// NO.25-041 | 08/2025

DISCUSSION PAPER

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Biodiversity Engel Curves: Estimating How Income and Inequality Shape Consumption-Driven Biodiversity Loss

Biodiversity Engel Curves: Estimating How Income and Inequality Shape Consumption-driven Biodiversity Loss

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August 7, 2025

Abstract

We examine the relationship between household incomes and the biodiversity footprints of consumption in the United States from 1996 to 2022. Combining detailed household expenditure surveys with environmentally-extended multi-regional input-output accounting methods, we calculate consumption-based (i) land-use and (ii) species-loss footprints as proxies for overall biodiversity pressure. We find that the average biodiversity footprints of US households declined between 1996 and the early 2010s but began increasing again thereafter, as rising consumption pressure outpaced technological improvements. To characterize the relationship between household income and biodiversity footprints, we construct Environmental Engel Curves (EECs). Just like aggregate footprints, EECs shifted downwards until the early 2010s but have moved upwards in recent years, mainly due to a more biodiversity-intensive composition of expenditures, as we show. Moreover, EECs for land use are concave, implying a "biodiversity-equality trade-off" of moderate size. In 2022, full redistribution to achieve perfect income equality would have raised aggregate land use by 3.2% all else equal, calling for additional efforts to maintain a given biodiversity conservation goal.

Keywords: Biodiversity, Land-use, Consumption, Environmental Engel Curve, Footprint, Inequality, Trade

JEL classification: D12, D31, H23, Q20, Q57

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We are grateful for comments from Alexander Silbersdorff (University of Göttingen) and Sebastian Rausch (ZEW Mannheim & University of Heidelberg), as well as from participants at the EAERE 2025 conference and seminars at iDiv Leipzig, ZEW Mannheim and SOCIUM Bremen. We also thank Julian Rodemann (LMU Munich) for valuable comments on applying non-parametric estimation methods.

1 Introduction

Humanity is witnessing a dramatic and accelerating loss of global biodiversity (Taylor and Weder, 2024; Tittensor et al., 2014). About one quarter of all plant and animal groups are currently threatened to become extinct and around one million will do so within the next decades (Díaz et al., 2019). Biodiversity describes the diversity of ecosystems, animal and plant species, and genes. It stabilizes natural capital stocks and the associated ecosystem services that are fundamental to human well-being. From a welfare perspective biodiversity is at an inefficiently low level (Dasgupta et al., 2021) and further losses have high social cost (e.g., Frank and Sudarshan, 2024). While governments around the world have increased efforts to conserve biodiversity, for example, through protected areas, human pressures on biodiversity, such as land-use change resulting from consumption, are intensifying (Secretariat of the Convention on Biological Diversity, 2020). Halting biodiversity loss therefore requires a structural change in the consumption, production and trade of goods (Díaz et al., 2019).

Biodiversity loss is occurring, and potentially growing more complex, in the context of another global trend: income inequality has been both high and increasing in many industrialized countries over recent decades (Piketty et al., 2017; Saez and Zucman, 2016). In the United States, for instance, the national income share of the richest 10% has risen from around 34% in 1980 to 45% in 2021 (Chancel et al., 2022). This economic inequality is complemented and often reinforced by an environmental inequality from the unequal access to and consumption of environmental goods (Sager, 2022; Meya, 2020).

While both biodiversity loss and inequality feature prominently in political debates, their interplay is not well understood (Drupp et al., 2025). As governments and societies become increasingly committed to both halting biodiversity loss and reducing inequality (e.g. with the UN Sustainable Development Goals), it is important to understand the synergies and trade-offs involved in achieving both goals. To systematically explore this, we estimate for the first time Environmental Engel Curves (EECs) for biodiversity. These Biodiversity Engel Curves (Biodiversity-EECs) characterize the global consumption-embedded biodiversity footprints of US households at different income levels.

Thus far, the empirical relationship between biodiversity, income, and inequality has been examined mainly at the aggregate level, particularly through cross-country analyses (e.g., Halkos, 2011; Kopp and Nabernegg, 2022). EECs based on household-level data have previously been estimated for local air pollutants (Levinson and O'Brien, 2019) and greenhouse gas (GHG) emissions (Baiocchi et al., 2010; Sager, 2019). We build on this work by (i) constructing EECs for consumption-embedded *biodiversity footprints* of US households between 1996 and 2022, and by (ii) assessing the potential impacts of income redistribution measures on aggregate biodiversity pressure. Household-level Biodiversity-EECs allow us to answer the following research questions: (1) How are consumption-embedded biodiversity footprints of US households related to their income? (2) Has this relationship changed over time? (3) How would income redistribution alter the biodiversity footprint of aggregate consumption?

To construct EECs and answer these questions, we combine income and spending data from the US Consumer Expenditure Survey (CEX) with environmentally-extended multiregional input-output (EE-MRIO) analysis using Exiobase 3 (Stadler et al., 2018). EE-MRIO analysis allows us to derive the biodiversity intensities (e.g., $\frac{ha}{USD}$ in the case of land use) of consumption goods, taking into account both *global value chains* and international *trade in final products*. We rely on the quantitatively most important drivers of global biodiversity loss (Díaz et al., 2019): First, we estimate *land-use* intensities of consumption goods since land use is the most important *pressure* on biodiversity loss (Caro et al., 2022; Haines-Young, 2009). Second, we estimate intensities reflecting the *impact* of greenhouse gas as well as sulfur and nitrogen emissions (i.e., terrestrial acidification) on species loss.[1] We match these biodiversity intensities with CEX expenditure data to calculate *consumption-embedded* biodiversity footprints of households. Since land-use and species-loss intensities differ across goods, households' biodiversity footprints depend not only on their total expenditure levels but also on the *composition* of consumption.

Our final sample comprises consumption-based biodiversity footprints for over 200,000 US households observed at different points in time between 1996 and 2022. Simple descriptive analyses yield some striking patterns. Average biodiversity footprints decreased between 1996 and the early 2010s, reaching minima in 2011 or 2013, depending on the biodiversity measure. We show this to be largely thanks to technological progress that lowered the biodiversity-intensity per unit of consumption. However, between 2011 and 2022, average biodiversity footprints have increased. We find that this trend reversal is owed to increasing biodiversity pressure from the scale and composition of consumption, which outpaced technological progress. We observe an especially large jump in biodiversity footprints in 2022, likely the result of the reopening economy after the COVID-19 lockdowns.

