# Outsourcing Extinction: Economic Complexity and the Geography of Biodiversity Loss*

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**Abstract**

Does the structure of an economy, beyond its level of income, shape the loss of biodiversity? We relate the Red List Index of aggregate extinction risk to economic complexity for up to 179 countries between 1993 and 2019. Conditional on income per capita, rising economic complexity raises extinction risk: a one-standard-deviation increase in the Economic Complexity Index lowers the Red List Index by between one and two percent, an effect robust to country and period fixed effects, to a long-difference design, to the full sectoral composition of value-added, to the temporal aggregation of the data, and to instrumenting complexity with its product-space diversification potential. The effect does not operate through domestic land use—agricultural extent, forest cover, fertilizer and pesticide intensity, agricultural productivity, and deforestation all leave the complexity coefficient unchanged. Instead, complex economies displace the pressure abroad: in a bilateral matrix of extinction-risk footprints, more complex economies are net importers of extinction risk, sourcing a larger share of their biodiversity footprint from other countries' species. Imports drawn from biome-sharing regions also predict steeper within-country declines in extinction-risk indices, evidence for the range-overlap channel that ties displacement to own-country loss. Structural transformation therefore relocates extinction risk rather than reducing it. Economic sophistication is not, on its own, a path to decoupling growth from biodiversity loss, and conservation policy anchored in domestic indicators will understate the biodiversity cost of complex economies.

*Keywords*: Biodiversity; Extinction risk; Red List Index; Economic complexity; Structural transformation; Trade-embodied footprint

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# 1 Introduction

Species are disappearing tens to hundreds of times faster than the average of the past ten million years, and economic activity is the proximate cause (IPBES 2019, Díaz et al. 2019, Pimm et al. 2014). The pressures behind this loss—changing use of land and sea, direct exploitation, climate change, pollution, and invasive species (IPBES 2019, Maxwell et al. 2016)—are each bound up with how economies produce and consume. Whether higher incomes must come at the expense of nature is among the central questions for sustainable development, because growth remains the principal instrument for reducing poverty (Bourguignon 2003). The answer shapes how countries reconcile the economic and environmental goals of the 2030 Agenda.

The literature has framed this question almost entirely in terms of the level of income. A large body of work tests for an Environmental Kuznets Curve (EKC) in biodiversity, an inverted-U in which threat first rises and then falls as countries grow richer (Naidoo & Adamowicz 2001, Asafu-Adjaye 2003, Mills & Waite 2009, Tan et al. 2022, Yiew et al. 2024). This framing asks how much an economy produces. It says less about what an economy produces, and how—about the structure of production. Two countries at the same income can differ sharply in the sophistication and composition of their output, and that difference may matter for biodiversity as much as income itself.

We ask whether economic complexity—the diversity and sophistication of a country's productive structure—shapes biodiversity threat, holding income constant. Economic complexity, measured by the Economic Complexity Index (ECI), summarizes the knowledge embedded in what a country makes and exports (Hidalgo & Hausmann 2009, Hausmann et al. 2007, Hidalgo 2021). Productive structure predicts outcomes that income alone does not, including growth and inequality (Hausmann et al. 2007, Hartmann et al. 2017), which invites the same question for biodiversity. Complexity rises as economies move from a narrow base of resource- and land-intensive products toward a diversified, knowledge-intensive base. One might expect this transformation to ease pressure on nature, mirroring evidence that complexity can lower carbon emissions and support greener production in advanced economies (Romero & Gramkow 2021, Can & Gozgor 2017, Mealy & Teytelboym 2022, Stojkoski et al. 2023). The evidence we find points the other way.

Our first result is that economic complexity raises biodiversity threat, conditional on income. Relating the Red List Index of aggregate extinction risk (Butchart et al. 2004, 2007) to the ECI for up to 179 countries between 1993 and 2019, we find that more complex economies face higher extinction risk among their own species. The estimate is robust to country and period fixed effects, to a long-difference design that removes all time-invariant national heterogeneity, to controlling for the full sectoral composition of output, to the temporal aggregation of the data, and to the choice of complexity measure. Reverse causation is unlikely, because export structure is predetermined: it is built from capabilities accumulated over decades, not from the current status of a country's species. Instrumenting complexity with its product-space diversification potential leaves a negative effect of similar or larger magnitude on a strong first stage. Sophistication, on this evidence, does not appear to spare a country's own biodiversity.

Our second result is that this effect does not run through the obvious domestic channel. If complex economies threatened their own species, one would expect the effect to operate through their own land use—more cropland, less forest, more intensive fertilizer and pesticide use, higher agricultural productivity, or faster deforestation. None of these domestic channels accounts for the complexity effect. Across every specification the complexity coefficient is unchanged, the channels are not themselves moved by complexity, and none mediates the relationship. The pressure that complexity exerts on biodiversity is not visible in a country's own land. This does not make land use irrelevant; it suggests that the land being converted lies abroad.

Our third result locates that pressure abroad. A growing literature traces the species threat and extinction risk embodied in international supply chains, showing that consumption in one country drives biodiversity loss in others (Lenzen et al. 2012, Moran & Kanemoto 2017, Marques et al. 2019, Wilting et al. 2017, Chaudhary & Kastner 2016). Using a bilateral matrix of extinction-risk footprints (Irwin et al. 2022), we find that more complex economies are net importers of extinction risk: they source a growing share of their biodiversity footprint from other countries' species. Economies in the top tercile of complexity place about ninety percent of their consumption footprint abroad and are net importers of extinction risk, while the least complex economies place far less abroad and are net exporters. Complexity, on this reading, does not reduce the biodiversity cost of consumption so much as relocate it to the ecosystems of trading partners. Familiar commodities make the point concrete—oil palm, soy, and the metals of the energy transition each convert biodiverse habitat far from where the final good is consumed—yet none of these costs appears in the importing country's domestic land accounts.

Taken together, these three results form a single contribution: structural transformation relocates extinction risk rather than reducing it. This reframes a debate that has centered on income. The biodiversity-EKC literature, by relying on cross-sectional income variation, compares the experience of poor and rich countries and can read relocation as recovery (Stern 2004, Vincent 1997). The complexity-and-environment literature, having established that sophistication can lower territorial emissions (Romero & Gramkow 2021, Can & Gozgor 2017) even as it raises aggregate ecological pressure (Neagu 2020), has not yet asked what it does to biodiversity in particular. We find that it does not, because biodiversity loss travels through trade in a way that carbon accounting within borders does not capture (Lenzen et al. 2012, Wiebe & Wilcove 2025, Li & Chen 2024). The policy implication follows directly: conservation targets and disclosure frameworks anchored in domestic indicators will tend to understate the biodiversity cost of the world's most complex economies.

**Related Literature.** This paper contributes to three strands of literature: the empirical literature on economic growth and biodiversity loss, the economics of productive complexity, and the trade-embodied accounting of biodiversity footprints. The first asks whether growth threatens or spares biodiversity, and frames the question in terms of the level of income. Borrowing the Environmental Kuznets Curve logic developed for pollution, a large empirical literature looks for an inverted-U between income and species threat, with threat rising among poor countries and falling once they are rich enough (Naidoo & Adamowicz 2001, Asafu-Adjaye 2003, Mills & Waite 2009, Tan et al. 2022, Yiew et al. 2024). The evidence is mixed, and it rests largely on cross-country comparisons of poor and rich nations at a point in time. Stern (2004) showed for carbon that such cross-sectional curves can be artifacts of confounding, or of mistaking the relocation of damage for its abatement—a caution that applies with particular force to biodiversity, whose damage is fixed to the converted habitat. We depart from this strand in both what we ask and how we identify it. We hold income constant and vary the structure of production, and we estimate the relationship within countries over time, where complexity raises extinction risk even though the cross-section is flat.

The second strand is the economics of complexity. Building on the product space and the idea that what a country exports reveals the capabilities it has accumulated, this literature measures economic complexity from the diversity and ubiquity of export baskets (Hidalgo & Hausmann 2009, Hausmann et al. 2007, Hidalgo 2021) and shows that it predicts future growth and inequality beyond what factor accumulation explains (Hartmann et al. 2017, Mealy & Teytelboym 2022). A more recent branch turns to the environment and finds, for carbon, that more complex economies emit less per unit of output and innovate toward cleaner technologies, so that sophistication and territorial decarbonization tend to move together (Romero & Gramkow 2021, Can & Gozgor 2017, Boleti et al. 2021). We carry this literature to biodiversity and find that the environmental dividend does not appear to generalize: complexity raises extinction risk. The contrast with carbon need not be a puzzle, because biodiversity damage, unlike emissions, is local to the habitat and is displaced through trade rather than abated.

The third strand quantifies the biodiversity loss embodied in international trade. Using multi-regional input–output and bilateral footprint accounts, it shows that consumption in wealthy economies drives a large and rising share of the species threat recorded in their trading partners, concentrated in the biodiverse tropics (Lenzen et al. 2012, Moran & Kanemoto 2017, Marques et al. 2019, Wilting et al. 2017, Chaudhary & Kastner 2016, Irwin et al. 2022). This work establishes the geography of the problem, and largely treats the footprint as a descriptive accounting object: it does not identify what makes some economies large net exporters of biodiversity pressure, nor does it connect the footprint to the extinction risk those economies record at home. We aim to provide both links. We show that economic complexity is a systematic structural driver of how much biodiversity pressure a country displaces abroad, and that the most externalized economies tend to be those whose own species grow more threatened. A trade model in which complexity shifts comparative advantage toward land-saving goods, joined to a species–area map with cross-border ranges, draws these facts together and frames the policy question of consumption-based accountability (Vergez et al. 2025, Dasgupta 2021).

**Outline.** The remainder of the paper is organized as follows. Section 2 develops the model and derives its predictions. Section 3 describes the data and the empirical strategy. Section 4 presents the results: the within-country relationship between complexity and extinction risk and its instrumental-variables estimate, the geography of the extinction-risk footprint, and the robustness checks that support them. Section 4.6 discusses what the findings mean, and Section 5 concludes.

## 2 Theoretical framework

The empirical regularities of this paper can be organized around a single mechanism: economic complexity acts as a composition shifter that relocates habitat conversion across borders. This section builds that mechanism into a two-region trade model in the tradition of Copeland & Taylor (1994, 2004), augments it with a species–area map from converted habitat to extinction risk (Pimm & Raven 2000, Brooks et al. 2002), and shows that the model delivers each of the three empirical results as a comparative-statics prediction. It then characterizes the inefficiency of the decentralized equilibrium and the policy instrument that would correct it.

## 2.1 Environment

Two regions, Home ($H$) and Foreign ($F$), trade two final goods. Good $x$ is habitat-intensive: producing it converts natural land that would otherwise shelter species (agriculture, pasture, and resource extraction). Good $y$ is knowledge-intensive and land-saving (sophisticated manufactures and services). Each region $i$ is endowed with labor $L_i$, mobile across its sectors, and a stock of convertible habitat $\bar{A}_i$.

Preferences are identical and homothetic. A representative consumer in region $i$ values the two goods and the biodiversity present in its territory,

$$U_i = \beta \log c_i^x + (1-\beta)\log c_i^y + \phi\, b_i, \qquad \beta \in (0,1),\ \phi \geq 0, \tag{2.1}$$

where $c_i^x, c_i^y$ are consumption levels, $b_i$ is the conservation status of the species present in $i$ (defined in Section 2.2), and $\phi$ is the weight placed on it. Cobb–Douglas preferences over goods fix expenditure shares, so that $p_x c_i^x = \beta I_i$ and $p_y c_i^y = (1-\beta) I_i$, where $I_i$ is income and $(p_x, p_y)$ are world prices. This is the property that lets the model speak to regressions that condition on income: at a given income and given prices, consumption is pinned down, so complexity can act only through the composition and the location of production.

