Greece | GR | 47.4 | — | 80.3 | 66.6 | 28.3 | 107.6 |
| Iceland | IS | 109.5 | 18.8 | 144.4 | 69.1 | 14.5 | 34.7 |
| Ireland | IE | — | — | 38.9 | — | — | — |
| Italy | IT | 89.6 | 68.5 | 109.5 | 114.2 | 80.1 | 125.0 |
| Malta | MT | — | — | 1.4 | 12.7 | 21.6 | 41.1 |
| Netherlands | NL | 210.0 | — | — | 52.0 | 41.8 | 124.5† |
| Norway | NO | — | — | 76.9 | 83.5 | — | — |
| Portugal | PT | 107.1 | 98.6 | 89.3 | 100.4 | 139.2 | 104.9 |
| Spain | ES | 100.6 | 80.6 | 87.0 | 97.6 | 89.7 | 95.7 |
| Sweden | SE | — | — | 130.6 | 80.2 | 99.5† | 106.2† |
| Switzerland | CH | — | — | 132.0 | 1.8 | — | 0.8 |

Revenue coverage (Orbis / Eurostat SBS, %, avg. 2021–23) | † = 0.5–5% consolidated firms
Adequate (60–110%) · Over-coverage + ≥5% consolidated · Limited (<30%) · Over-coverage (>110%) · Partial (30–60%) · No benchmark data

Table 19: Orbis revenue coverage by country and Enclosure I industry

*Notes:* Revenue coverage ratio = Orbis aggregate revenue / Eurostat SBS net turnover, averaged over 2021–2023, expressed as a percentage. Coverage categories: adequate (60–110%, green); over-coverage (above 110%, light orange); over-coverage with $\geq$5% consolidated firms (dark orange, †); partial (30–60%, yellow); limited (below 30%, pink); no benchmark data available (grey). The † symbol indicates cells where consolidated accounts (C1) account for 0.5–5% of the sample, which may inflate Orbis revenue relative to the Eurostat enterprise unit benchmark. Restricted to country-sector cells where Eurostat SBS data are available at the NACE Rev.2 class or group level corresponding to the Enclosure I sector mapping. OECD SDBS country results are not shown as benchmark data for most non-EU countries are only available at the division level.

*Source:* Author's calculations based on Orbis (Moody's Analytics) and Eurostat SBS.

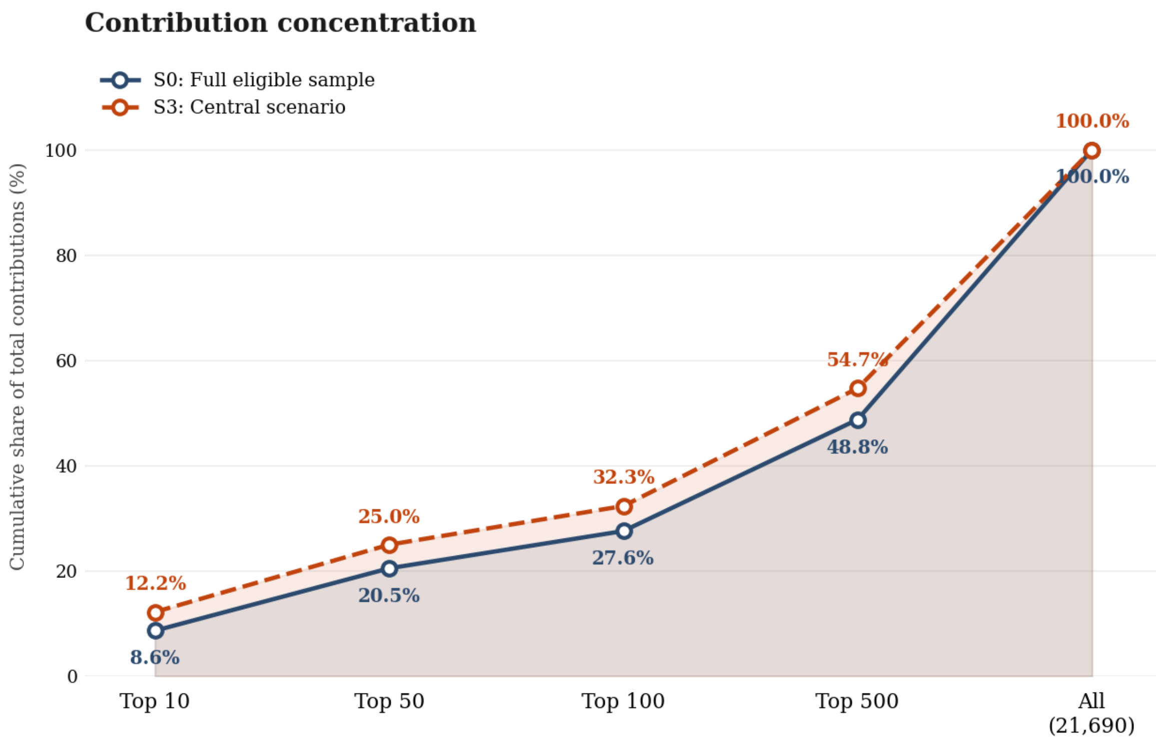



Figure 10: Contribution concentration under the full eligible sample (S0) and central scenario (S3)