We then turn our attention to household-level Biodiversity-EECs for both land use (Land-EEC) as well as climate change and terrestrial acidification impacts on species loss (Species-EEC). We find that Land-EECs are upward sloping and concave, implying that consumption-embedded land use is akin to a normal good (income elasticity > 0) and a necessity (income elasticity < 1). Species-EECs are also upward-sloping, but their curvature is less pronounced and systematic. Overall, since land use is the dominant driver of biodiversity loss (Jaureguiberry et al., 2022), overall biodiversity pressure can be assumed to behave like a necessity, at least in the United States. This mirrors the findings by Levinson and O'Brien (2019) and Sager (2019) who study EECs for local air pollutants and GHG emissions respectively. In line with aggregate biodiversity footprints, EECs shifted downwards between 1996 and 2014, so that biodiversity footprints fell across the entire income spectrum. However, since 2014 EECs have begun shifting upwards again, mainly because of a trend towards a more land-intensive composition of consumption bundles.

Finally, we derive implications of the estimated shapes of EECs for policies targeting income inequality. Since Land-EECs are concave, progressive income redistribution–an income transfer from a richer to a poorer household–mechanically raises the aggregate demand for land use. We quantify this "biodiversity-equality trade-off" for quadratic Land-EECs, predicting that in 2022, a marginal income transfer of USD 1000 from a household at the 75^{th} income percentile (USD 78.2k, after taxes) to a household at the 25^{th} percentile (USD 24.4k) would raise aggregate land-use demand by $80m^2$. Similarly, land use would increase by 3.2% or 1,444m^2 per household under perfect income equality. The size of our estimate is similar to the effect on aggregate GHG emissions estimated by Sager (2019) for US households.

Our paper contributes new micro-level evidence to the literature linking biodiversity loss and (income) inequality, which has thus far mainly focused on the aggregate level.[2] Reviewing the literature on the biodiversity-inequality nexus, Berthe and Elie (2015) find that inequality is associated with negative effects on biodiversity (Halkos, 2011; Holland et al., 2009; Mikkelson et al., 2007). However, recent contributions by Kopp and Nabernegg (2022) and Wilting et al. (2021) suggest that the overall assessment of the inequality-biodiversity nexus is less clear-cut.

We make three main methodological contributions to that literature. First, while applied biodiversity

[1]The methodological difference between "pressures" and "impacts" is described in more detail in Section 3.1 as well as the definite concept of species loss.

[2]To that end, a biodiversity index is usually regressed on a measure of inequality, mostly Gini index, and on additional control variables (of course, applied regression techniques vary between studies). For a compact overview of cross-country analyses that examine the relationship between biodiversity on one hand, and economic as well as institutional development (including GDP, democracy, and inequality) on the other hand see also Table 1 in Gren et al. (2015).

indicators cover only impacts that occur within a specific country or region, we include impacts from consumption by US consumers that occur elsewhere in the world by accounting for both global value chains and trade in final products.[3] This allows us to quantify consumption-embedded *biodiversity footprints of US households* for an extended time period (1996-2022) and for both land use and species loss biodiversity pressure around the globe.

Second, while EE-MRIO has already been extensively used to investigate *aggregate* biodiversity footprints of countries and regions (Irwin et al., 2022; Verones et al., 2017; Wiedmann and Lenzen, 2018; Wilting et al., 2017, 2021), products (Bjelle et al., 2021; Moran et al., 2016) and trade flows (Cabernard et al., 2019; Chaudhary and Brooks, 2019; Chaudhary and Kastner, 2016; Lenzen et al., 2012b), research on the micro household level remains sparse. An important exception is Koslowski et al. (2020) who quantify (consumption-embedded) biodiversity footprints of European households in 2005 and 2010. Focusing on differences between income deciles, Koslowski et al. (2020) find that in 2005 European per capita biodiversity footprints did not differ significantly between income quintiles, while in 2010 the per capita footprints steadily increased from the first to the fifth quintile. While they do not estimate EECs, this hints at upward sloping EECs in 2010, in line with what we find for US households. Here we construct EECs for land use and species loss to describe the relationship between household income and biodiversity pressure, both in an unconditional form and after conditioning on other household characteristics.

Third, while existing regression analysis of the inequality-biodiversity nexus focuses mainly on conditional correlations at the aggregate level (Harbaugh et al., 2002), with results that are sensitive to statistical specifications (see e.g., Pandit and Laband, 2009), we explore a micro-founded mechanism linking inequality to biodiversity pressure through individual household consumption decisions. Formalizing the relationship between household income and consumption with EECs allows us to then *quantify the effect of income redistribution policies* (within the US) on aggregate global biodiversity impacts.

The rest of this paper is organized as follows. Section 2 outlines our conceptual framework. In Section 3, we describe the compilation of the household data and EE-MRIO analysis to obtain consumption-embedded biodiversity footprints. In Section 4 we use simple descriptive EECs to explore time trends in biodiversity footprints and their relationship to income, spending and technology. Section 5 contains a formal exploration of the shape of EECs, both unconditional and conditional, culminating in estimates of the effect of income redistribution on biodiversity pressure. Finally, results are discussed and summarized in Sections 6 and 7.

2 Conceptual Framework

Environmental Engel Curves (EEC)s describe the consumption-embedded environmental footprints of households as a function of their income. EEC are an emerging analytical concept in the study of the inequality-environment nexus (Sager, 2019; Drupp et al., 2025). We construct EECs for biodiversity (Biodiversity-EECs). Following Scruggs (1998) and Heerink et al. (2001) we assume that the biodiversity footprint ($e_{i,t}$) of a household i in year t, is a function of income ($y_{i,t}$) and an idiosyncratic residual term ($\epsilon_{i,t}$):

$$e_{i,t}(y_{i,t}) = f(y_{i,t}) + \epsilon_{i,t} = \alpha(y_{i,t})\, y_{i,t} + \epsilon_{i,t} \tag{1}$$

Here, $\alpha(y_{i,t})$ is the average biodiversity intensity per dollar of spending, which results from the composition of consumption and is itself a function of income. The income elasticity of demand for biodiversity ($\eta_{i,t}$)

[3] Wilting et al. (2021) show that accounting for biodiversity threats exerted abroad can have substantial consequences for estimated biodiversity footprints.

of household i in year t is then given by:

$$\eta_{i,t} := \frac{de(y_{i,t})}{dy_{i,t}} \frac{y_{i,t}}{e(y_{i,t})} \overset{(1)}{=} 1 + \frac{\alpha'(y_{i,t})}{\alpha(y_{i,t})} y_{i,t}, \tag{2}$$

which measures the percentage change in biodiversity pressure for a (one) percentage change of income. Eq. (2) shows that an average biodiversity intensity that falls with income (i.e., $\alpha'(y_{i,t}) < 0$) implies an income elasticity below one (i.e., $\eta_{i,t} < 1$), while $\alpha'(y_{i,t}) > 0$ implies $\eta_{i,t} > 1$. More generally, the shape of EECs is linked to income elasticities as follows.[4] When biodiversity footprints rise with income, EECs are upward-sloping and biodiversity pressure is akin to a *normal good* ($\eta_{i,t} > 0$). In the special case when the relationship between income and biodiversity pressure is proportional, we have $\eta_{i,t} = 1$. On the other hand, if EECs are concave, this implies that average biodiversity intensity falls with income ($\alpha'(y_{i,t}) < 0$) and biodiversity pressure is akin to a *necessity good* ($\eta_{i,t} < 1$).