Technology uses labor under diminishing returns, each sector employing a fixed complementary factor (knowledge capital in $y$, land in $x$) in the manner of a specific-factors economy:

$$y_i = \kappa_i\,(L_i^y)^\eta, \qquad x_i = B\,(L_i^x)^\eta, \qquad L_i^x + L_i^y = L_i, \qquad \eta \in (0,1). \tag{2.2}$$

Producing the habitat-intensive good converts land in fixed proportion, $h_i = \gamma_i x_i$, where $h_i$ is hectares of habitat lost and $\gamma_i > 0$ its land intensity. We interpret $h_i$ broadly. Cropland cleared for export agriculture is the most direct case, but the same logic covers the forest opened by logging, the ground broken by mining for the metals of the green transition, the rivers and soils contaminated by industrial and agricultural runoff, and the roads and ports laid through ecosystems to move what these activities produce. The species–area map below treats them as equivalent because each subtracts effective habitat from the species of region $i$. The parameter $\kappa_i$ is economic complexity: the diversity and sophistication of a region's capabilities, which raise productivity in the knowledge-intensive sector. This is the reduced-form image of the product space of Hidalgo & Hausmann (2009), Hausmann et al. (2007), in which complex economies command the capabilities to produce many sophisticated, land-saving goods. Higher $\kappa_i$ raises the relative return to allocating labor to $y$ and therefore the relative cost of producing $x$, giving complex economies a comparative advantage in land-saving goods.

## 2.2 Habitat, species, and conservation status

Converted habitat drives extinction through the species–area relationship, one of the most robust regularities in ecology (Pimm & Raven 2000, Brooks et al. 2002). With original habitat $\bar{A}_i$ and conversion $h_i$, the surviving habitat is $A_i = \bar{A}_i - h_i$, and the share of species in region $i$ committed to extinction is

$$E_i = 1 - \left(\frac{A_i}{\bar{A}_i}\right)^z = 1 - \left(1 - \frac{h_i}{\bar{A}_i}\right)^z, \qquad z \in (0,1), \tag{2.3}$$

increasing and convex in conversion, with the canonical exponent $z \approx 1/4$ (derived theoretically by Preston 1962, Brooks et al. 2002, Pimm & Raven 2000, and routinely used in habitat-loss extinction predictions).

Species ranges cross borders, so the biodiversity status of the species present in one region depends on habitat loss in others. Let $\omega_{ij} \geq 0$ be the share of region $i$'s species assemblage whose range includes region $j$, with $\sum_j \omega_{ij} = 1$; $\omega_{ii}$ is the weight of locally endemic species and $\omega_{ij}$ for $j \neq i$ the cross-border overlap created by shared, migratory, or biome-spanning ranges. The *biodiversity index* of region $i$ is the overlap-weighted share of its species not yet committed to extinction,

$$b_i = 1 - \sum_j \omega_{ij} E_j = \sum_j \omega_{ij} \left(1 - \frac{h_j}{\bar{A}_j}\right)^z. \tag{2.4}$$

The marginal effect of conversion in region $j$ on the biodiversity index of region $i$ is

$$\frac{\partial b_i}{\partial h_j} = -\,\omega_{ij} m_j, \qquad m_j \equiv \frac{z}{\bar{A}_j} \left(1 - \frac{h_j}{\bar{A}_j}\right)^{z-1} > 0, \tag{2.5}$$

where $m_j$ is the marginal extinction intensity of region $j$: the species lost per hectare converted. It is larger where habitat is biodiverse and intact, so conversion relocated into species-rich frontiers is especially damaging. The empirical footprint accounts, in which the consumption of rich economies falls on biodiverse tropical habitat (Lenzen et al. 2012, Chaudhary & Kastner 2016, Irwin et al. 2022), motivate the following ranking.

**Definition 1.** *Foreign is the biodiverse region and Home the converted one: $m_F \geq m_H$ at the relevant margin, and species ranges overlap across borders, $\omega_{HF} > 0$.*

### 2.3 Trade equilibrium and the composition of production

Take world prices as given and normalize $p_y = 1$, writing $p \equiv p_x$ for the relative price of the habitat-intensive good. Cost minimization equates the value marginal product of labor across sectors, $\kappa_i \eta (L_i^y)^{\eta-1} = pB\eta (L_i^x)^{\eta-1}$, so that

$$\frac{L_i^y}{L_i^x} = \left(\frac{\kappa_i}{pB}\right)^{\frac{1}{1-\eta}}, \qquad L_i^x = \frac{L_i}{1 + (\kappa_i/pB)^{1/(1-\eta)}}. \tag{2.6}$$

Labor reallocates toward the knowledge-intensive sector as complexity rises, which establishes the central supply-side property of the model.

**Lemma 2.1** (Composition effect)**.** *At given prices, the supply of the habitat-intensive good and the habitat converted to produce it are strictly decreasing in complexity: $\partial x_i / \partial \kappa_i < 0$ and $\partial h_i / \partial \kappa_i = \gamma_i \partial x_i / \partial \kappa_i < 0$.*

The proof is immediate from Equation (2.6), since $L_i^x$ falls in $\kappa_i$ and $x_i = B(L_i^x)^\eta$, $h_i = \gamma_i x_i$; the explicit derivative is in Appendix A.1.

The two regions trade to clear world markets. Home is the complex region, $\kappa_H > \kappa_F$, and by Lemma 2.1 it produces relatively more $y$ and less $x$. World market clearing for the habitat-intensive good,

$$x_H(p,\kappa_H) + x_F(p,\kappa_F) = c_H^x + c_F^x, \tag{2.7}$$

together with balanced trade determines the equilibrium price $p$. A rise in $\kappa_H$ contracts Home's supply of $x$, raises its relative supply of $y$, and so raises the equilibrium relative price $p$ of the habitat-intensive good; Foreign expands its production of $x$ in response, and Home meets a larger part of its fixed consumption $c_H^x$ through imports. Habitat conversion therefore migrates from Home to Foreign as Home grows more complex: $dh_H/d\kappa_H < 0$ and $dh_F/d\kappa_H > 0$ (see Appendix A.3).

Define the conditional effect of complexity as the change in Home's biodiversity index holding income $I_H$ and prices constant,

$$\left.\frac{d\,b_H}{d\kappa_H}\right|_{I_H} = -\,\omega_{HH}\,m_H\,\frac{dh_H}{d\kappa_H} \;-\; \omega_{HF}\,m_F\,\frac{dh_F}{d\kappa_H}, \tag{2.8}$$

obtained by differentiating Equation (2.4) and using Equation (2.5) (see Appendix A.2). The first term is the domestic channel and the second the foreign channel; the experiment isolates the composition and location of production, which is the structural counterpart of the regression coefficient on complexity.

## 2.4 Complexity and extinction risk

Equation (2.8) carries the central argument. The two terms are forces of opposite sign. The first is positive: complexity lowers domestic conversion, which on its own would push Home's biodiversity index up. The second is negative: complexity raises foreign conversion, which through shared ranges pushes the index down. The sign of the total depends on which force dominates, and Definition 1 settles the question.

**Proposition I** (Complexity raises own extinction risk)**.** *Holding income and prices fixed,* $d\,b_H/d\kappa_H|_{I_H} < 0$ *whenever*

$$\omega_{HF}\,m_F\,\frac{dh_F}{d\kappa_H} \;>\; \omega_{HH}\,m_H\left(-\frac{dh_H}{d\kappa_H}\right). \tag{2.9}$$

*Under Definition 1 this holds, so a more complex economy faces higher extinction risk among its own species.*

The intuition is that a complex economy cannot fully insulate its species from its own consumption. Cutting domestic conversion spares only locally endemic species, weighted by $\omega_{HH}m_H$, while the conversion it displaces lands on biodiverse foreign habitat, weighted by $\omega_{HF}m_F$, and returns home through overlapping ranges. When the displaced damage is large enough—because the frontier is species-rich ($m_F$ high) and ranges are shared ($\omega_{HF} > 0$)—Home's biodiversity index falls. This is the within-country, conditional-on-income relationship estimated in Section 4.

**Proposition II** (The domestic channel does not mediate)**.** *Complexity weakly reduces domestic habitat conversion,* $dh_H/d\kappa_H \le 0$ *(Lemma 2.1). Conditioning the effect of complexity on domestic land use therefore leaves it negative; in the limit in which Home ceases to produce the habitat-intensive good, the domestic term in Equation (2.8) vanishes and the effect runs entirely through the foreign channel,* $\partial\,b_H/\partial\kappa_H|_{h_H} = -\,\omega_{HF}\,m_F\,(dh_F/d\kappa_H) < 0.$

Because complexity lowers rather than raises domestic conversion, no domestic land-use variable can account for the effect, and controlling for such variables cannot displace it. This is why, in Section 4.5, agricultural and land-cover controls leave the complexity coefficient intact: the model predicts that the mediating channel is foreign, not territorial.

**Proposition III** (Leakage and net imports of extinction risk)**.** *Let $\sigma_H$ be the share of the extinction risk embodied in Home's consumption that is incurred abroad, and $N_H$ its net imported extinction risk—the risk its consumption causes abroad minus the risk foreign consumption causes within it. Then $d\sigma_H/d\kappa_H > 0$ and $dN_H/d\kappa_H > 0$.*

As Home grows more complex it produces less of the habitat-intensive good and imports more, so a rising share of the habitat conversion behind its consumption occurs in Foreign, and its net position turns toward importing extinction risk. This is the cross-sectional gradient documented in Section 4.3.

**Corollary 2.1** (Spatial structure)**.** *Because $b_i = \sum_j \omega_{ij}(1-h_j/\bar{A}_j)^z$ with $\omega_{ij} > 0$ for biome-sharing regions, biodiversity indices are spatially correlated: any two regions overlapping with a common region covary positively. A first-order expansion of Equation (2.4) yields a spatial-autoregressive form $b_i = \rho \sum_k W_{ik} b_k + \xi_i$ with $\rho > 0$.*

Shared ranges make a country's biodiversity status partly a function of its neighbors'. When habitat is converted in one country it commits species to extinction wherever their range extends, so countries that share biogeographic space share biodiversity outcomes. The corollary states this formally: biodiversity indices satisfy a spatial-autoregressive relation in which each country's index loads positively on the indices of the regions it overlaps with.

### 2.5 Welfare and policy

The decentralized equilibrium is inefficient because the extinction caused abroad by a region's consumption is unpriced. A world planner maximizing $\sum_i n_i U_i$ (with $n_i$ the population of region $i$) internalizes, for every unit of habitat converted in region $j$, the loss it inflicts on the species of all regions whose ranges overlap $j$,

$$\text{social cost of converting in } j \;=\; \phi \sum_i n_i\, \omega_{ij}\, m_j, \tag{2.10}$$

whereas a consumer in region $\ell$ who drives that conversion through demand internalizes at most the part falling on its own species, $\phi\, n_\ell\, \omega_{\ell j}\, m_j$. The wedge is the cross-border component $\phi \sum_{i\neq\ell} n_i\, \omega_{ij}\, m_j > 0$: the extinction a complex importer exports to the species of its trading partners.

**Proposition IV** (Inefficiency and consumption-based correction)**.** *A territorial instrument that taxes each region's own conversion at $t_i = \phi\, n_i\, \omega_{ii}\, m_i$ internalizes only the damage a region does to its own species; it leaves the cross-border externality unpriced, under-conserves biodiverse exporters, and credits complex importers for a footprint they have displaced. The first-best is implemented by a consumption-based charge on the extinction content of consumption, including imports,*

$$\tau \;=\; \phi \sum_i n_i\, \omega_{ij}\, m_j \quad \textit{per unit of habitat its consumption converts in region } j, \tag{2.11}$$

*equivalently an international transfer from complex importing regions to biodiverse exporting regions equal to the embodied cross-border extinction. Under $\tau$, territorial and consumption-based accounts coincide and the allocation is efficient.*

The policy reading follows directly, and aligns with the wealth- and footprint-based accounting urged by Dasgupta (2021): conservation targets and disclosure rules anchored in domestic indicators price only $\omega_{ii}m_i$ and so understate the true cost of the most complex economies, whose damage is increasingly carried by $\omega_{ij}m_j$ abroad. Appendix A.4 gives the full derivation.