*Notes:* Cumulative share of total estimated contributions across 21,690 eligible entities at selected firm-count thresholds, ranked by contribution size from largest to smallest. Reference year 2023.
*Source:* Author's calculations based on Orbis (Moody's Analytics).

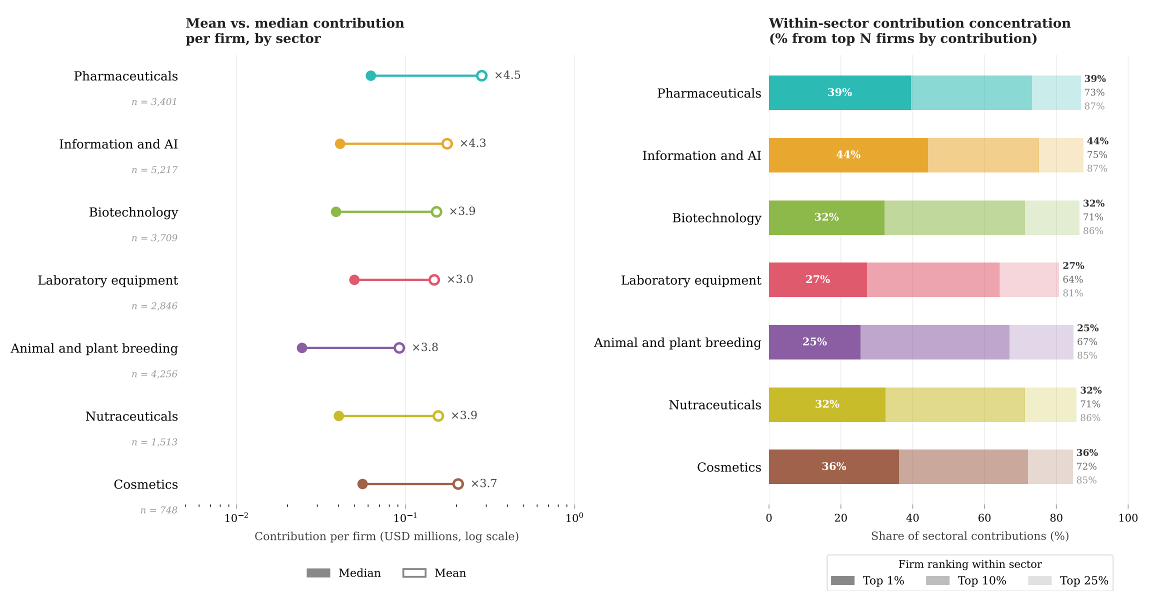



Figure 11: Within-sector firm size distribution and contribution concentration under the S0 scenario

*Notes:* Left: mean and median contribution per firm (log scale); annotated ratio is mean-to-median. Right: share of sectoral contributions from top 1%, 10%, and 25% of firms. Reference year 2023.
*Source:* Author's calculations based on Orbis (Moody's Analytics).

Table 20: Sensitivity of revenue estimates to alternative assumptions and parameter shifts

| **Test** | **Variant** | **S0 ($mn)** | **S3 ($mn)** |
|---|---|---|---|
| *Panel A: Methodological sensitivity* | | | |
| Reference scenario | 2021–2023 window, base year 2023 | 3,646 | 929 |
| Averaging window | 2018–2020 (base year 2020) | 2,986 | 791 |
| | 2019–2021 (base year 2021) | 3,860 | 1,006 |
| | 2020–2022 (base year 2022) | 3,927 | 1,031 |
| Contribution rates | 25% of indicative rates | 912 | 231 |
| | 50% of indicative rates | 1,823 | 463 |
| | 75% of indicative rates | 2,735 | 694 |
| | 125% of indicative rates | 4,557 | 1,157 |
| Contribution base | Revenue only (0.1% of $R$) | 7,035 | 1,673 |
| | Profit only (1% of $\pi$) | 7,320 | 2,016 |
| Winsorisation | 99th percentile within sector | 2,825 | 695 |
| | 95th percentile within sector | 2,041 | 489 |
| *Panel B: Monte Carlo parameter sensitivity (annual revenue, $mn)* | | | |
| | | **Low** | **High** |
| S1 $\alpha \pm 0.10$ | | 799 | 1,529 |
| S2 $\alpha \pm 0.10$ | | 835 | 1,567 |
| $\gamma \pm 0.10$ | | 1,089 | 1,317 |
| S3 $\alpha \pm 0.10$ | | 646 | 1,215 |
| $\gamma \pm 0.10$ | | 838 | 1,018 |
| $\omega \pm 0.10$ | | 810 | 1,043 |
| *Panel C: Discount rate sensitivity (S4 NPV, $bn)* | | | |
| | | **To 2030** | **To 2035** |
| | $r = 1\%$ | 1.4 | 4.8 |
| | $r = 2\%$ | 1.3 | 4.5 |
| | $r = 3\%$ | 1.3 | 4.3 |
| | $r = 4\%$ | 1.3 | 4.1 |
| | $r = 5\%$ | 1.2 | 3.8 |