EECs are a helpful tool in studying the relationship between the distribution of incomes and aggregate biodiversity footprints (E_t), represented as the sum across all N households:

$$E_t = \sum_{i=1}^{N} e_{i,t}(y_{i,t}) \overset{(1)}{=} \sum_{i=1}^{N} f(y_{i,t}) + \epsilon_{i,t} \tag{3}$$

In particular, the degree of income inequality and the effect of income redistribution are linked to aggregate environmental impacts (E_t) through aggregation properties. As shown by Heerink et al. (2001) this is the case if $f(y_{i,t})$ in Eq. (1) is non-linear. Concave EECs (i.e., $f''(y_{i,t}) < 0$) suggest that less inequality is associated with larger environmental pressure from consumption. This is because the *increase in* environmental footprint associated with the extra income of poorer households will be larger than the *reduction* in environmental footprint associated with the income decrease of richer households. The opposite is true for convex EECs with $f''(y_{i,t}) > 0$.

We thus can state a condition for a "biodiversity-equality trade-off"[5]: *If lower income households have a higher propensity for consumption-based biodiversity footprints from additional income (i.e. EECs are concave), then progressive redistribution can raise aggregate consumption-driven impacts on biodiversity.* For convex EECs the reverse is true and one might speak of a "biodiversity-equality synergy".

3 Data and Methodology

We estimate Land-EECs and Species-EECs for US households, pairing information on income and household expenditures from the US Consumer Expenditure Survey (CEX) with good-specific biodiversity intensities calculated using environmentally-extended multi-regional input-output (EE-MRIO) accounting methods. Specifically, we estimate the biodiversity footprint ($e_{i,t}$) of a household i in year t by:

$$e_{i,t} = \sum_{k=1}^{K} b_{k,t} \, c_{i,k,t} \tag{4}$$

with $c_{i,k,t}$ denoting the expenditures (in USD) of household i on consumption item k in year t, and $b_{k,t}$ denoting the biodiversity intensity (land use per USD or species loss per USD) of consumption item k in year t. In a first step, we compute biodiversity intensities for different product-classes employing

[4] Note that the "regularities" described below only strictly hold if $e_{i,t}(y_{i,t}) = f(y_{i,t} = 0) + \epsilon_{i,t} = 0$, i.e., consumers with no income do not generate a biodiversity impact, which is not generally the case.

[5] In light of concave EECs for GHG emissions, Sager (2019) coined this observation the "equity-pollution dilemma".

EE-MRIO analysis using Exiobase tables (Stadler et al., 2018). In a second step, we match these to CEX consumption items.

3.1 Computing Biodiversity Intensities

For the EE-MRIO analysis, we use Exiobase monetary tables v3.8.2 (Stadler et al., 2021) covering 200 product-types across 49 countries (EU28 plus 16 major economies) and 5 rest of the world (RoW) regions. Exiobase tables capture the structure of the world economy by indicating all input flows between country-sectors, total final outputs of country-sectors and composition of final demand. In addition, Exiobase tables include environmental account data (in physical units) for various pressures (e.g., CO_2, land use) and impacts (e.g., human health, biodiversity).

Indicators for Biodiversity Impacts

From Exiobase environmental accounts, we use three indicators as proxies for biodiversity footprints, namely (i) land use (in *ha*), (ii) species loss related to climate change (in *number* of disappearing species), and (iii) species loss related to terrestrial acidification (in *number* of disappearing species). We briefly motivate those measures below.

Land use, on the one hand, is the main driver for current and past biodiversity loss through land cover conversion (e.g., infrastructure, mining, deforestation), changes in management (e.g., due to intensification of agricultural practices) and landscape changes (e.g. fragmentation of habitats) (Jaureguiberry et al., 2022; Caro et al., 2022; Haines-Young, 2009; Díaz et al., 2019; Newbold et al., 2016). Based on the life cycle impact assessment (LCIA) model LC-Impact, Verones et al. (2017) estimate that land use is responsible for about 66% of global species loss. While Exiobase currently does not comprise an impact indicator for the effect of land use on biodiversity change (such as species loss), consumption embedded land use represents a reliable proxy for the biodiversity footprint of US households. Exiobase's initial land-use accounts contain data for agricultural and forestry sectors, which are, by far the most important drivers of land-use related impacts on biodiversity (Green et al., 2019; Tilman et al., 2017; Zabel et al., 2019).[6] In 2022, global land-use cover amounted to 5bn hectares of which 98% is used for agriculture and 2% for built-up area (Ritchie and Roser, 2019).

For climate change and terrestrial acidification, on the other hand, direct impact indicators on biodiversity are available at the species level.[7] Species loss is measured as the absolute number of endemic species going extinct. Impacts account for the damage to (terrestrial) ecosystems and are computed based on ReCiPe 2008, a life cycle impact assessment method modeling the effects of environmental pressures (e.g. land use, CO_2, SO_2) on endpoint indicators for human health, ecosystems and resource availability (Goedkoop et al., 2008).[8] For the climate change pathway, ReCiPe 2008 estimates the effect of greenhouse gases on global temperature. Subsequently, the authors employ the estimates of Thomas et al. (2004) to model the impact of global temperature increases on species loss in specific areas. Accordingly, species

[6]Agricultural land-use changes affect biodiversity loss mainly via the conversion of natural land for pasture and crop production, intensification and changes in agricultural practices (Kleijn et al., 2008; Meehan et al., 2011; Allan et al., 2015; Chaplin-Kramer et al., 2015; Joppa et al., 2016; Díaz et al., 2019; Zabel et al., 2019). Since 1600 the land area used for agricultural production has increased by about 5.5 times occupying more than one third of the total terrestrial area and about half of the global habitable land (Kok et al., 2020; Poore and Nemecek, 2018).

[7]After land use, climate change is considered as the most important threat for biodiversity, notably through future changes in temperature, seasonality and precipitation (Thomas et al., 2004; Díaz et al., 2019).

[8]ReCiPe is recommended by the International Reference Life Cycle Data System (ILCD) as default LCIA method for modeling the impacts of climate change and acidification on ecosystems (at endpoint level) (IES, 2011). Note however that ReCiPe 2008 is a rather early LCIA method and considered as an interim solution by IES (2011). Correspondingly, Goedkoop et al. (2008) remark that their estimates might rather overestimate the reality when comparing their results with other studies. However, since we are mainly interested in the (relative) change of biodiversity impacts with changing income, this is less of a concern for our analysis.