**Testable predictions.** The framework yields four sign predictions: complexity lowers the biodiversity index within countries conditional on income (Proposition I); domestic land-use controls do not mediate this effect (Proposition II); complex economies are net importers of extinction risk (Proposition III); and biodiversity indices are positively spatially dependent (Corollary 2.1). The empirical sections that follow are organized to test each in turn, and Proposition IV frames the policy reading of the results.

# 3 Data and Empirical Strategy

Our strategy has three parts, each answering one link in the argument. First, we estimate whether economic complexity is associated with extinction risk within countries over time. Second, we ask whether any domestic land-use channel accounts for that association. Third, we test whether complex economies displace biodiversity pressure abroad.

## 3.1 Data sources

The dependent variable is the Red List Index (RLI), which tracks aggregate extinction risk across groups of species (Butchart et al. 2004, 2007, Hoffmann et al. 2010). The index ranges from zero, when all species in a group are extinct, to one, when all are of Least Concern; higher values mean less threat. It is the empirical counterpart of the conservation-status index $b_i$ in the framework of Section 2. It underpins SDG indicator 15.5.1 and changes only through genuine shifts in species' extinction-risk categories on the IUCN Red List (IUCN 2019, BirdLife International and Handbook of the Birds of the World 2019). Two features of this measure shape the interpretation that follows. A country's RLI is the aggregated global conservation status of the species present in that country: a species listed as Vulnerable, Endangered, or Critically Endangered carries that status in every country where it occurs. And most species' ranges cross borders—the Amazon basin spans nine countries, the Congo basin six, the rainforests of Southeast Asia eight, and migratory and widely distributed taxa span continents. A country's RLI therefore moves with habitat loss anywhere its species live, not only on its own territory. In our sample the RLI averages 0.87, ranging from 0.42 (Mauritius) to near unity (Finland, Sweden).

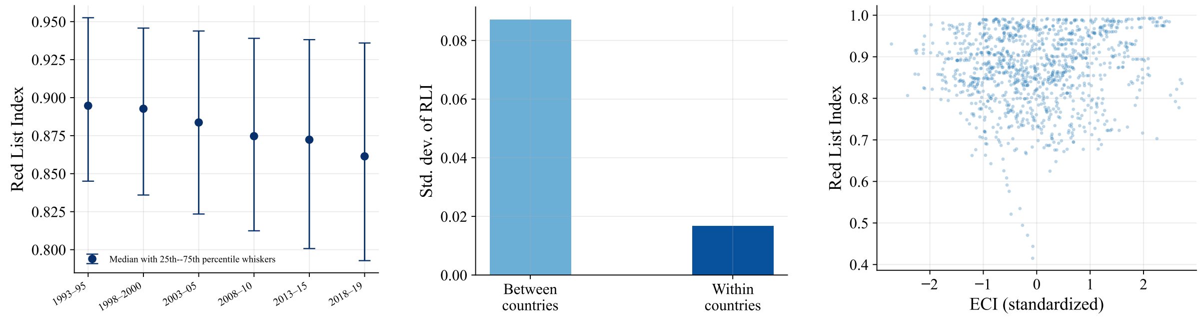
The variable of interest is the Economic Complexity Index (ECI), produced by the Growth Lab at Harvard University from the structure of countries' export baskets (Hidalgo & Hausmann 2009, Hausmann et al. 2007, 2014, Growth Lab at Harvard University 2024). The ECI is high for economies that export a diverse range of sophisticated, ubiquitously-rare products and low for those concentrated in a few widely-produced, typically resource- or land-intensive goods. We standardize the ECI so that coefficients report the effect of a one-standard-deviation change. The ECI summarizes a country's export basket—the bundle of goods it sells to the rest of the world—and is built from capabilities accumulated over decades. It therefore evolves slowly and is plausibly more predetermined with respect to current-period extinction risk than contemporaneous income (Hidalgo et al. 2007, Hidalgo 2021).

GDP per capita, population density, foreign direct investment, and protected-area coverage come from the World Bank (The World Bank 2020), with protected area benchmarked to the Millennium Development Goals series (United Nations 2015); the Human Development Index is from UNDP (United Nations Development Programme 2020). We organize the data into six periods spaced five years apart between 1993 and 2019 (1993–95, 1998–2000, 2003–05, 2008–10, 2013–15, and 2018–19), each a two- or three-year average to dampen single-year noise in the economic series. The five-year spacing is dictated by how often the dependent variable can actually move: the IUCN reassesses each species' extinction-risk category at most once a decade and ideally once every five years (IUCN 2019, Butchart et al. 2007), so the Red List Index carries little genuine annual variation, and finer (for instance, annual) data would mainly overstate the effective sample size. Five-year spacing is therefore the finest cadence the reassessment cycle supports. We confirm in Section 4.5 that the result is insensitive to coarser, roughly decadal aggregation. The full panel covers up to 179 countries; the balanced panel, used for robustness, covers those observed in all six periods.

For the mechanism analysis we draw on land-use shares (agricultural, forest, and urban), agricultural land extent, fertilizer and pesticide use, agricultural total factor productivity and output, and rates of forest and primary-forest change, assembled from the World Bank, FAO, and ESA land-cover products. For the leakage analysis we use a bilateral matrix of extinction-risk footprints for 2013, which records the extinction risk borne by each source country's species on account of consumption in each destination country (Irwin et al. 2022, Lenzen et al. 2012, Moran & Kanemoto 2017). From this matrix we construct, for every country, the domestic footprint (own consumption falling on own species), the imported footprint (own consumption falling on other countries' species), the exported footprint (foreign consumption falling on own species), and the net position.

Figure 1 summarizes the estimation sample. Two features shape the analysis. The Red List Index is high and tightly distributed (panel a), and it varies far more across countries than within them (panel b): the within-country standard deviation is about one-fifth of the between-country standard deviation, because extinction-risk categories are reassessed only once per decade. The fixed-effects estimator therefore works with limited within-country variation, which is why we read the complexity association as evidence of sign and direction rather than of magnitude, and why we lean on the long-difference design.

Figure 2 plots, for each country, the change in the Red List Index against the change in economic complexity over 1993–2019, so that each country is compared only with itself. The fitted line is negative: where complexity rose, extinction risk rose with it. Across countries the raw association is instead flat, so the relationship is a within-country phenomenon rather than a comparison of rich with poor, and the wide scatter means the line traces a systematic tendency rather than a tight fit.




**(a)** Median RLI by period **(b)** Between vs. within variation **(c)** ECI vs. RLI, all country-periods

**Figure 1:** Overview of the estimation sample.

*Notes:* Panel (a) plots the median Red List Index across countries in each of the six periods (1993–95, 1998–2000, 2003–05, 2008–10, 2013–15, 2018–19); the whiskers at each period span the 25th to the 75th percentile. Panel (b) decomposes the standard deviation of the Red List Index into its between-country and within-country components; the within component is about one-fifth of the between component, which limits the variation available to the fixed-effects estimator (Eq. 3.1) and motivates the long-difference design (Eq. 3.2). Panel (c) plots the raw association between the standardized Economic Complexity Index and the Red List Index across all country-periods.

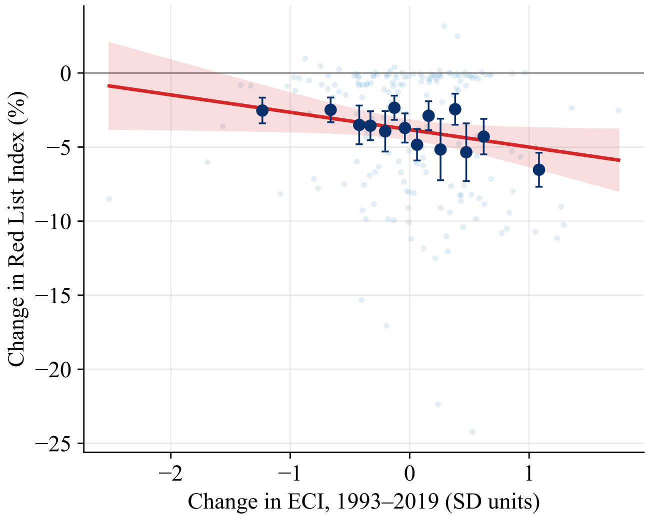



**Figure 2:** Economic complexity and biodiversity

*Notes:* The horizontal axis is the change in a country's standardized Economic Complexity Index over 1993–2019 (in standard-deviation units); the vertical axis is the corresponding percentage change in its Red List Index. Each faint point is a country; solid markers are means within equal-count bins of complexity, with $\pm 1$ standard-error bars, and the shaded band is the 95% confidence interval of the fitted line. The fitted line is negative: where complexity rose, extinction risk rose with it. The scatter is wide, so the line summarizes a systematic within-country tendency rather than a tight predictive relationship.

## 3.2 Econometric specification

We estimate a panel model of the Red List Index on economic complexity, conditioning on income and other drivers, with country and period fixed effects:

$$\log RLI_{it} = \beta_0 + \beta_1 ECI_{it} + \beta_2 \log GDP_{it} + \beta_3 \log Popden_{it} + \beta_4 HDI_{it} + \theta_i + \delta_t + \varepsilon_{it}, \tag{3.1}$$

where $RLI_{it}$ is the Red List Index of country $i$ in period $t$ and $ECI_{it}$ is the standardized Economic Complexity Index; $\theta_i$ and $\delta_t$ are country and period fixed effects, the former absorbing all time-invariant national heterogeneity (country size, biogeography, initial biodiversity endowment) and the latter global shocks common to all countries. The controls are the recognized confounders of the growth–biodiversity relationship, each included for a specific reason rather than for completeness: income per capita ($GDP_{it}$, constant 2017 PPP US dollars) separates the level of economic activity from its structure, which is the object of the exercise; population density ($Popden_{it}$) proxies the direct human pressure on habitat that characterizes biodiversity hotspots (Cincotta et al. 2000); and the Human Development Index ($HDI_{it}$) captures the institutional capacity and social demand for conservation that accompany development. We keep this core specification deliberately parsimonious and test a wider set of motivated confounders and channels—protected-area coverage, foreign investment, institutional quality, land use, and production intensity—one at a time in Section 4.5. Throughout, log denotes the natural logarithm. Standard errors are clustered by country, and $\beta_1$ is the within-country association between complexity and extinction risk, holding income and the other drivers fixed.

We complement the fixed-effects estimator with a long-difference design that relates the change in the Red List Index between the first and last periods to the contemporaneous changes in complexity and the controls:

$$\Delta \log RLI_i = \beta_1 \Delta ECI_i + \beta_2 \Delta \log GDP_i + \beta_4 \Delta \log Popden_i + \beta_5 \Delta HDI_i + \Delta\varepsilon_i, \tag{3.2}$$

where $\Delta$ denotes the change between the first and last periods, so that all time-invariant country characteristics $\theta_i$ difference out. The long difference is the more credible specification here: the RLI is reassessed only once per decade, so most of its variation is between rather than within countries, and differencing the first and last observations removes country fixed effects while exploiting the longest available change. We report both throughout.