*Notes:* Panel A varies one methodological assumption at a time holding all others at reference scenario values. The 2018–2020 window uses 2020 as the contribution base year, which coincides with the COVID-19 pandemic and results in a materially lower estimate. Earlier averaging windows may also reflect lower Orbis coverage for some countries and sectors, as reporting completeness improves over time; estimates for those windows should therefore be interpreted as lower bounds to a greater degree than the reference scenario (see Section B.1). Contribution base alternatives apply the single-base levy to all eligible entities regardless of which base is binding under the minimum rule; both alternatives yield substantially higher estimates than the minimum rule. Winsorisation caps firm-level contributions at the within-sector percentile threshold prior to aggregation. Panel B shifts one parameter by ±0.10 while holding all others at central calibrated values; 10,000 simulation draws per run. Central estimates: S1 $1,162mn, S2 $1,203mn, S3 $929mn. Panel C uses S4 as the central NPV scenario (Section 5.1.3); S4 applies the maturation trajectory to the S3 central estimate. Reference year 2023.
*Source:* Author's calculations.

Table 21: Bound on potential double-counting bias from C1 inclusion, by sector

| **Sector** | **N C1** | **% of sector firms** | **C1 contribution (USD mn)** | **% of sector S0 contribution** |
|---|---|---|---|---|
| Pharmaceuticals | 216 | 6.4 | 165.7 | 17.3 |
| Information and AI | 282 | 5.4 | 120.1 | 13.1 |
| Biotechnology | 170 | 4.6 | 84.1 | 14.9 |
| Nutraceuticals | 156 | 10.3 | 70.6 | 29.9 |
| Animal & plant breeding | 368 | 8.6 | 71.8 | 18.4 |
| Cosmetics | 55 | 7.4 | 40.6 | 26.5 |
| Laboratory equipment | 108 | 3.8 | 35.4 | 8.4 |
| *All sectors* | *1,355* | *6.2* | *588.4* | *16.1* |

*Notes:* C1 firms are entities reporting only consolidated accounts in Orbis, retained in the eligible sample where unconsolidated equivalents are not available. The figures represent an upper bound on potential double-counting bias: removing all C1 firms would reduce S0 contributions by 16.1% across all sectors. The realised bias is smaller, as double-counting arises only where subsidiaries of C1 parents appear separately under different identifiers and cannot be matched, and it is further offset by incomplete Orbis coverage in some developing-country economies (Section B.1). Reference year 2023.
*Source:* Author's calculations based on Orbis (Moody's Analytics).

Table 22: S3 participating revenue by sector

| **Sector** | **S3 participating rev. (USD bn)** |
|---|---|
| Pharmaceuticals | 712 |
| Biotechnology | 365 |
| Information and AI | 191 |
| Animal and plant breeding | 164 |
| Nutraceuticals | 110 |
| Laboratory equipment | 77 |
| Cosmetics | 48 |
| *Total* | *1,668* |

*Notes:* S3 participating revenue is the mean of 10,000 Monte Carlo draws under calibrated sector participation ($\alpha$), ownership ($\gamma$), and DSI-intensity ($\omega$) parameters (Table 3), reference year 2023. The corresponding aggregate eligible firm revenue base under S0, summing operating revenue across all firms meeting the Decision 16/2 financial thresholds in the seven Enclosure I NACE classifications, is USD 7,035 billion; this figure may be inflated by the retention of consolidated accounts where unconsolidated equivalents are unavailable (Table 21) and by the inclusion of firms whose primary commercial activity diverges from the Enclosure I sector intended scope, a distinction that cannot be observed at the firm level in Orbis. Sectors ordered by S3 contribution.
*Source:* Author's calculations based on Orbis (Moody's Analytics).