Table 1: Summary Statistics - Interview and Diary Survey

	Mean	SD	Min	Max
Diary Survey (n = 132,118), 1996-2022				
Income before tax (k 2010 USD)	56.45	47.67	8.53e-04	390.69
Income after tax (k 2010 USD)	52.68	42.24	0.69	260.46
Expenditures (k 2010 USD)	31.81	47.49	0.08	3931.16
Age (household head)	49.75	17.55	15	94
Family size	2.52	1.47	1	24
Land use (ha, closed)	2.79	3.53	0.001	268.72
Land use (ha, open)	3.35	4.2	0.001	282.93
Land use (ha, open+trade)	3.93	4.74	0.002	293.35
Interview Survey (n = 106,823), 1996-2022				
Income before tax (k 2010 USD)	62.1	50.55	8.05e-04	408.57
Income after tax (k 2010 USD)	57.54	44.46	0.7	271.65
Expenditures (k 2010 USD)	48.88	36.62	1.58	1796.22
Age (household head)	52.57	17.03	15	94
Family size	2.52	1.49	1	16
Species loss Climate Change (open+trade)	2.15e-04	1.34e-04	2.55e-06	3.18e-03
Species loss Acidification (open+trade)	1.34e-06	7.57e-07	8.15e-09	1.52e-05
Species loss CC & acidification (open+trade)	2.16e-04	1.35e-04	2.56e-06	3.19e-03

Note: Consumption-embedded land-use and species-loss footprints of households estimated as described in Section 3 (using Exiobase EE-MRIO tables v.3.8.2). Species-loss footprints are displayed for consumption-embedded impacts of (i) acidification, (ii) climate change (CC), and (iii) aggregate impacts of both. Other variables are from US CEX. Household weights provided by CEX applied.

loss can be interpreted as number of species disappearing from the regions investigated in Thomas et al. (2004), which sample approximately 20% of the Earth's terrestrial surface.[9] Similarly, ReCiPe 2008 models the impact of acidifying substances (NOx, NH3, and SO2) on the number of disappeared species based on estimates for European forests following van Zelm et al. (2007). In a final step, we merge species-loss estimates related to climate change and terrestrial acidification into a single indicator (see "Species loss CC & acidification (open+trade)" in Table 1).

Environmentally-Extended Input-Output Analysis

To calculate biodiversity intensities, i.e. the footprints per USD, for various product-classes and years, we employ EE-MRIO analysis in the tradition of Leontief (1970).[10] We start by preserving the vector of *total biodiversity intensities* of final demands for all 9,800 Exiobase country-sectors $\boldsymbol{b} = \boldsymbol{L'}\ \boldsymbol{s}$, where $\boldsymbol{L'}$ is the transpose of the Leontief matrix $\boldsymbol{L}$, reflecting the input-output structure of the economy (in EUR), and $\boldsymbol{s}$ is the vector of *direct* biodiversity intensities of sectors. This ensures that intensities account for biodiversity impacts along the entire *global value chain*. The vector $\boldsymbol{s}$ contains for all sectors land-use intensities ($\frac{ha}{EUR}$) respectively species-loss intensities from climate change and acidification ($\frac{number}{EUR}$).

Next, we estimate total biodiversity intensities for each sector-type. This is done by computing the weighted sum of all intensities of the same sector-type, where the weights are the sectors' shares in the provision of total final demand by US households. Taken together, computed intensities of product-classes thus consider *global value chains* and *trade in final products* (*open+trade*).

[9] Thomas et al. (2004) evaluate the extinction risk for various regions and species. Their study predicts, "on the basis of mid-range climate-warming scenarios for 2050, that 15–37% of species in our sample of regions and taxa will be 'committed to extinction'". The sample includes the regions Australia, Brazil, Europe, Mexico, Queensland, and South Africa as well as species like mammals, birds, frogs, reptiles, butterflies and plants. Furthermore, their "approach has been validated by successfully predicting distributions of invading species when they arrive in new continents and by predicting distributional changes in response to glacial climate changes".

[10] For a detailed discussion of EE-MRIO analysis the reader is refereed to Kitzes (2013). Tukker and Dietzenbacher (2013) and Inomata and Owen (2014) give a comprehensive overview of databases covering their construction as well as limitations.

We construct two further vectors of *total biodiversity intensities* (for details see Appendix A.1.1). First, we consider global value chains with trade in intermediates, but no trade in final products (*open*). To that end, we extract the intensities of *US sectors* from the vector of *total biodiversity intensities* $\boldsymbol{b}$. Second, we consider only emissions of US sectors and assume a closed economy supply chain (*closed*). Table 1 shows that moving from the assumption of a *closed* to an *open* economy increases the average estimate of yearly consumption-embedded land use from 2.79 ha to 3.35 ha (over the entire 1996-2022 sample period). When also considering trade in final products (*open + trade*) the average land-use footprint of households grows to 3.93 ha.

In addition to computing biodiversity intensities for Exiobase product-types, we also compute them for "Classification of individual consumption by purpose" (COICOP) categories, which are used as standardized consumption categories in European consumer surveys. To do so, we employ a bridge table constructed by Ivanova and Wood (2020) specifying for each COICOP category how much input it receives from which Exiobase sector. This refinement helps us to more clearly link individual expenditure items in the CEX data to appropriate biodiversity intensities (see Section 3.2). In the following, we will refer to Exiobase product-types and COICOP categories together as *product-classes*.[11] Finally, we convert biodiversity intensities of product-classes from per EUR into per USD terms using annual Euro/ECU exchange rates by Eurostat (2022). The entire EE-MRIO analysis is described in Appendix Section A.1.1.

3.2 Household Income and Biodiversity Footprints

After calculating biodiversity intensities for 264 product-classes, we combine them with household expenditure data from the US consumer expenditure survey (CEX) following Eq. (4) and derive household biodiversity footprints. The CEX is a nationwide survey conducted by the U.S. Bureau of Labor Statistics (BLS) collecting expenditures (identified by a universal classification code, UCC) and income data as well as demographic characteristics, on a household level (BLS, 2018). The CEX consists of two separate surveys, the Interview Survey and the Diary Survey, which cover together the entire range of consumer expenditures. The Interview Survey quarterly collects expenditures that are either relatively large like major appliances, automobiles, and property, or occur on a fairly regular basis like utilities and rent, which account for 60% to 70% of total household expenditures. In addition, the Diary Survey interviews households in two consecutive one-week periods to collect detailed data on small and frequently purchased items that may be difficult to recall like food expenses, clothing items, nonprescription drugs and personal care products.[12]