A causal reading of $\beta_1$ requires that economic complexity be uncorrelated with the within-country disturbance once fixed effects and controls are partialled out. We probe this with an instrumental-variables strategy. The Complexity Outlook Index ($COI$)—the Hidalgo–Hausmann measure of a country's potential to diversify into new, more sophisticated products given its current position in the global product space (Hausmann et al. 2014, Hidalgo 2021)—enters the first stage,

$$ECI_{it} = \pi_0 + \pi_1 COI_{it} + \pi_2 \log GDP_{it} + \pi_3 \log Popden_{it} + \pi_4 HDI_{it} + \theta_i + \delta_t + u_{it}, \tag{3.3}$$

and the second stage replaces $ECI_{it}$ with its fitted value in Equation (3.1). The exclusion restriction is that a country's diversification opportunities, fixed by the structure of the product space and the capabilities it has already accumulated, affect extinction risk only through complexity. We also estimate the IV with $COI$ lagged one period, which is predetermined with respect to current-period extinction risk by construction.

# 4 Results

This section presents the paper's three empirical results. We first relate economic complexity to extinction risk within countries and probe its causal interpretation with an instrumental-variables strategy.

We then locate the pressure abroad through the bilateral matrix of extinction-risk footprints and test the model's range-overlap mechanism by linking each country's imported footprint to the change in its own Red List Index. Robustness checks and a discussion of mechanism and policy close the section.

## 4.1 Economic complexity and biodiversity threat

Conditional on income, economic complexity is negatively related to the Red List Index: more complex economies face higher aggregate extinction risk. Table 1 reports the estimates. A one-standard-deviation increase in the Economic Complexity Index lowers the Red List Index by about 1 percent (columns 1–2), an estimate essentially unchanged when the full set of controls enters. The long-difference design, which relates the change in extinction risk over 1993–2019 to the contemporaneous change in complexity, returns a larger coefficient of about 2 percent and a higher level of significance (columns 3–4). Income per capita alone bears no within-country relationship to extinction risk once fixed effects are present; it is the structure of an economy, not its income level, that co-moves with biodiversity within countries.

**Table 1:** Economic complexity and the Red List Index

| | Country + period FE | | Long difference | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Economic Complexity Index | -0.010$^{***}$ | -0.012$^{***}$ | -0.018$^{***}$ | -0.022$^{***}$ |
| | (0.004) | (0.004) | (0.006) | (0.006) |
| log GDP per capita | 0.002 | -0.020$^{**}$ | 0.004 | -0.047$^{***}$ |
| | (0.005) | (0.008) | (0.007) | (0.012) |
| log Population density | | -0.030$^{***}$ | | -0.054$^{***}$ |
| | | (0.011) | | (0.013) |
| Human Development Index | | 0.134$^{**}$ | | 0.286$^{***}$ |
| | | (0.061) | | (0.106) |
| Country FE | Yes | Yes | Diff. | Diff. |
| Period FE | Yes | Yes | | |
| Within $R^2$ | 0.405 | 0.418 | 0.042 | 0.141 |
| Observations | 1,078 | 1,000 | 165 | 129 |

*Notes:* This table estimates the within-country fixed-effects model, Equation (3.1) (columns 1–2), and its long difference between the first and last periods, Equation (3.2) (columns 3–4). The dependent variable is the log Red List Index. The Economic Complexity Index is standardized, so its coefficient is the effect of a one-standard-deviation change. Standard errors in parentheses are cluster-robust by country (columns 1–2) and heteroskedasticity-robust (columns 3–4). The reported $R^2$ is the within (net-of-fixed-effects) $R^2$ for columns 1–2 and the regression $R^2$ for the long-difference columns 3–4. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The other coefficients behave as expected and confirm that complexity is not standing in for income or population. Once complexity and the controls are included, income per capita carries the negative and significant sign familiar from the biodiversity-growth literature, and population density does likewise; human development enters positively, consistent with richer institutional and conservation capacity. Complexity adds an independent margin on top of these.

The magnitudes are modest, and it is worth being clear about why. The Red List Index moves very little within countries over time—its within-country standard deviation is roughly one-fifth of its overall standard deviation—because species' extinction-risk categories are reassessed only once per decade. The complexity association is therefore precisely estimated but small in level terms. Its importance is qualitative: it reverses the sign that the decoupling hypothesis would predict.

The direction of this within-country result runs against the cross-sectional biodiversity–income literature, which finds an inverted-U between income and species threat and forecasts that further growth eases pressure on biodiversity (Naidoo & Adamowicz 2001, Asafu-Adjaye 2003, Mills & Waite 2009, Tan et al. 2022); it also reverses the message of the complexity-and-carbon literature, which finds that complexity lowers territorial emissions (Romero & Gramkow 2021, Can & Gozgor 2017, Mealy & Teytelboym 2022, Boleti et al. 2021). The closest precedent in our direction is Neagu (2020), who finds that complexity raises the aggregate ecological footprint across 48 complex economies; our panel sharpens that finding by isolating the effect at the biodiversity margin and stripping out the cross-country confounding to which the EKC literature has long been vulnerable.

## 4.2 Instrumenting economic complexity

We estimate the instrumental-variables strategy specified in Section 3.2 (Eq. 3.3 for the first stage; the second stage replaces $ECI_{it}$ in Eq. 3.1 with its fitted value). The COI is a powerful predictor of subsequent complexity: the first-stage $F$-statistic is 31 (and 11 when the instrument is lagged one period), far above conventional weak-instrument thresholds. Appendix B.3 reports a battery of validity tests for the COI as an instrument—relevance, exclusion conditional on ECI, falsification with a lead of the COI, and overidentification with the COI and its lag jointly.

**Table 2:** Instrumental-variables estimates of the effect of complexity on extinction risk

| | (1)<br>OLS | (2)<br>IV: COI | (3)<br>IV: COI (lag) |
|---|---|---|---|
| Economic Complexity Index | -0.012$^{***}$ | -0.016$^{*}$ | -0.038$^{*}$ |
| | (0.004) | (0.009) | (0.020) |
| log GDP per capita | -0.020$^{**}$ | -0.020$^{**}$ | -0.016$^{*}$ |
| | (0.008) | (0.008) | (0.009) |
| log Population density | -0.030$^{***}$ | -0.031$^{***}$ | -0.027$^{**}$ |
| | (0.011) | (0.011) | (0.012) |
| Human Development Index | 0.134$^{**}$ | 0.143$^{**}$ | 0.189$^{**}$ |
| | (0.061) | (0.058) | (0.079) |
| First-stage F | | 31.4 | 11.3 |
| Observations | 999 | 999 | 863 |

*Notes:* Estimates use the six-period (5-year-window) panel, 1993–2019, with country and period fixed effects and the controls of Equation (3.1) (income per capita, population density, the Human Development Index; coefficients omitted). Column 1 is OLS; columns 2–3 instrument the standardized Economic Complexity Index with the Complexity Outlook Index (Hausmann et al. 2014, Hidalgo 2021), contemporaneous and lagged one period respectively. Standard errors clustered by country in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 2 reports the estimates. The OLS coefficient is $-0.012$; instrumenting with the contemporaneous COI gives $-0.016$, and with the predetermined, one-period-lagged COI gives $-0.038$. All three are negative, of similar or larger magnitude, and significant at least at the ten-percent level. The informative comparison is between the instrumented and the OLS coefficient. Instrumental-variables estimates are inherently less precise than OLS, so their confidence intervals are wider; the question is less whether an individual IV coefficient clears a significance threshold than whether it drifts away from OLS once endogeneity is purged. It does not: the IV estimates are statistically indistinguishable from OLS, which suggests the OLS estimate is not contaminated by reverse causation or a common shock. We read the relationship as the causal effect of complexity on extinction risk, and the larger instrumented coefficients, if anything, suggest that OLS understates it.

### 4.3 The geography of the extinction-risk footprint

Where does this pressure fall? Not on a country's own land: agricultural expansion, forest loss, fertilizer and pesticide intensity, and agricultural productivity leave the complexity coefficient unchanged, and none is itself moved by complexity, so the domestic land-use explanation can be set aside (Section 4.5). The pressure that complexity exerts on biodiversity instead falls increasingly on other countries.

The displacement operates through several familiar production activities in the supplier countries. The most direct is land-use change for export agriculture, such as plantation crops and aquaculture that clear biodiverse ecosystems for a single export commodity. Alongside it runs resource extraction for manufacturing supply chains, together with the chemical and water pressure—pesticide and fertilizer runoff, mining tailings—that these activities carry, and the transport infrastructure that moves the output to distant markets. The bilateral matrix of extinction-risk footprints (Irwin et al. 2022, Lenzen et al. 2012, Moran & Kanemoto 2017) aggregates these channels into a single accounting of which species' habitat is converted to satisfy which country's consumption.

We test this across countries in the 2013 cross-section,

$$y_i = \alpha + \delta_1 ECI_i + \delta_2 \log GNI_i + u_i, \tag{4.1}$$

where the outcome $y_i$ is, in turn, the log imported footprint, the log domestic footprint, the foreign share of the consumption footprint, and the net import position (Table 3).

**Table 3:** Complexity, income, and the geography of the extinction-risk footprint

| | (1) log Imported | (2) log Domestic | (3) Foreign share | (4) Net import |
|---|---|---|---|---|
| Economic Complexity Index | $0.294^{*}$ | $-0.255$ | $0.040^{***}$ | $662.6^{***}$ |
| | (0.160) | (0.246) | (0.008) | (230.3) |
| log GNI per capita | 0.002 | $-0.730^{***}$ | $0.042^{***}$ | 211.1 |
| | (0.138) | (0.235) | (0.008) | (162.7) |
| Observations | 173 | 173 | 173 | 173 |
| $R^2$ | 0.028 | 0.108 | 0.475 | 0.158 |

*Notes:* Each column estimates the 2013 cross-sectional regression Equation (4.1) for a different outcome: the log imported footprint (1), the log domestic footprint (2), the share of the consumption footprint falling abroad (3), and the net import position (4). "Net import" is imported minus exported extinction-risk footprint, positive for net importers. The Economic Complexity Index is standardized. Heteroskedasticity-robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

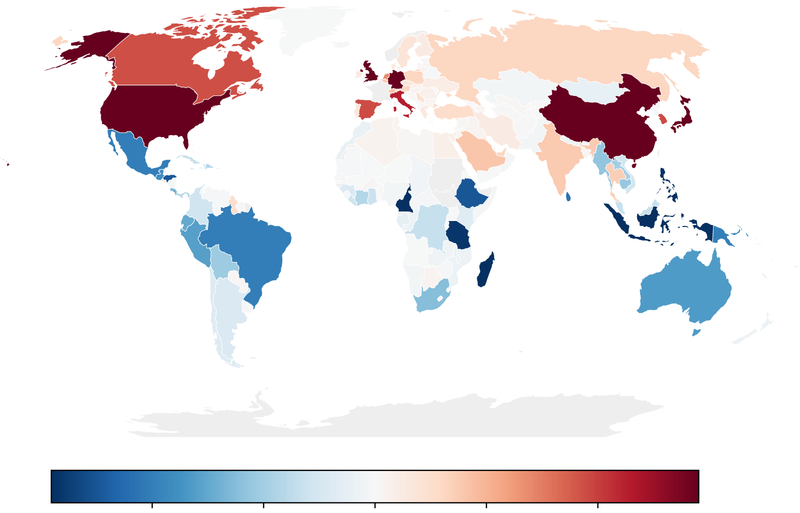



**Figure 3:** The geography of outsourced extinction risk, 2013.

*Notes:* Each country is shaded by its net imported extinction risk—the extinction risk its consumption causes abroad minus the risk foreign consumption causes within it. Red denotes net importers (consumption causes more loss abroad than is borne at home) and blue denotes net exporters. Values are computed from the 2013 bilateral extinction-risk footprint matrix (Irwin et al. 2022, Lenzen et al. 2012).