Table 23: Sensitivity of the eligible population and S0 contributions to threshold revision

| Scenario | Eligible firms | Change (%) | Contributions (USD bn) | Change (%) |
|---|---|---|---|---|
| *Baseline* | 21,690 | — | 3.646 | — |
| *Panel A: Upward threshold revisions* | | | | |
| Assets +50% | 20,357 | −6.1 | 3.619 | −0.7 |
| Assets +100% | 18,967 | −12.6 | 3.587 | −1.6 |
| Sales +25% | 19,740 | −9.0 | 3.611 | −1.0 |
| Sales +50% | 18,451 | −14.9 | 3.587 | −1.6 |
| Sales +100% | 16,902 | −22.1 | 3.558 | −2.4 |
| Profit +50% | 20,051 | −7.6 | 3.602 | −1.2 |
| Profit +100% | 19,280 | −11.1 | 3.579 | −1.8 |
| All thresholds +25% | 18,156 | −16.3 | 3.567 | −2.2 |
| All thresholds +50% | 15,644 | −27.9 | 3.496 | −4.1 |
| All thresholds +100% | 12,249 | −43.5 | 3.375 | −7.4 |
| *Panel B: Downward threshold revisions* | | | | |
| Assets −25% | 22,195 | +2.3 | 3.655 | +0.2 |
| Assets −50% | 22,588 | +4.1 | 3.660 | +0.4 |
| Sales −25% | 24,525 | +13.1 | 3.694 | +1.3 |
| Sales −50% | 29,223 | +34.7 | 3.759 | +3.1 |
| Profit −50% | 25,820 | +19.0 | 3.736 | +2.5 |
| Profit −75% | 29,780 | +37.3 | 3.790 | +3.9 |
| All thresholds −25% | 26,832 | +23.7 | 3.737 | +2.5 |
| All thresholds −50% | 36,007 | +66.0 | 3.847 | +5.5 |

*Notes:* Eligible firm counts and S0 contributions re-computed by applying the two-of-three eligibility test at alternative threshold levels. Upward revisions applied to the 21,690 eligible firms in the baseline sample. Downward revisions applied to the full in-scope firm population to capture firms that become eligible under lower thresholds; contributions for newly eligible firms are computed from 2023 reference-year financials. Percentage changes in thresholds are applied uniformly to the Decision 16/2 levels of USD 20 million (assets), USD 50 million (sales), and USD 5 million (profit). S0 assumes full participation at the indicative contribution rates of 0.1% of revenue and 1% of profit. Reference year 2023. *Source:* Author's calculations.

Table 24: Sectoral distribution of estimated Cali Fund contributions under alternative compliance scenarios (central estimates)

| | S0 | | S1 | | S2 | | S3 | |
|---|---|---|---|---|---|---|---|---|
| **Sector** | **$mn** | **%** | **$mn** | **%** | **$mn** | **%** | **$mn** | **%** |
| Pharmaceuticals | 960 | 26.3 | 476 | 40.9 | 513 | 42.7 | 461 | 49.6 |
| Information and AI | 919 | 25.2 | 139 | 11.9 | 135 | 11.2 | 103 | 11.1 |
| Biotechnology | 565 | 15.5 | 198 | 17.0 | 197 | 16.4 | 178 | 19.2 |
| Laboratory equipment | 421 | 11.5 | 84 | 7.2 | 85 | 7.1 | 46 | 5.0 |
| Animal and plant breeding | 391 | 10.7 | 79 | 6.8 | 79 | 6.6 | 63 | 6.8 |
| Nutraceuticals | 236 | 6.5 | 95 | 8.2 | 97 | 8.1 | 44 | 4.7 |
| Cosmetics | 153 | 4.2 | 92 | 7.9 | 96 | 8.0 | 34 | 3.7 |
| *Total* | *3,646* | *100* | *1,162* | *100* | *1,203* | *100* | *929* | *100* |

*Notes:* S0 denotes full compliance (deterministic). S1 adds sector-level participation heterogeneity; S2 further applies ownership multipliers ($\gamma$); S3 further applies DSI intensity adjustments ($\omega$). All Monte Carlo figures are central estimates (mean of 10,000 draws). Sector ordering follows S0 contribution size. Under the central scenario (S3), the pharmaceutical sector's share rises from 26.3% to 49.6% of total contributions, reflecting its relatively high participation rate ($\alpha = 0.50$) and DSI intensity ($\omega = 0.90$), while the information and AI sector's share falls from 25.2% to 11.1% ($\alpha = 0.15$, $\omega = 0.75$). Reference year 2023.
*Source:* Author's calculations.