Combining Biodiversity Intensities with Household Data

We assign all consumption item categories (UCCs) contained in the surveys (ca. 1000 in total) to one of the 265 product-classes, either Exiobase product-type or COICOP consumption category, and its corresponding biodiversity intensity (see Table A6). In some cases, COICOP categories present a better match to a UCC than Exiobase product-types. For instance, Interview UCC "average food expenses" is better matched to the weighted food category of COICOP than to a specific food sector in Exiobase. After matching, annual household biodiversity footprints are calculated as described in Eq. (4). In addition, we

[11] To prevent confusion with upcoming terms with respect to sectors, products, etc., we give a short overview: (i) (Exiobase) country-sector: Sector of type x in a particular country l (e.g., construction sector in Germany). (ii) Exiobase product-type/ sector-type (terms are used interchangeably): In contrast to a particular country-sector, product-type refers to the general sector/ product (e.g., construction work). In particular, we finally compute biodiversity intensities for product-types (which are weighted averages of country-sector intensities of the same product-type). (iii) COICOP categories: Product classification categories of COICOP (for which we compute biodiversity intensities analogous to Exiobase product-types). (iv) Product-class: Includes both, Exiobase product-types and COICOP categories.

[12] More details on scope of Diary and Interview Survey as well as how data was processed can be found in Appendix Section A.1.2.

compute two further hypothetical household biodiversity footprints i.e., if technology remained constant on the level of (a) 1996 and (b) 2022. This is simply done by multiplying household expenditures with the biodiversity intensities of 1996 respectively 2022 (instead of using the intensities of the actual year).

Diary and Interview portions cover, in parts, different consumption items and use different household samples which is why they can not be merged into one dataset on the household level. While both portions overlap in large parts, neither one is designed to present a full account of expenditures. We thus match expenditures as follows. Since *land-use* intensities of product-classes consider (direct and indirect) land use of *agricultural and forestry sectors only*[13], they are most relevant for food and beverage products.[14] In contrast, species-loss estimates related to climate change and terrestrial acidification are based on direct intensities vectors with data available for all types of Exiobase sectors. Consequently, we combine (a) *land-use intensities* with expenditures of the *Diary Survey* (covering more detailed food categories) and (b) *species-loss intensities* with expenditures of the *Interview Survey* (covering a larger share of the consumption basket). Applying Eq. (4) with (a) land intensities ($\frac{ha}{USD}$) to the Diary Survey gives us an estimate of household total land-use footprint associated with direct and indirect consumption of agricultural and forestry products. Whereas applying Eq. (4) with (b) species loss as biodiversity indicator to the Interview Survey, results in an estimate of household total impact on species loss associated with overall consumption-embedded climate change and terrestrial acidification emissions. Moreover, corresponding Environmental Engel Curves are related either to (a) land use of households' "everyday expenditures" (mostly food) with a refined distinction of these items (hereafter denoted by Land-EEC), or (b) climate change and terrestrial acidification impacts on species loss embedded in (almost) all household expenditures (Species-EEC).

3.3 Final Sample

We combine the calculated household biodiversity footprints with data on incomes and socio-demographic characteristics. Income and other monetary variables are converted from nominal into real terms using consumer price indices (base year 2010) (World Bank, 2022). Household income and other characteristics are in line with data officially published by the U.S. Bureau of Labor statistics (BLS) based on CEX (BLS, 2013).[15] In the CEX Diary surveys, the after-tax variable is only available through 2014, as detailed tax information was no longer collected afterwards. From 2015 on, we thus impute after-tax household income using a multiple imputation approach based on random forest models (see Appendix A.1.3 for details). We restrict the sample to households with a positive after and before tax income. Moreover, we drop observations with negative yearly biodiversity footprints, most likely due to "negative expenses" by self-employed individuals. Since CEX is not representative for households in the tails of the income distribution, we trim observations with the top and bottom 2% of after-tax income within each year. The final sample covers all years from 1996-2022, with 132,118 households for Land-EECs (Diary Survey) and 106,823 households for Species-EECs (Interview Survey). Summary statistics of key variables are presented in Table 1.

Mean consumption-based land use of US households (over the 1996 to 2022 sample period) is 3.93 ha per year. When dividing that by the average family size, we obtain a per capita land-use footprint of

[13]Exiobase contains direct *land* intensities only for agricultural and forestry sectors. The resulting *total land intensities* computed for *all* Exiobase sectors must thus be interpreted as intensities considering all direct and indirect inputs from *agricultural and forestry sectors (only)*. Furthermore, after 2011 land-use accounts in Exiobase v3.8.2 are now-casted implying a lower reliability for these years.

[14]This can also be seen in Table A6 showing that land-use intensities are the highest for agriculture and forestry and related product-classes like charcoal.

[15]For 2011, BLS (2013) reports an average age of household reference person of 49.7 years (compared to 50.8 in our combined sample for 2011), average family size of 2.5 (compared to 2.5 in our sample) and average household before-tax income of USD 63.69k (compared to USD 60.7k in our sample).

1.56 ha for the entire period (1996 to 2022) and 1.88 ha in 2001 (1.8 ha in 2022), broadly in line with previous estimates.[16] Average consumption-embedded species loss of US households through climate change and terrestrial acidification (1996 to 2022) is 2.16e-04 units. However, total figures are subject to limitations as no harmonization between total expenditures, implied by household level data, and total final US demand, implied by Exiobase, was applied.[17] Since we are mainly interested in *relative* changes of biodiversity footprints (over time and with changing income), this is less of a concern in the present analysis.

4 The shapes and shifts of Biodiversity Engel Curves

In this section we present Environmental Engel Curves (EEC) for biodiversity over 1996 to 2022. We focus on simple descriptive curves that show average biodiversity footprints across income deciles. This allows for impartial inspection without assuming any specific functional form of the income-biodiversity relationship. Already some interesting insights emerge, both in terms the shape of Biodiversity-EECs and their shift over time.

4.1 Insights from descriptive EECs

We begin by plotting descriptive, non-parametric EECs, following the earlier examples of EECs for emissions of greenhouse gases and local air pollutants (Sager, 2019; Levinson and O'Brien, 2019). Specifically, we plot in Figure 1 the average household biodiversity footprint (open+trade) at each income decile for the years 1996, 2005, 2014, 2019 and 2022.[18], suggesting the following insights:

1) **Biodiversity-EECs are upward sloping:** While there are some small non-monotonicities, consumption-embedded biodiversity footprints tend to rise with increasing income suggesting that biodiversity is a normal good (i.e., $\eta_{i,t} > 0$).
2) **Biodiversity-EECs tend to be concave:** The ratios of land-use and species-loss footprints relative to income tend to fall with increasing incomes (i.e., $\eta_{i,t} < 1$) suggesting that "biodiversity consumption" is a necessity good.[19] We will investigate the curvature of EECs in more detail below (Section 5).
3) **Biodiversity-EECs first shift down, then up:** For all income levels, average household biodiversity footprints were lower in 2014 than in 1996. However, this trend seems to have reversed and the curves in 2022 are again higher than in 2014.