Two outcomes are decisive. The share of a country's consumption footprint that falls abroad rises steeply with complexity: a one-standard-deviation increase in the ECI raises the foreign share by four percentage points, and complexity and income together explain nearly half of its cross-country variation (column 3). The net position—imported minus exported extinction risk—turns positive with complexity: more complex economies are net importers of extinction risk (column 4). Decomposing the levels, complexity is associated with a larger imported footprint (column 1) while domestic footprint falls with income (column 2): complex, high-income economies cause comparatively little loss at home and a great deal abroad.

The gradient is pronounced across the complexity distribution. Countries in the top tercile of complexity place about ninety percent of their consumption footprint abroad and are net importers of extinction risk; those in the bottom tercile place about seventy-four percent abroad and are net exporters. The map in Figure 3 shows the resulting geography: the complex economies of North America, Western Europe, and East Asia are net importers of extinction risk, while the biodiverse, less complex economies of Latin America, sub-Saharan Africa, and Southeast Asia are net exporters. The within-country result and this cross-sectional pattern fit together: as economies grow more complex their own species' risk still rises, but a widening share of the biodiversity cost of their consumption is borne by the ecosystems of their trading partners.

This outsourcing pattern echoes the multi-regional input–output literature, which has documented that wealthy economies displace a large share of their species-threat footprint to biodiverse trading partners (Lenzen et al. 2012, Moran & Kanemoto 2017, Marques et al. 2019, Wilting et al. 2017, Chaudhary & Kastner 2016, Irwin et al. 2022). We are consistent with that literature in direction and extend it by identifying economic complexity, rather than income alone, as the structural driver: the foreign share of the footprint rises along the complexity axis even after controlling for income.

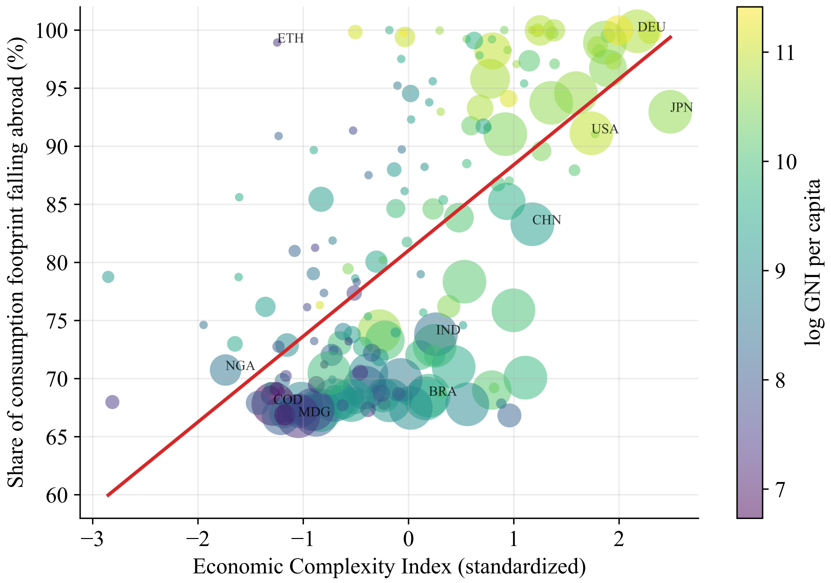
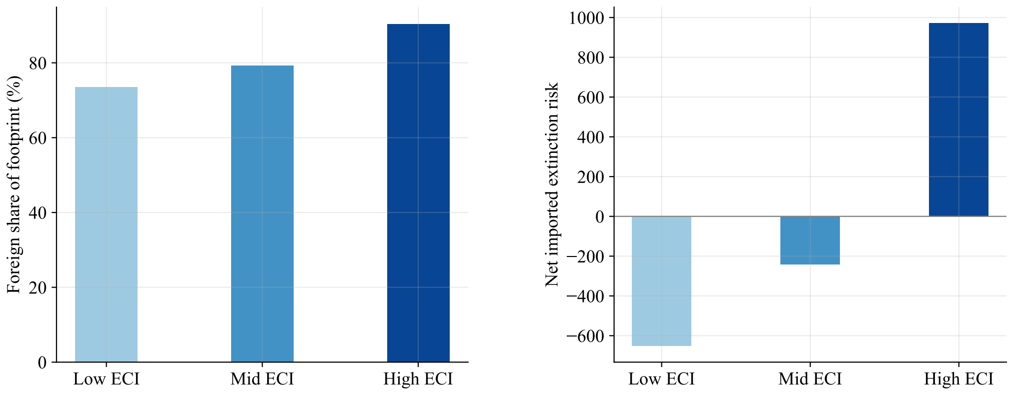



**Figure 4:** Economic complexity and the share of the consumption footprint that falls abroad

*Notes:* Each point is a country in the 2013 cross-section. The vertical axis is the share of a country's consumption footprint that falls on other countries' species; the horizontal axis is the standardized Economic Complexity Index. Point size is proportional to the total consumption footprint and color encodes log GNI per capita. The fitted line corresponds to the foreign-share regression, Equation (4.1).

The leakage gradient is continuous along the entire complexity distribution, not a step from the bottom tercile to the top. Figure 4 plots, for each country in the 2013 cross-section, the share of its consumption footprint that falls abroad against its standardized Economic Complexity Index. The relationship is steep and tight: a one-standard-deviation rise in complexity raises the foreign share by about four percentage points (Table 3, column 3), and complexity and income together explain nearly half of the cross-country variation in that share. It is complexity, not income, that organizes the geography: color encodes log GNI per capita and the gradient runs along the complexity axis rather than along income contours, so high-income but resource-intensive producers sit below the fitted line while less wealthy but more sophisticated economies sit above it. Complexity captures a margin that income alone misses.

Aggregating to terciles makes the same point with the simplest possible summary. Figure 5, panel (a), shows the mean foreign share within each third of the complexity distribution: countries in the bottom tercile already place about three-quarters of their consumption footprint abroad, the share rises monotonically with complexity, and the top tercile reaches close to ninety percent. Panel (b) plots the mean net imported extinction risk—imports minus exports of footprint—across the same three groups. It is negative in the bottom tercile and firmly positive in the top: the most complex economies are not only sourcing more of their footprint abroad in relative terms but are net importers of extinction risk in absolute terms, while the least complex economies are net exporters who bear the biodiversity cost of others' consumption. The two panels describe the same asymmetry from two angles, and they sharpen the cross-sectional regression of Table 3: as complexity rises the footprint sits abroad in growing share, and the country shifts from supplier to net consumer of global biodiversity loss.




**(a)** Share of footprint falling abroad

**(b)** Net imported extinction risk

**Figure 5:** The extinction-risk footprint by tercile of economic complexity

*Notes:* Countries are grouped into terciles of the standardized Economic Complexity Index. Panel (a) shows the mean share of the consumption footprint that falls abroad; panel (b) shows the mean net imported extinction risk (positive values denote net importers). Both rise monotonically with complexity.

## 4.4 Imports from biome-sharing regions and own-country decline

The leakage result shows that complex economies impose a growing share of their consumption footprint on foreign ecosystems; the within-country result shows that their own Red List Index falls. The model joins these two facts through the overlap matrix $\omega$: when a country imports goods produced through habitat conversion in regions that share its species, that conversion returns home through the shared ranges. We test the bridge directly by estimating

$$\Delta \log RLI_i = \alpha + \beta_1 \log F_i^{\omega} + \beta_2 \log F_i^{\text{dom}} + \beta_3 \log F_i^{\text{exp}} + \gamma \Delta ECI_i + \pi' \Delta \mathbf{z}_i + \varepsilon_i, \tag{4.2}$$

where $\Delta$ denotes the long difference between the 1993–95 and 2018–19 windows; $F_i^{\omega} = \sum_{j \neq i} \omega_{ij} F_{j \to i}$ is the overlap-weighted imported footprint, with $F_{j \to i}$ the bilateral extinction-risk flow caused in source $j$ by $i$'s consumption (from the 2013 footprint matrix) and $\omega_{ij}$ the proxy for shared species range; $F_i^{\text{dom}}$ and $F_i^{\text{exp}}$ are the domestic and exported footprints that absorb direct damage to home species; and $\Delta \mathbf{z}_i$ collects the long-difference controls in $\log GDP$ per capita, $\log Popden$, and $HDI$. The bridge prediction is $\beta_1 < 0$. The four columns of Table 4 vary the bridge variable: total imported footprint $F_i^{\text{imp}} = \sum_{j \neq i} F_{j \to i}$ replaces $F_i^{\omega}$ in columns 1–2, and the scale-free overlap share $F_i^{\omega} / F_i^{\text{imp}}$ replaces it in column 4.

The overlap weights $\omega_{ij}$ are a same-continent indicator built from the country geometry, which captures the within-continent species-sharing of regional biomes and migratory ranges. Column 1 uses the level of imported footprint alone; column 2 adds the domestic and exported footprint to absorb the part of the correlation that runs through scale and through direct damage to home species; column 3 replaces total imports with the overlap-weighted version, the direct empirical analogue of the model's bridge channel; column 4 examines the structural overlap share itself.

The raw level of imported footprint predicts a steeper RLI decline ($-0.011$, $p < 0.01$), but the relationship is largely an artifact of scale: once domestic and exported footprint are added (column 2), the coefficient loses precision, because countries with large footprints in any direction face larger biodiversity pressures of every kind. The cleaner specifications support the model's bridge. The overlap-weighted imported footprint carries the predicted negative sign after controlling for direct damage to

**Table 4:** Imports from biome-sharing regions and own-country extinction-risk decline

| | (1) Direct | (2) Net of direct | (3) $\omega$ net of direct | (4) Overlap share |
|---|---|---|---|---|
| log Imported footprint | -0.011*** | -0.015 | | -0.011*** |
| | (0.002) | (0.013) | | (0.002) |
| log $\omega$-weighted imported | | | -0.006* | |
| | | | (0.003) | |
| Overlap share of imports | | | | -0.153** |
| | | | | (0.070) |
| log Domestic footprint | | -0.002 | -0.001 | |
| | | (0.002) | (0.002) | |
| log Exported footprint | | 0.007 | -0.004 | |
| | | (0.014) | (0.004) | |
| $\Delta$ ECI | -0.016*** | -0.016*** | -0.015*** | -0.015*** |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| $\Delta$ log GDP per capita | -0.040*** | -0.040*** | -0.039*** | -0.041*** |
| | (0.011) | (0.011) | (0.010) | (0.011) |
| $\Delta$ log Population density | -0.050*** | -0.049*** | -0.043*** | -0.046*** |
| | (0.012) | (0.012) | (0.012) | (0.012) |
| $\Delta$ HDI | 0.212** | 0.224** | 0.214** | 0.203** |
| | (0.100) | (0.100) | (0.100) | (0.100) |
| $R^2$ | 0.336 | 0.341 | 0.356 | 0.359 |
| Observations | 118 | 118 | 118 | 118 |

*Notes:* The dependent variable is the long-difference $\Delta \log RLI$ for each country between the 1993–95 and 2018–19 windows. The bridge variables are built from the 2013 bilateral extinction-risk footprint matrix (Irwin et al. 2022). "Overlap share" is the share of imported footprint sourced from countries on the same continent (a proxy for the model's $\omega_{ij}$ that captures within-continent species sharing); "$\omega$-weighted imported" multiplies imported footprint by that overlap. Columns 2 and 3 include the country's domestic and exported footprint to absorb direct damage to its own species. Heteroskedasticity-robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

home ($-0.006$, $p < 0.10$), and the scale-free share of imports drawn from overlap sources is negative and significant at the five-percent level ($-0.153$, $p < 0.05$): countries whose import basket draws disproportionately from species-sharing regions experience a steeper decline in their own Red List Index than countries whose imports come from biogeographically distant sources. The complexity coefficient itself is unchanged across the four specifications at $-0.015$ to $-0.016$ ($p < 0.01$), so the bridge variables add information about the within-country decline beyond what complexity alone explains.