Table 25: Estimated annual contributions by country and sector under the full eligible sample scenario (S0), top 10 contributing countries

| Country | Pharma | Info & AI | Biotech | Lab equip. | Breeding | Nutraceu. | Cosmetics | Total |
|---|---|---|---|---|---|---|---|---|
| China | 288.6 | 98.3 | 192.7 | 155.2 | 123.8 | 95.1 | 17.7 | 971.4 |
| United Kingdom | 116.9 | 109.7 | 53.1 | 19.4 | 7.6 | 24.9 | 21.9 | 353.5 |
| India | 49.1 | 187.7 | 19.4 | 5.7 | 29.9 | 6.3 | 12.8 | 311.0 |
| Japan | 68.2 | 88.5 | 34.5 | 40.1 | 5.6 | 9.5 | 9.6 | 256.1 |
| Ireland | 40.1 | 102.4 | 27.0 | 25.7 | 1.5 | 8.4 | 0.1 | 205.3 |
| Germany | 57.9 | 33.4 | 21.7 | 29.4 | 1.2 | 4.3 | 6.5 | 154.4 |
| France | 33.0 | 40.0 | 26.3 | 25.4 | 4.6 | 3.0 | 18.4 | 150.7 |
| Russia | 15.2 | 25.2 | 17.4 | 7.0 | 42.0 | 2.0 | 3.9 | 112.8 |
| Belgium | 53.1 | 13.1 | 14.7 | 3.9 | 1.4 | 1.3 | 1.0 | 88.5 |
| Singapore | 10.6 | 39.8 | 9.9 | 14.7 | 2.3 | 4.1 | 1.0 | 82.4 |
| *Subtotal (top 10)* | 732.8 | 738.2 | 416.9 | 326.5 | 219.9 | 158.9 | 92.9 | 2,686.1 |
| *S0 full eligible sample* | | | | | | | | 3,646.0 |

*Notes:* Contributions estimated under $C_f = \min(0.001 \times R_f,\, 0.01 \times \max(0, \pi_f))$, reference year 2023. Values in $mn, rounded to one decimal place. Countries ranked by total contribution. The top 10 countries account for $2,686.1mn (73.7%) of the S0 total of $3,646.0mn across 100 CBD Party jurisdictions. The United States is excluded as a non-Party to the CBD; its inclusion would substantially raise the total. Switzerland, Canada, and the United Kingdom are likely materially affected by incomplete or consolidated account coverage: the UK figure in particular reflects a substantial share of C1 consolidated accounts of multinationals registered there, which may overstate genuine commercial presence. Ireland's estimate reflects the concentration of multinational registered activity for tax purposes and should not be read as indicating genuine commercial presence of that scale. Pharma = Pharmaceuticals; Info & AI = Information and AI; Biotech = Biotechnology; Lab equip. = Laboratory equipment; Breeding = Animal and plant breeding; Nutraceu. = Nutraceuticals.
*Source:* Author's calculations based on Orbis (Moody's Analytics).