These results are similar to those by Sager (2019) and Levinson and O'Brien (2019) who also found upward-sloping and concave EECs for GHG emissions and local air pollutants between 1996-2009 and 1984-2012 respectively. However, the two aforementioned studies found EECs that consistently shifted downwards over time. This contrasts with our findings that, while Biodiversity-EECs shifted down between 1996 and 2014, they have shifted up between 2014 and 2022. We now investigate this reversal in more detail.

[16] Wilting and Vringer (2009) find a per capita consumption-based land use of slightly below 3 ha for the US in 2001, while Ivanova et al. (2015) find a land footprint related to household consumption of 2.4 ha for the US in 2007.

[17] See e.g., Ivanova and Wood (2020)

[18] 1996 and 2022 are the first and last years included in our sample. We also show 2019 as the last year before the COVID-19 pandemic, and 2014 as the last year without income imputation in the CEX Diary survey. 2005 is the mid-point between 1996 and 2014.

[19] Of course, households do not directly choose to consume biodiversity but rather the goods and service that come along with biodiversity impacts. Hence, a more precise statement might be that goods and services related to relatively more biodiversity impacts tend to be necessities, on average.

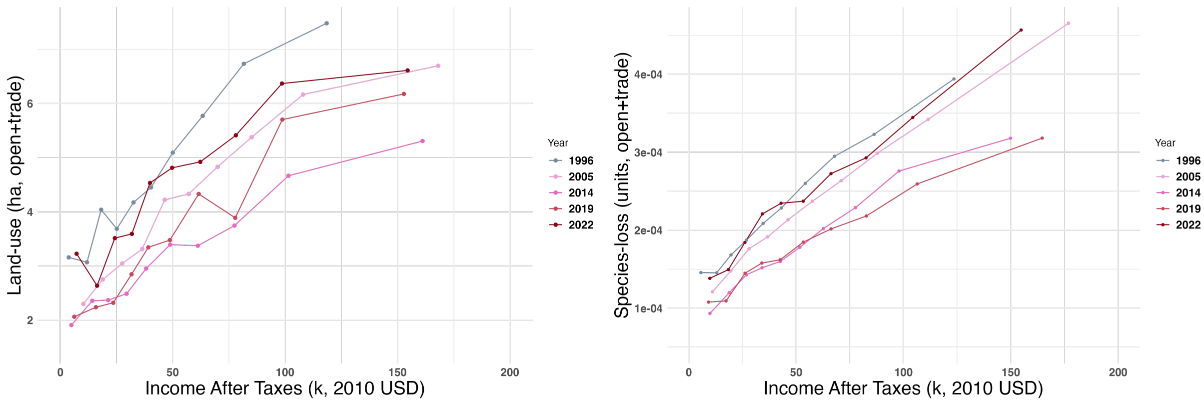


Figure 1: Descriptive Environmental Engel Curves for Land use (Land-EEC) and Species loss (Species-EEC)

Notes: Binned scatterplots of average household biodiversity footprints (Land-use and Species-loss, open+trade) by income deciles (2010 USD). Consumption-embedded land-use and species-loss footprints calculated as described in Section 3 (using Exiobase EE-MRIO tables v.3.8.2). Household weights provided by CEX applied.

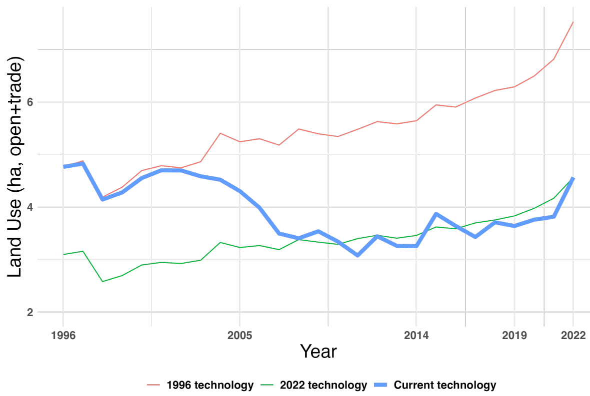
4.2 The race between consumption and technology

We have seen that both Land-EECs and Species-EECs were continuously shifting downwards between 1996 and 2014. In other words, for all income levels, households' biodiversity footprints were, on average, lower in 2014 than in 1996, decoupling consumption growth from biodiversity impacts. Since then, however, EECs shifted up again, so that EECs in 2022 are at similar levels as in 1996. The trend reversal mirrors the overall biodiversity pressure from consumption, which is the average of the 10 deciles within each year. As shown in Figure 2 (blue line), the biodiversity impact from consumption by US consumers follows a U-shaped pattern, falling between 1996 and the early 2010s, and rising thereafter until 2022. Specifically, land-use demand reached a minimum in 2011 while species-loss footprints did so in 2013. For example, the average land-use footprint (open+trade) of households fell from 4.76 ha in 1996 to 3.26 ha in 2014, it increased again to 4.56 ha in 2022 (see Appendix Table A5).

These trends in mean biodiversity footprints are driven by changes in both the scale and composition of consumption, as well as the biodiversity intensity of production (i.e. technology). To separate consumption and technology channels, Figure 2 shows hypothetical biodiversity footprints holding technology constant at either 1996 (red) or 2022 (green) levels. These lines slope up more consistently, suggesting that changes in consumption continuously contributed to higher biodiversity pressure over the entire sample period (since 1998 for land use).

The downward trend in average biodiversity footprints between 1996 and the early 2010s was the result of continued improvements in technology, producing given goods and services in less biodiversity-intensive ways. For example, while actual average land use fell slightly from 4.76 ha in 1996 to 4.56 ha in 2022, they would have increased to 7.53 ha if land-use intensities had remained at 1996 levels. Similarly, if 2022 technology had been available already in 1996, average land-use footprints would have been 35% lower (-1.66 ha). Starting in the early 2010s technological improvements no longer sufficed to counter the continued increase in biodiversity pressure from consumption, and average biodiversity footprints began to rise.