These results offer direct empirical support for the range-overlap channel that the model formalizes. Appendix C details the construction of $\omega$ and the bridge variables, and reports the sensitivity of the estimates to alternative overlap proxies.

## 4.5 Robustness

The complexity result survives the checks that matter most for a within-country panel with few periods. This section also reports the mechanism analysis: the domestic channels through which complexity might have been expected to act, and why they do not appear to explain the effect. The supporting tables are collected in Appendix B.

**Domestic channels and sensitivity to controls.** Could complexity merely stand in for a domestic driver of habitat loss? To address this, we augment the preferred specification—which already includes income, population density, and the Human Development Index—with each potential confounder and channel, one at a time. Each is motivated by the literature rather than added for completeness: conservation effort that should slow extinction (protected-area share); the pollution-haven channel by which foreign investment may relocate damaging production (Cole 2004) (FDI); the composition of land cover (forest, agricultural, and urban shares); the intensity of production that most directly degrades habitat (energy use, fertilizer and pesticide application, and agricultural productivity); and the sectoral composition that complexity might simply proxy (manufacturing, services, and agricultural value-added shares).

Table B.3 reports the complexity coefficient from these twelve augmentations, and it is stable: it stays between $-0.008$ and $-0.012$ and remains statistically significant in every case. No domestic land-use or agricultural variable displaces it. The agricultural controls—fertilizer, pesticides, and agricultural productivity—attenuate it modestly on their smaller samples but leave it negative and significant, so the effect does not appear to run through domestic agriculture. Adding the manufacturing, services, or agricultural value-added share leaves the coefficient unchanged, which suggests that what complexity captures is the sophistication of production rather than merely which sectors dominate it.

These regressions separate two questions that conditioning on land use might otherwise blur. The first is whether land use affects extinction risk at all, and it does: forest cover, the most direct measure of habitat, enters with a positive and significant own coefficient ($p < 0.05$), so countries that retain more natural forest face lower extinction risk. The second is whether complexity acts through domestic land use, and the evidence suggests it does not: complexity leaves forest cover, cropland, urban land, and the rate of deforestation statistically unchanged, and where it moves domestic agriculture at all it reduces agricultural output ($p < 0.05$), the composition effect of Section 2. The first link of any domestic complexity–land–biodiversity pathway is therefore absent. Habitat clearly matters for extinction risk; what complexity does not seem to do is raise the habitat pressure exerted at home.

Why, then, do domestic channels fail to explain the effect? A natural reading is that the biodiversity cost of a complex economy is not borne mainly at home. As Section 4.3 shows, complex economies increasingly source their consumption footprint abroad, so the biodiversity pressure associated with complexity is largely invisible in domestic land-use accounts—the mechanism is trade-embodied rather than territorial. This result is at odds with mechanism-based readings of the biodiversity–income relationship that locate any EKC in domestic land-use efficiency or conservation institutions, and it aligns with the pollution-haven and Copeland & Taylor (1994, 2004) view—supported empirically by Cole (2004)—that complex economies relocate ecologically intensive production to weaker-regulation partners rather than reform it at home. We add the controls one at a time rather than jointly, both to preserve within-country degrees of freedom and to avoid absorbing the effect through post-treatment channels, so the preferred specification remains parsimonious.

**Sample, functional form, and frequency.** Table B.1 collects three further checks against the preferred six-period specification. The coefficient is unchanged when we restrict attention to the balanced panel of countries observed in all six periods ($-0.013$, $p < 0.01$). Allowing a quadratic in income does not produce the inverted-U of the biodiversity Environmental Kuznets Curve—neither income term is significant and the complexity effect itself remains linear—consistent with the view that the curve is an artifact of cross-sectional income variation (Stern 2004, Vincent 1997). Finally, the result is insensitive to the temporal aggregation of the data: re-estimating on three longer periods (1993–95 / 2005–07 / 2017–19) instead of the preferred six-period panel leaves it intact and, if anything, slightly larger ($-0.015$, $p < 0.01$). In every case the complexity coefficient stays close to its preferred value of $-0.012$ and remains statistically significant.

**Spatial dependence.** Extinction risk is strongly correlated across neighboring countries, both ecologically and because a species classed as threatened is threatened everywhere it occurs (Pandit & Laband 2007); the contiguity Moran's $I$ of the Red List Index is 0.54, and the spatial autoregressive parameter is large and significant. Two results in Table B.2 show that this spatial structure does not generate the complexity association. First, absorbing regional shocks with continent-by-period fixed effects leaves the within-country complexity coefficient negative and significant, though somewhat attenuated ($-0.007$, $p = 0.05$). Second, we estimate a spatial autoregressive model in changes,

$$\Delta \log RLI_i = \rho \sum_j w_{ij} \Delta \log RLI_j + \beta_1 \Delta ECI_i + \mathbf{z}_i' \gamma + \varepsilon_i, \tag{4.3}$$

where $w_{ij}$ are row-standardized queen-contiguity weights, the term $\sum_j w_{ij} \Delta \log RLI_j$ is the neighbor-average change in extinction risk, and $\rho$ measures spatial spillover; the model is fit by spatial two-stage least squares, instrumenting the spatial lag with the spatial lags of the regressors. This within-country design preserves the negative sign of the complexity coefficient ($-0.011$), though it is imprecise in the smaller differenced sample ($p \approx 0.11$). The spatial-lag parameter is itself large and significant ($\rho = 0.61$) and positive, as expected if biodiversity status clusters geographically; cross-border dependence is therefore real, but it does not overturn the within-country complexity association. (Estimated in levels rather than changes, the relationship is not negative—the between-country confounding that the within-country design removes.)

### 4.6 Discussion

The three results combine into one claim: economic complexity relocates extinction risk rather than reducing it. Within countries, rising complexity raises the risk to their own species; that rise is not explained by their own land use; and across countries, complex economies increasingly source their biodiversity footprint from abroad. Sophistication changes where biodiversity pressure falls, not whether it falls. Each of the three results sits in a different relation to the existing literature, and the comparison is informative in each case.

The first result runs against the prevailing reading of the cross-sectional biodiversity–income literature, which finds an inverted-U between income and species threat and predicts that further growth will relieve pressure on biodiversity (Naidoo & Adamowicz 2001, Asafu-Adjaye 2003, Mills & Waite 2009, Tan et al. 2022). Our within-country panel evidence is less optimistic, for the same reason Stern (2004) questioned the carbon EKC: cross-sectional income variation compares poor and rich countries and can mistake the relocation of damage for its disappearance. The complexity-and-carbon literature points the same way as the EKC, finding that more complex economies emit less per unit of output and innovate toward cleaner technologies (Romero & Gramkow 2021, Can & Gozgor 2017, Mealy & Teytelboym 2022, Stojkoski et al. 2023, Boleti et al. 2021). Our biodiversity result moves in the opposite direction, and the asymmetry has a clear reason: carbon damage is global and is increasingly accounted for, however imperfectly, at the point of emission, whereas biodiversity damage is local to the species affected and travels through trade to wherever the habitat is converted (Lenzen et al. 2012, Moran & Kanemoto 2017, Marques et al. 2019). A complex economy can decarbonize its own territory while its consumption continues to drive land conversion in biodiverse trading partners. The closest precedent in direction is Neagu (2020), who finds that economic complexity raises the aggregate ecological footprint across 48 complex economies; we extend that finding to biodiversity specifically, identify the effect within countries with country and period fixed effects rather than from a cross-sectional cointegration, and trace the mechanism.

The second result speaks to mechanism-based accounts of the biodiversity–income relationship that locate any EKC in domestic land-use efficiency gains, conservation institutions, or agricultural intensification. The agricultural and land-cover variables that those accounts predict should mediate the effect—forest cover, cropland, urban land, deforestation rate, fertilizer and pesticide intensity, agricultural productivity—leave the complexity coefficient unchanged in our panel, and complexity itself does not move them (Appendix D). The finding instead aligns with the pollution-haven and Copeland & Taylor (1994, 2004) view that complex, capital-rich economies relocate ecologically intensive production to weaker-regulation partners rather than reform it at home, an empirical regularity also reported by Cole (2004) for industrial pollution. In our setting the analog is land conversion rather than emissions: the biodiversity cost of a complex economy is largely invisible in its domestic land accounts because the mechanism is trade-embodied rather than territorial.

The third result extends the multi-regional input–output footprint literature (Lenzen et al. 2012, Moran & Kanemoto 2017, Marques et al. 2019, Wilting et al. 2017, Chaudhary & Kastner 2016, Irwin et al. 2022), which has documented that wealthy economies displace a large and rising share of their species-threat footprint to biodiverse trading partners, concentrated in the tropics. We agree in direction and add two things that the descriptive accounting cannot deliver on its own. First, we identify economic complexity, rather than income alone, as the structural driver of how much biodiversity pressure a country displaces abroad, with the foreign share of the footprint rising steeply across the complexity distribution. Second, we tie the bilateral footprint to within-country extinction-risk dynamics through the model's range-overlap channel: countries that import more of their footprint from biome-sharing partners experience steeper declines in their own Red List Index. The link from displacement to home-country loss is the one the footprint literature has not pursued, and the recent companions of Wiebe & Wilcove (2025) and Li & Chen (2024) are consistent with it.

The natural intuition cuts the other way: an economy that outsources resource-intensive production should impose less pressure on its own ecosystems and record a higher Red List Index. Our evidence rejects that intuition, and two facts close the apparent gap. First, the Red List Index of a country aggregates the global conservation status of the species present in it, and most of those species share ranges with other countries; the habitat conversion that complexity displaces abroad therefore returns home through those shared ranges. Second, outsourcing does not zero out domestic ecological pressure: complexity barely moves a country's forest cover, agricultural land, urban land, or rate of deforestation, nor the broader pressures of energy use, foreign investment, conservation effort, and the sectoral composition of value added (Appendix D). Home species are hit by what complexity displaces abroad and by what it leaves at home; the two effects compound.

The geography our results trace is asymmetric: complex economies hold the consumption, less complex economies the production and the ecological cost that follows from it. Production-based and territorial indicators—the Red List Index of a country's own species, the protected share of its own land—will understate the biodiversity cost of the most complex economies, because that cost is increasingly incurred elsewhere (Wiebe & Wilcove 2025, Chaudhary & Kastner 2016, Irwin et al. 2022). The model of Section 2 makes the point precise: a territorial conservation instrument prices only the damage a country does to its own species and leaves the cross-border externality unpriced, so it credits rich, complex economies for a problem they have displaced elsewhere. The efficient correction is a consumption-based charge, or an equivalent transfer to biodiverse exporters, and agricultural support and trade policy are the concrete margins on which it would operate (Vergez et al. 2025). A wealth- and footprint-based view of the kind urged by Dasgupta (2021) is better suited to the geography our results reveal.

# 5 Conclusion

We asked whether the structure of an economy, beyond its income, shapes biodiversity loss, and found that it does—in the opposite direction to the decoupling intuition. Conditional on income, more complex economies face higher extinction risk among their own species, and that risk is not explained by their domestic land use. Instead, complex economies appear to relocate the biodiversity cost of their consumption abroad, emerging as net importers of extinction risk. Structural transformation is therefore not, by itself, a path away from biodiversity loss; it changes the geography of that loss.

The contribution is to bring the structure of production, not only its level, into the analysis of biodiversity loss, and to show that a single mechanism accounts for the evidence. A trade model in which complexity shifts comparative advantage toward land-saving goods, joined to a species–area map with cross-border ranges, explains at once why complexity raises a country's own extinction risk, why that risk is invisible in its domestic land use, and why it surfaces in the footprint it imposes abroad. The same framework identifies the policy failure and its remedy.