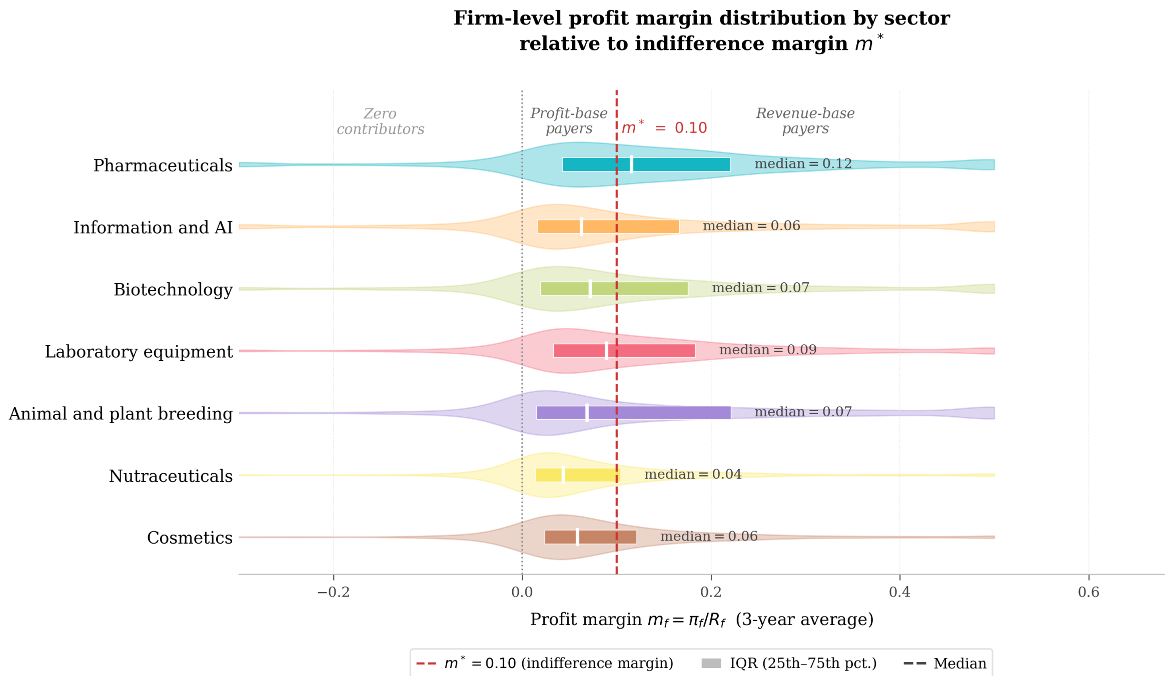



Figure 12: Firm-level profit margin distribution by sector relative to $m^*$ (full eligible sample, S0)

*Notes:* Kernel density of $m_f = \pi_f / R_f$ from three-year averaged financials (2021–2023), clipped to $[-0.30, 0.50]$. Dashed red line: $m^* = 0.10$; dotted grey line: zero margin. Sectors ordered by total contribution, highest to lowest. Reference year 2023.

*Source:* Author's calculations based on Orbis (Moody's Analytics).

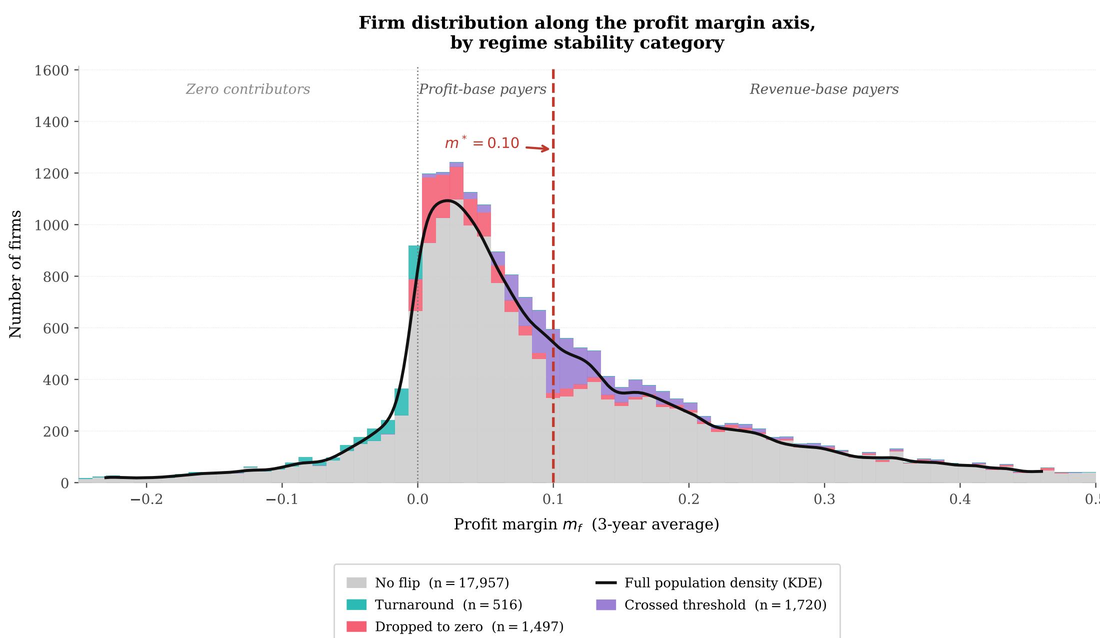



Figure 13: Distribution of eligible firms along the profit margin axis, by regime stability category (full eligible sample, S0)

*Notes:* Bars show firm counts by averaged $m_f$ bin, stacked by regime stability: *no flip* (grey, $n$ = 17,957); *dropped to zero* (coral, $n$ = 1,497); *crossed threshold* (purple, $n$ = 1,720); *turnaround* (teal, $n$ = 516). Black curve: kernel density for the full population. Dotted grey line: zero margin; dashed red line: $m^* = 0.10$. Firms with $m_f < -0.25$ or $m_f > 0.50$ excluded from histogram. Reference year 2023.

*Source:* Author's calculations based on Orbis (Moody's Analytics).