A final noteworthy point is the recent uptick in biodiversity pressure from household consumption in 2022 (even relative to 2021). Figure 2 suggests that this came from a combination of consumption and technology shocks in the direction of higher biodiversity pressure. One plausible explanation might be the increase in demand following the COVID-19 lockdown period in 2020 and 2021, as well coinciding



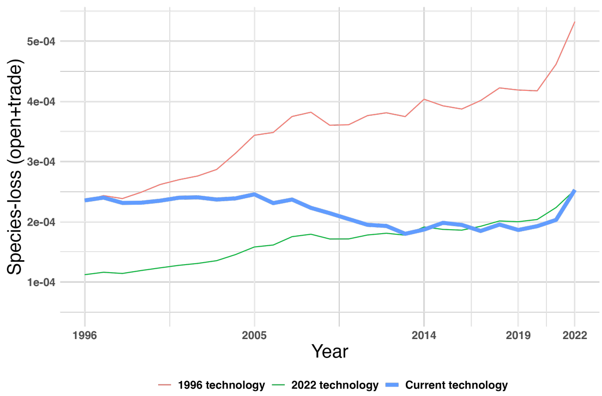


Figure 2: The race between consumption and technological progress
Notes: Average household land use (left) and species loss (right) footprints by year. For 1996/2022 technology estimates, households' expenditures of each year were linked to land-use/species-loss intensities of product-classes of the year 1996 respectively 2022. Current technology estimates result from linking expenditures with the land-use/species-loss intensities of the same year when they actually occurred. Household weights provided by CEX applied.

supply chain shocks. Albeit worrying, future work will be needed to confirm whether this is a persistent or temporary phenomenon.

4.3 Shifts of EECs: The role of technology, savings and composition

We have seen that both average biodiversity footprints and biodiversity-EECs experienced downward shifts from 1996 to the early 2010s, but started rising again thereafter. Focusing on the case of land use, we now explore the contribution to the shifts in EECs from three potential developments:

1) Technological change: Decreasing biodiversity intensity ($\frac{ha}{USD}$) of consumption items, the same output is produced with less biodiversity impacts (comprising direct biodiversity impacts in the production process as well as changes in value chains).
2) Savings effect: Households' expenditures per USD income in-/decreased.
3) Composition effect: Households shifted to more/less biodiversity-intensive consumption baskets.

Figure 3 explores the roles of these potential ECC shifting drivers. Panel 3A shows Land-EECs for 1996 and 2022 based on income quintiles (analogous to Figure 1). Panel 3B shows that Land-ECCs would have actually moved upwards if technology had remained constant on 1996 level. In other words, at a given income level (inflation-adjusted) and holding technology constant, households had more land-use intensive consumption habits. We next look at the role of spending vs. savings behavior. Panel 3C illustrates that total expenditures per income decreased (i.e., savings ratio increased) at all income levels. In other words, the upward pressure on EECs did not primarily come from a tendency to spend more at a given income. In contrast, Land-EECs are clearly pushed *upwards* by changes in the composition of consumption baskets. Panel 3D shows that the average land-use intensity increased at every expenditure level and holding technology constant. This indicates that the composition of household consumption shifted towards more land-use intensive products.

Taken together, our analysis suggests that decreases in land-use footprints between 1996 and the early 2010s (Figure 2) were thanks to technological progress and increasing savings rates, and despite of more land-use intensive consumption baskets. But since 2014, the composition effect dominated, putting upward pressure on EECs. Combining the upward-shift in EECs with (moderate) increases in real after-tax incomes led to the higher average land-use footprint observed in Figure 2.

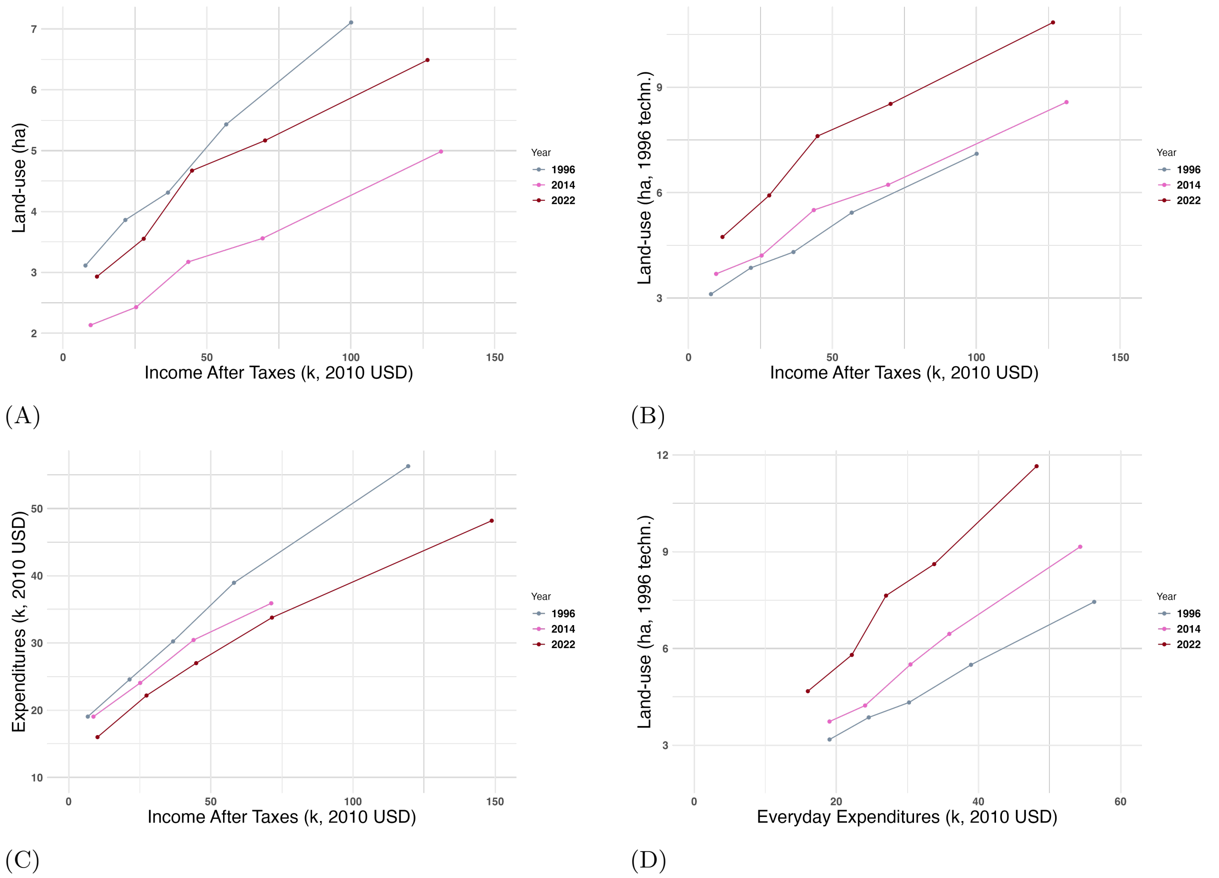


Figure 3: Shift of ECCs over Time – Technology, Savings and Composition Effects

Notes: Binned scatterplots by quintile (income or expenditure, 2010 USD) for (A) household income and land use, (B) income and land use at constant 1996 technology, (C) income and consumption expenditures, and (D) expenditures and land use at constant 1996 technology. Panel A is equivalent to Figure 1 but using income quintiles. All measures of land use are "ha, open+trade". Household weights provided by CEX applied.