For policy, the implication is that biodiversity goals cannot be assessed one country at a time. Targets and disclosures anchored in domestic species and domestic land will flatter the economies whose consumption drives habitat conversion elsewhere. Aligning conservation with the footprint of consumption, rather than the boundaries of production, is the harder but necessary task that the geography of extinction risk demands. The consumption that drives biodiversity loss and the ecosystems that absorb it now belong to different countries; conservation that recognizes only the latter will not slow the former.

The natural next step for this research is to extend the bilateral extinction-risk footprint accounts to a panel. With multi-year footprint matrices, the relocation pattern documented here could be traced over time, and the bridge linking domestic decline to foreign conversion could be estimated within countries rather than across them. Constructing such a panel—a sustained effort already under way at the World Bank, IUCN, and the Sydney input–output group—would let the framework offered here speak directly to how the geography of biodiversity loss is evolving with the structural transformation of the world economy.

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# Online Appendix

**Outsourcing Extinction: Economic Complexity and the Geography of Biodiversity Loss**

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## A Derivations for the theoretical framework

This appendix collects the derivations underlying the propositions, lemmas, and key equations of Section 2.

### A.1 Proof of Lemma 2.1 (composition effect)

Cost minimization in region $i$ equates the value marginal product of labor across sectors,

$$\kappa_i \, \eta \, (L_i^y)^{\eta-1} \;=\; pB\eta \, (L_i^x)^{\eta-1}, \tag{A.1}$$

which gives the labor ratio

$$\frac{L_i^y}{L_i^x} \;=\; \left(\frac{\kappa_i}{pB}\right)^{1/(1-\eta)}. \tag{A.2}$$

Imposing the labor constraint $L_i^x + L_i^y = L_i$ delivers $L_i^x$ as in Equation (2.6). Differentiating at fixed $p$,

$$\frac{\partial L_i^x}{\partial \kappa_i} \;=\; -\frac{L_i}{\left[1+(\kappa_i/pB)^{1/(1-\eta)}\right]^2} \cdot \frac{(\kappa_i/pB)^{\eta/(1-\eta)}}{(1-\eta)\,pB} \;<\; 0. \tag{A.3}$$

Since $x_i = B(L_i^x)^{\eta}$ and $h_i = \gamma_i x_i$,

$$\frac{\partial x_i}{\partial \kappa_i} \;=\; B\eta\,(L_i^x)^{\eta-1}\,\frac{\partial L_i^x}{\partial \kappa_i} \;<\; 0, \qquad \frac{\partial h_i}{\partial \kappa_i} \;=\; \gamma_i\,\frac{\partial x_i}{\partial \kappa_i} \;<\; 0, \tag{A.4}$$

which is the statement of Lemma 2.1. ■

### A.2 Derivation of the conditional effect (Eq. 2.8)

In the two-region case, the conservation status of Home is

$$b_H \;=\; \omega_{HH}\left(1-\tfrac{h_H}{\bar{A}_H}\right)^{z} \;+\; \omega_{HF}\left(1-\tfrac{h_F}{\bar{A}_F}\right)^{z}. \tag{A.5}$$

At fixed Home income $I_H$ and prices, $h_H$ and $h_F$ both depend on $\kappa_H$ through the trade equilibrium. Differentiating $b_H$ with respect to $\kappa_H$,

$$\frac{db_H}{d\kappa_H} \;=\; -\,\omega_{HH}\cdot\frac{z}{\bar{A}_H}\left(1-\tfrac{h_H}{\bar{A}_H}\right)^{z-1}\frac{dh_H}{d\kappa_H} \;-\; \omega_{HF}\cdot\frac{z}{\bar{A}_F}\left(1-\tfrac{h_F}{\bar{A}_F}\right)^{z-1}\frac{dh_F}{d\kappa_H}. \tag{A.6}$$

Substituting the definition $m_j \equiv (z/\bar{A}_j)(1-h_j/\bar{A}_j)^{z-1} > 0$ from Equation (2.5) yields

$$\frac{db_H}{d\kappa_H} = -\omega_{HH}\, m_H \frac{dh_H}{d\kappa_H} - \omega_{HF}\, m_F \frac{dh_F}{d\kappa_H}, \tag{A.7}$$

which is Equation (2.8). The first term is non-negative, since $dh_H/d\kappa_H \leq 0$ by Lemma 2.1; the second is non-positive, since $dh_F/d\kappa_H \geq 0$ by Section A.3. Proposition I states the conditions under which the second term dominates.

## A.3 World price response and the signs of $dh_H/d\kappa_H$ and $dh_F/d\kappa_H$

Let $S(p,\kappa_H,\kappa_F) \equiv x_H(p,\kappa_H)+x_F(p,\kappa_F)$ denote world supply of the habitat-intensive good, and $D(p,I_H,I_F) \equiv \beta(I_H+I_F)/p$ world demand (from Cobb–Douglas, $c_i^x = \beta I_i/p$). World market clearing,

$$S(p,\kappa_H,\kappa_F) = D(p,I_H,I_F), \tag{A.8}$$

defines the equilibrium price $p$ implicitly. Differentiating at fixed $(I_H,I_F,\kappa_F)$ and applying the implicit function theorem,

$$\frac{dp}{d\kappa_H} = -\frac{\partial S/\partial \kappa_H}{\partial S/\partial p - \partial D/\partial p}. \tag{A.9}$$

The denominator is the standard excess-supply slope, positive under upward-sloping supply ($\partial S/\partial p > 0$) and downward-sloping demand ($\partial D/\partial p = -\beta(I_H+I_F)/p^2 < 0$). The numerator is negative because $\partial x_H/\partial \kappa_H < 0$ (Lemma 2.1). Hence

$$\frac{dp}{d\kappa_H} > 0, \tag{A.10}$$

the equilibrium relative price of the habitat-intensive good rises as Home grows more complex. The implied movements in habitat conversion follow from $h_i = \gamma_i x_i$:

$$\frac{dh_H}{d\kappa_H} = \gamma_H \left[\frac{\partial x_H}{\partial \kappa_H} + \frac{\partial x_H}{\partial p}\frac{dp}{d\kappa_H}\right] < 0, \qquad \frac{dh_F}{d\kappa_H} = \gamma_F \frac{\partial x_F}{\partial p}\frac{dp}{d\kappa_H} > 0. \tag{A.11}$$

Conversion migrates from Home to Foreign as Home grows more complex.

## A.4 Decentralized equilibrium and the consumption-based instrument (Proof of Proposition IV)

A planner maximizing $\sum_i n_i \phi\, b_i$ over the allocation of habitat conversion $\{h_j\}$, taking world consumption demand as given, internalizes the full marginal damage of converting habitat in $j$,

$$\text{social marginal damage of } h_j = \phi \sum_i n_i\, \omega_{ij}\, m_j. \tag{A.12}$$

The sum runs over every region $i$ whose species' ranges overlap with $j$, weighted by population $n_i$ and the marginal extinction intensity $m_j$.

In the decentralized economy, the firm in $j$ converts habitat to satisfy demand and pays no environmental cost; a consumer in $\ell$ whose consumption drives that conversion internalizes only the damage to its own assemblage, $\phi\, n_\ell\, \omega_{\ell j}\, m_j$. The wedge between the social and the private valuation of a unit of conversion in $j$ induced by consumption in $\ell$ is

$$\Delta_{\ell j} \;=\; \phi \sum_{i \neq \ell} n_i\, \omega_{ij}\, m_j \;>\; 0 \tag{A.13}$$

whenever $\omega_{ij} > 0$ for some $i \neq \ell$, that is, whenever conversion in $j$ affects species shared by countries other than $\ell$.

A consumption-based charge $\tau_j$ on the embodied-extinction content of consumption restores efficiency. Setting

$$\tau_j \;=\; \phi \sum_{i} n_i\, \omega_{ij}\, m_j \tag{A.14}$$

adds the full social damage to every consumer's price for the part of consumption that drives conversion in region $j$. With this charge, the consumer's first-order condition coincides with the planner's, and the allocation is efficient. An equivalent decentralization is an international transfer from importing regions to exporting regions equal to the embodied cross-border extinction $\sum_i n_i \omega_{ij} m_j - n_\ell \omega_{\ell j} m_j$ for each importer–exporter pair $(\ell, j)$. ■

# B Robustness

This appendix collects the tables that support the robustness exercises of Section 4.5: the sample, functional-form, and frequency checks; the spatial-dependence checks; the stability of the complexity coefficient under sequential additions of controls; and the validity of the Complexity Outlook Index as an instrument for complexity.

## B.1 Sample, functional form, and frequency

**Table B.1:** Further robustness checks

| Specification | ECI coefficient | | N |
|---|---|---|---|
| Preferred specification (six periods) | $-0.012^{***}$ | (0.004) | 999 |
| Balanced panel (countries in all six periods) | $-0.013^{***}$ | (0.004) | 774 |
| Quadratic in income (rejects the EKC) | $-0.012^{***}$ | (0.004) | 999 |
| Three-period panel (1993–95 / 2005–07 / 2017–19) | $-0.015^{***}$ | (0.005) | 481 |

*Notes:* Each row reports the coefficient on the standardized Economic Complexity Index from a variant of the preferred six-period specification, Equation (3.1). "Balanced panel" restricts the sample to countries observed in all six periods; "Quadratic in income" adds income squared (neither income term is significant); "Three-period panel" re-estimates the model on three longer periods (1993–95 / 2005–07 / 2017–19) instead of the preferred six-period panel, testing sensitivity to the temporal aggregation. Standard errors clustered by country in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

**Table B.3:** Stability of the complexity coefficient under additional controls

| | (1) Pref. | (2) +Prot. area | (3) +FDI | (4) +Forest | (5) +Cropland | (6) +Urban | (7) +Energy | (8) +Fert. | (9) +Pest. | (10) +AgTFP | (11) +Manuf. | (12) +Serv. | (13) +Agric. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Economic Complexity Index** | **-0.012**$^{***}$ | **-0.010**$^{**}$ | **-0.012**$^{***}$ | **-0.012**$^{***}$ | **-0.012**$^{***}$ | **-0.012**$^{***}$ | **-0.010**$^{***}$ | **-0.008**$^{**}$ | **-0.009**$^{**}$ | **-0.010**$^{**}$ | **-0.013**$^{***}$ | **-0.012**$^{***}$ | **-0.012**$^{***}$ |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.003) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Protected-area share | | 0.134$^{*}$ | | | | | | | | | | | |
| | | (0.073) | | | | | | | | | | | |
| FDI (% of GDP) | | | -0.000 | | | | | | | | | | |
| | | | (0.000) | | | | | | | | | | |
| Forest share | | | | 0.287$^{**}$ | | | | | | | | | |
| | | | | (0.140) | | | | | | | | | |
| Agricultural land share | | | | | 0.000 | | | | | | | | |
| | | | | | (0.000) | | | | | | | | |
| Urban land share | | | | | | -0.099 | | | | | | | |
| | | | | | | (0.061) | | | | | | | |
| log Energy consumption | | | | | | | -0.012$^{**}$ | | | | | | |
| | | | | | | | (0.005) | | | | | | |
| log Fertilizer (N) | | | | | | | | 0.004$^{*}$ | | | | | |
| | | | | | | | | (0.002) | | | | | |
| log Pesticides | | | | | | | | | 0.002 | | | | |
| | | | | | | | | | (0.003) | | | | |
| Agricultural TFP (log) | | | | | | | | | | -0.000 | | | |
| | | | | | | | | | | (0.007) | | | |
| log Manufacturing VA share | | | | | | | | | | | 0.006 | | |
| | | | | | | | | | | | (0.004) | | |
| log Services VA share | | | | | | | | | | | | 0.008 | |
| | | | | | | | | | | | | (0.007) | |
| log Agriculture VA share | | | | | | | | | | | | | -0.001 |
| | | | | | | | | | | | | | (0.005) |
| Within $R^2$ | 0.418 | 0.408 | 0.420 | 0.444 | 0.419 | 0.418 | 0.448 | 0.432 | 0.427 | 0.415 | 0.416 | 0.392 | 0.418 |
| Observations | 1,000 | 810 | 997 | 993 | 995 | 993 | 992 | 758 | 718 | 920 | 930 | 946 | 970 |