Table 26: Allocation shares under alternative normalisation methods, additive formula (%)

| Weight configuration | Regional group | Proportional | Min-max | Log $G_i$ |
|---|---|---|---|---|
| | African States | 25.1 | 31.6 | 31.6 |
| | WEOG | 21.3 | 9.5 | 10.7 |
| Equal weights | Asia-Pacific | 29.1 | 28.3 | 28.7 |
| | Latin America | 16.9 | 22.7 | 18.1 |
| | Eastern European | 7.5 | 7.9 | 10.9 |
| | African States | 6.4 | 6.4 | 25.7 |
| | WEOG | 47.8 | 47.8 | 16.0 |
| DSI-only ($w_G = 1$) | Asia-Pacific | 27.4 | 27.4 | 26.2 |
| | Latin America | 13.7 | 13.7 | 17.4 |
| | Eastern European | 4.6 | 4.6 | 14.7 |
| | African States | 27.8 | 27.8 | 27.8 |
| | WEOG | 13.6 | 11.5 | 13.6 |
| Biodiversity-only ($w_B = 1$) | Asia-Pacific | 26.0 | 25.5 | 26.0 |
| | Latin America | 19.0 | 25.4 | 19.0 |
| | Eastern European | 13.6 | 9.7 | 13.6 |
| | African States | 41.2 | 41.2 | 41.2 |
| | WEOG | 2.5 | 2.5 | 2.5 |
| Needs-only ($w_N = 1$) | Asia-Pacific | 33.9 | 33.9 | 33.9 |
| | Latin America | 18.0 | 18.0 | 18.0 |
| | Eastern European | 4.4 | 4.4 | 4.4 |

*Notes: Min-max* is the baseline normalisation used throughout the paper, where each raw indicator is rescaled to $[0, 1]$ before entering the formula. *Proportional* expresses each indicator as each country's share of the cross-country total ($\sum_i B_i = \sum_i G_i = \sum_i N_i = 1$). *Log $G_i$* replaces raw INSDC sequence counts with $\log(1 + \text{count})$ prior to proportional normalisation, compressing Canada's dominant share. Biodiversity-only and needs-only configurations are invariant to the $G_i$ normalisation choice and largely invariant to the $B_i$ and $N_i$ normalisation choice respectively. The most consequential differences arise under DSI-only weighting, where log normalisation of $G_i$ reduces WEOG's share from 47.8% to 16.0% and raises African States from 6.4% to 25.7%.
*Source:* Author's calculations.

Table 27: Net transfer positions of sign-switching countries under alternative weight configurations, additive formula (USD mn)

| Country | Regional group | Equal | Biodiv. | DSI | Needs |
|---|---|---|---|---|---|
| Brazil | Latin America | −3.7 | −2.9 | +6.9 | −6.3 |
| Viet Nam | Asia-Pacific | −2.3 | −1.9 | +0.1 | −3.4 |
| Thailand | Asia-Pacific | −1.9 | −1.6 | +2.6 | −2.8 |
| Chile | Latin America | −0.8 | +0.5 | −0.5 | −3.3 |
| Pakistan | Asia-Pacific | −0.8 | −0.8 | +3.2 | −1.1 |
| Bangladesh | Asia-Pacific | −0.6 | −1.0 | +0.5 | +0.1 |
| Czechia | Eastern European | −0.6 | −0.2 | +0.2 | −1.5 |
| Finland | WEOG | −0.4 | +0.5 | +2.0 | −2.5 |
| Portugal | WEOG | −0.4 | +0.1 | +1.3 | −1.5 |
| Bulgaria | Eastern European | −0.2 | +0.1 | −0.4 | −0.9 |
| Croatia | Eastern European | −0.1 | +0.2 | −0.1 | −0.7 |
| Kazakhstan | Eastern European | −0.0 | +0.7 | −0.9 | −1.3 |
| Mexico | Latin America | −0.0 | +0.8 | +5.8 | −2.2 |
| Serbia | Eastern European | +0.2 | +0.4 | +0.1 | −0.2 |
| Greece | WEOG | +0.2 | +0.8 | +1.1 | −0.9 |

*Continued on next page*

*Table 27 continued*

| **Country** | **Regional group** | **Equal** | **Biodiv.** | **DSI** | **Needs** |
|---|---|---|---|---|---|
| Luxembourg | WEOG | +0.5 | +0.9 | −0.3 | −0.3 |
| Nigeria | African States | +0.5 | +0.8 | +1.1 | −0.3 |
| Slovakia | Eastern European | +0.5 | +0.9 | +0.3 | −0.3 |
| Argentina | Latin America | +0.6 | +1.3 | +4.7 | −1.0 |
| Belarus | Eastern European | +0.7 | +1.2 | −0.4 | −0.3 |
| Malta | WEOG | +0.7 | +0.9 | −0.1 | +0.4 |
| Morocco | African States | +0.7 | +1.4 | +0.3 | −0.5 |
| UAE | Asia-Pacific | +0.8 | +1.6 | −0.5 | −0.6 |
| Lithuania | Eastern European | +0.8 | +1.4 | −0.0 | −0.2 |
| New Zealand | WEOG | +1.0 | +2.0 | +2.6 | −0.9 |
| Kuwait | Asia-Pacific | +1.2 | +2.1 | −0.2 | −0.4 |
| Algeria | African States | +1.4 | +2.3 | −0.0 | −0.3 |
| Egypt | African States | +1.4 | +2.3 | +1.5 | −0.5 |
| Bahrain | Asia-Pacific | +1.5 | +2.3 | −0.1 | +0.1 |
| Colombia | Latin America | +1.6 | +3.0 | +0.7 | −1.2 |
| Canada | WEOG | +2.2 | +0.4 | +131.2 | −4.4 |
| Trinidad & Tobago | Latin America | +2.6 | +4.0 | −0.1 | +0.1 |
| Eswatini | African States | +3.3 | +2.4 | −0.0 | +5.3 |