*Notes:* Column 1 reports the preferred within-country specification, Equation (3.1) (country and period fixed effects, log income per capita, log population density, and the Human Development Index). Columns 2–13 add, one at a time, the additional control named at the head of the column; only the coefficient on the standardized Economic Complexity Index (row 1) and on the added control (its own row) is shown, with the base controls suppressed for compactness. Standard errors clustered by country in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

## B.2 Spatial dependence

**Table B.2:** Spatial robustness of the complexity–extinction-risk association

| | (1) Continent×period FE | (2) Spatial lag, changes |
|---|---|---|
| Economic Complexity Index | $-0.007^{**}$ | $-0.011$ |
| | (0.003) | (0.007) |
| Spatial lag $\rho$ | — | $0.609^{***}$ |
| | | (0.150) |
| Country FE | ✓ | — |
| Period FE | ✓ | — |
| Estimator | Within (FE) | Spatial 2SLS |
| Specification | Levels (panel) | Long difference |
| Observations | 878 | 119 |

*Notes:* The dependent variable is the log Red List Index (column 1) and its long difference (column 2). Column 1 adds continent-by-period fixed effects to the preferred within-country specification, Equation (3.1), with cluster-robust (by country) standard errors. Column 2 estimates the spatial autoregressive model Equation (4.3) by spatial two-stage least squares with a row-standardized queen-contiguity weight matrix, with heteroskedasticity-robust standard errors; $\rho$ is the spatial-lag parameter. The contiguity Moran's $I$ of the Red List Index is 0.54. Both specifications include income per capita, population density, and the Human Development Index (coefficients omitted). $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

## B.3 Validity of the Complexity Outlook Index as an instrument

To assess the validity of the Complexity Outlook Index (COI) as an instrument for economic complexity, we run a battery of tests, collected in Table B.4. First, instrument relevance is established by a strong first stage ($F = 32$), far above conventional weak-instrument thresholds. Second, and most directly bearing on the exclusion restriction, when the COI is entered into the structural equation alongside complexity its coefficient is small and statistically insignificant: the instrument has no effect on extinction risk other than through complexity. Third, a falsification test using a lead of the COI returns a null effect, so the instrument does not pick up anticipation or pre-trends in the outcome. Together these exercises support the validity of the instrument.

**Table B.4:** Instrument-validity tests for the Complexity Outlook Index

| Test | Statistic | Implication |
|---|---|---|
| (1) Relevance: first-stage coef. on COI | $0.381^{***}$ (0.068) | strong first stage, $F = 31.7$ |
| (2) Exclusion: COI \| ECI in structural eq. (3.1) | $-0.002$ (0.004) | no direct effect |
| (3) Falsification: lead of COI | $-0.003$ (0.003) | no anticipation/pre-trend |

*Notes:* Six-period panel, 1993–2019, with country and period fixed effects and the controls of Equation (3.1); standard errors clustered by country. Row (1) reports the first-stage coefficient of ECI on the COI, with its significance stars, and the corresponding $F$-statistic. Row (2) adds the COI to the structural equation alongside ECI; an insignificant coefficient supports the exclusion restriction. Row (3) replaces the COI with its one-period lead. Coefficients carry significance stars where significant; for the exclusion and falsification rows (2)–(3), statistical *insignificance* is the outcome that supports instrument validity. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

# C Construction of the overlap proxy and bridge variables (Section 4.4)

This appendix details the construction of the overlap weights $\omega$ and the bridge variables that enter Equation (4.2) and Table 4, and reports the sensitivity of the estimates to alternative choices of $\omega$.

## C.1 The country-overlap proxy $\omega_{ij}$

The main estimation uses a binary same-continent indicator,

$$\omega_{ij} = \mathbf{1}\{c(i) = c(j)\}, \tag{C.1}$$

where $c(\cdot)$ assigns each country to one of the seven continents of the Natural Earth admin_0 dataset (Africa, Antarctica, Asia, Europe, North America, Oceania, South America). The off-diagonal mean of $\omega$ on the 161-country sample is 0.21: roughly one country pair in five shares a continent. The same-continent indicator captures, at a level the cross-section can resolve, the within-continent species sharing that arises from regional biomes contiguous with national borders and from migratory ranges linking countries within continents.

The continent indicator is one point in a family of overlap proxies built from increasingly fine biogeographic partitions:

- **Biogeographic realm.** Each country is mapped to one of the eight Wallace/Olson realms (Afrotropical, Palearctic, Nearctic, Neotropical, Indomalayan, Australasian, Oceania, Antarctic) using a fixed crosswalk on the Natural Earth SUBREGION field; $\omega_{ij}$ is the same-realm indicator. This separates, for example, Sub-Saharan Africa (Afrotropical) from Northern Africa (Palearctic), and Southern and South-Eastern Asia (Indomalayan) from Northern and Western Asia (Palearctic).
- **Biome cosine.** For each country we compute the share of its land area in each of the fourteen biomes of Olson et al. (2001), intersecting the Natural Earth boundaries with the WWF Terrestrial Ecoregions of the World shapefile. $\omega_{ij}$ is the cosine similarity of the two countries' biome-share vectors, a continuous measure in $[0, 1]$.
- **Realm $\times$ biome ecoregion cells.** The same cosine construction over 63 realm-biome cells (each TEOW polygon is tagged by both a realm and a biome). This distinguishes the tropical moist

forest of the Neotropical realm from the tropical moist forest of the Indomalayan realm, which share habitat type but no species.

### C.2 Construction of the bridge variables

Let $M[s,d]$ denote the entry of the 2013 bilateral extinction-risk footprint matrix (Irwin et al. 2022), giving the extinction risk borne by source $s$'s species on account of consumption in destination $d$. For each destination $i$ we construct

$$F_i^{\text{imp}} = \sum_{s \neq i} M[s,i] \qquad \text{(imported footprint: own consumption falling abroad)}, \tag{C.2}$$

$$F_i^{\text{exp}} = \sum_{d \neq i} M[i,d] \qquad \text{(exported footprint: foreign consumption falling in } i\text{)}, \tag{C.3}$$

$$F_i^{\text{dom}} = M[i,i] \qquad \text{(domestic footprint: own consumption falling in } i\text{)}, \tag{C.4}$$

$$F_i^{\omega} = \sum_{s \neq i} \omega_{is} M[s,i] \qquad \text{(overlap-weighted imported footprint)}, \tag{C.5}$$

$$\sigma_i = F_i^{\omega} \,/\, F_i^{\text{imp}} \qquad \text{(structural overlap share of imports)}. \tag{C.6}$$

On the 161-country sample, $F_i^{\text{imp}}$ averages roughly 4,450 extinction-equivalents with a median of 1,005; the foreign share $F_i^{\text{imp}}/(F_i^{\text{imp}} + F_i^{\text{dom}})$ averages 0.80; $\sigma_i$ averages 0.04 with a median of 0.02. The dependent variable in Table 4 is the long-difference $\Delta \log RLI_i$ between the 1993–95 and 2018–19 windows of the six-period panel.

### C.3 Sensitivity to the overlap proxy

Table 4 reports estimates with the continent-based $\omega$. Re-estimating with the alternative proxies leaves the qualitative result intact: the structural overlap share carries a coefficient of $-0.117$ with the biogeographic-realm $\omega$, $-0.160$ with the biome-cosine $\omega$, and $-0.111$ with the realm-by-biome cell $\omega$, against $-0.153$ in the table; the corresponding coefficients on the overlap-weighted imported footprint range from $-0.005$ to $-0.006$. The signs are uniformly consistent with the model's bridge mechanism, and the magnitudes are stable across partitions.

## D First-link tests for the candidate domestic channels

A domestic channel can mediate the effect of complexity on extinction risk only if complexity actually moves it. This appendix tests that first link directly: for each candidate channel $X_{it}$, we estimate

$$X_{it} = \pi_0 + \pi_1 ECI_{it} + \pi_2 \log GDP_{it} + \pi_3 \log Popden_{it} + \pi_4 HDI_{it} + \theta_i + \delta_t + u_{it}, \tag{D.1}$$

on the six-period panel, with cluster-robust (by country) standard errors. A near-zero $\pi_1$ implies that complexity does not move the candidate channel and therefore cannot mediate its effect on extinction risk through that channel.

We restrict attention to channels with a defensible a-priori link to economic complexity. Forest cover, agricultural land share, urban land share, and the rate of deforestation are the headline land-use margins through which a structural shift in the economy might reasonably be expected to act. Agricultural productivity tracks the diffusion of technologies that complexity proxies. Energy consumption, foreign investment, and the protected-area share capture the broader pressures often invoked in the trade–environment debate: industrial energy use, externally financed capital formation, and the institutional capacity for conservation. The sectoral composition of value added—manufacturing, services, and agriculture—measures complexity's own composition margin directly.

Table D.5 reports the eleven first-link estimates.

**Table D.5:** First-link tests: effect of economic complexity on candidate domestic channels

| Dependent variable | ECI coefficient | Std. error | Obs. |
|---|---|---|---|
| Forest share | 0.0001 | ( 0.0022) | 997 |
| Agricultural land share | 0.0058 | ( 0.4936) | 999 |
| Urban land share | 0.0045 | ( 0.0034) | 997 |
| Deforestation rate | 0.0950 | ( 0.6519) | 993 |
| Agricultural TFP (log) | 0.0347 | ( 0.0292) | 920 |
| log Energy consumption | 0.0713 | ( 0.0513) | 997 |
| FDI (% of GDP) | 1.8905 | ( 1.2076) | 998 |
| Protected-area share | 0.0025 | ( 0.0025) | 808 |
| log Manufacturing VA share | $0.0802^{*}$ | ( 0.0444) | 934 |
| log Services VA share | 0.0024 | ( 0.0193) | 950 |
| log Agriculture VA share | 0.0160 | ( 0.0350) | 974 |

*Notes:* Each row reports the coefficient on the standardized Economic Complexity Index from Equation (D.1), with the named variable as the dependent variable. All regressions include country and period fixed effects, log GDP per capita, log population density, and the Human Development Index. Standard errors clustered by country in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Ten of the eleven coefficients are statistically indistinguishable from zero ($p > 0.10$). Complexity does not, conditional on income and the other controls, raise or lower forest cover, agricultural land, urban land, the rate of deforestation, agricultural TFP, energy consumption, foreign investment, the protected-area share, or the services or agriculture value-added shares. None of these channels can therefore mediate the within-country complexity–RLI association: the first link is absent.

The one channel that complexity does shift is the manufacturing value-added share, which rises modestly with complexity ($+0.08$, $p = 0.07$). This direction is consistent with the composition effect the model assigns to complexity (Lemma 2.1): rising productivity in the knowledge-intensive sector reallocates labor toward manufacturing and away from the land-intensive sector. It is, however, a result we want to be careful about. If a larger manufacturing share carries its own domestic environmental pressure—industrial water use, effluents, or capital-stock-related land take—then the manufacturing margin could in principle constitute a domestic mediation channel that runs alongside the relocation story. The direct test of this concern is whether adding the manufacturing share to the structural RLI regression displaces the complexity coefficient. Table B.3 shows that it does not: the complexity coefficient is $-0.012$ ($p < 0.01$) both with and without the manufacturing share. Whatever domestic pressure the manufacturing margin generates, it is not large enough to absorb the within-country relationship between complexity and the Red List Index.