*Notes:* A country is a sign-switcher if its net transfer $T_i$ (Equation 9) is positive under at least one weight configuration and negative under at least one other, across the four additive-formula corner solutions (equal weights, biodiversity-only, DSI-origin-only, needs-only). Positive values indicate net recipient status; negative values indicate net contributor status. Countries are ordered by their equal-weights net transfer, from most negative to most positive. Column headers: *Equal* ($w_B = w_G = w_N = 1/3$); *Biodiv.* ($w_B = 1$); *DSI* ($w_G = 1$); *Needs* ($w_N = 1$). All four configurations use the additive formula with min-max normalisation and the S3 central scenario contributions. Canada's DSI-weighting value (+\$131mn) should be interpreted with caution: Orbis coverage for Canada is incomplete and contribution obligations are likely understated, so the true net transfer under DSI-origin weighting would be lower. UAE is the United Arab Emirates. Values rounded to one decimal place; −0.0 indicates a small negative value below 0.05 mn.
*Source:* Author's calculations.

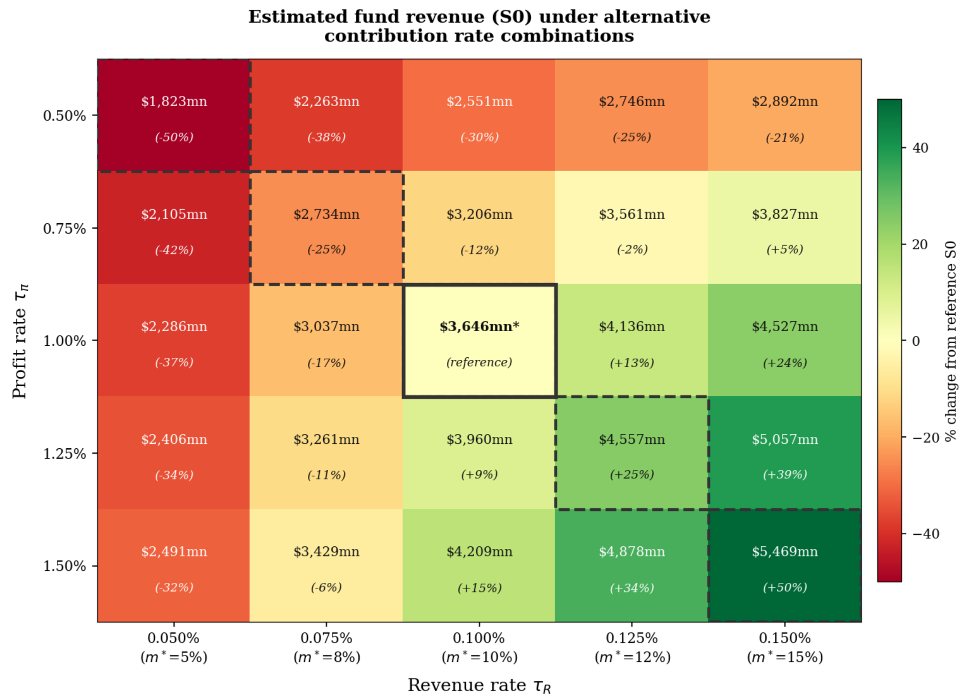



Figure 14: Estimated fund revenue (S0) under alternative contribution rate combinations

*Notes:* Each cell shows total estimated contributions under the corresponding $\tau_R/\tau_\pi$ combination in USD millions, with the percentage change from the reference S0 of $3,646 million shown in italics. Green cells indicate higher contributions than the reference; red cells indicate lower contributions. Dashed borders: proportional rate pairs where $m^* = \tau_R/\tau_\pi$ is unchanged at 10%. Solid border: reference scenario ($\tau_R = 0.1\%$, $\tau_\pi = 1\%$). Reference year 2023.
*Source:* Author's calculations based on Orbis (Moody's Analytics).

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