4.4 Product-specific contributions to land-use pressure

Finally, it is worth pointing out that, while we focus mainly on aggregate biodiversity footprints of total consumption expenditures, the various components of household consumption contribute to biodiversity pressures in different ways. In particular, our results confirm the outsize contribution of food products in average land-use footprints of US households. As shown in Figure 4, food persistently contributes the bulk of consumption-induced land-use change. In 2022, the contribution of food exceeded 70% (3.3 ha out of 4.6 ha), half of which came from beef and other meat/animal products alone. Figure 4 also suggests that a substantial portion of the upward trend in land-use footprints since the early 2010s can be linked to food consumption. The right panel shows major components of Land-EECs for 2014. The land-use pressure linked to food consumption also appear somewhat more concave than that of non-food consumption. Food expenses have less weight in Species-EECs, which may go some way towards explaining why Species-EECs are less concave than Land-EECs. However, disaggregating biodiversity pressures by product categories in this way relies strongly on the comparability of product-level biodiversity intensities within the data, which is why we maintain a focus on aggregate biodiversity pressure for the remainder of the analysis.

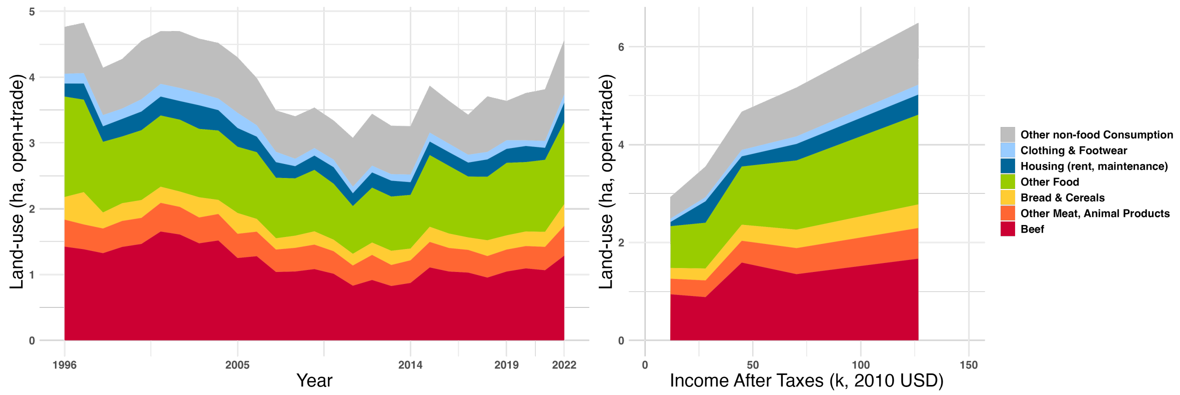


Figure 4: Composition of average land-use footprints over 1996-2022 and Land-EEC in 2022
Notes: Binned area plots of average household land-use footprints (ha, open+trade) by major expenditure categories over time [left panel] and in 2022 by income quintiles (2010 USD) [right panel]. 'Other Meat, Animal Products' includes 'Meat', 'Fish products', 'Products of meat pigs', 'Meat products nec', 'Milk. cheese and eggs', 'Dairy products'. 'Other Food' includes 'Sugar. jam. honey. chocolate and confectionery', 'Non-alcoholic beverages', 'Food products n.e.c.', 'Vegetables, fruit, nuts', 'Food products n.e.c.', 'Oils and fats', 'Alcoholic beverages', 'Catering services', 'Processed rice'. 'Other non-food Consumption' includes all other expenditures included in the CEX Diary Survey as described in Section A.1.2. Consumption-embedded land-use footprints calculated as described in Section 3 (using Exiobase EE-MRIO tables v.3.8.2). Household weights provided by CEX applied.

5 The curvature of Biodiversity Engel Curves and Inequality

The descriptive discussion above has focused on trends in average biodiversity footprints of US households, as well as shifts over time in Environmental Engel curves (EECs) depicting the relationship between household income and consumption-based biodiversity pressure. We now turn to a more thorough analysis of the curvature of EECs, which relates income *inequality* and environmental pressure (Sager, 2019; Drupp et al., 2025). To do so we first estimate parametric versions of EECs that allow us to pin down a functional form and to control for various household characteristics. Once we are confident in the shape of EECs we discuss implications for income redistribution.

5.1 Parametric EEC

To capture non-linear patterns in the relationship we run ordinary least squares (OLS) with second-order polynomials for household income.

$$e_{i,t} = \beta_{0,t} + \beta_{1,t} y_{i,t} + \beta_{2,t} y_{i,t}^2 + \theta'_{i,t}\delta_t + \epsilon \tag{5}$$

For each yearly cross-section, we estimate a linear regression model with consumption-embedded biodiversity footprint ($e_{i,t}$) of household i as outcome variable. The main explanatory variables are household real after-tax income, $y_{i,t}$ as well as its square $y_{i,t}^2$. Covariates $\theta_{i,t}$ included in the 'full' specification include family size, squared family size, household head age, household head age squared, marital status (binary) as well as categorical race, education and region variables. Including these controls gives us the partial association between consumption-embedded biodiversity footprints and income holding other household characteristics constant. These models may be more appropriate when considering the short-term relationship between income and biodiversity footprints, since household characteristics like educational level are expected to remain constant. Models without these controls, on the other hand, may be more relevant when considering long-term, structural redistribution policies which can simultaneously affect income and e.g. educational attainment.

Table 2: Parametric Regressions of quadratic Land-EECs for 1996, 2014 and 2022

	(1)	(2)	(3)	(4)	(5)	(6)
	1996	1996 full	2014	2014 full	2022	2022 full
Income (k USD)	578.69***	283.97***	353.18***	188.17***	525.39***	279.77***
	(55.31)	(58.79)	(30.12)	(31.08)	(55.20)	(72.17)
Income squared	−1.39***	−0.21	−0.79***	−0.27*	−1.51***	−0.74**
	(0.46)	(0.46)	(0.17)	(0.16)	(0.31)	(0.34)
Controls included	NO	YES	NO	YES	NO	YES
Num. obs.	3996	3996	4836	4836	4959	4959
R^2	0.11	0.19	0.09	0.16	0.04	0.08
Adj. R^2	0.11	0.18	0.09	0.16	0.04	0.07

Notes: Estimates from heteroscedasticity-consistent OLS regression following Eq. 5 for Land-EECs in 1996, 2005, 2022. In all specifications dependent variable is consumption-embedded land-use (m2, open+trade) calculated as described in Section 3 (using Exiobase EE-MRIO tables v.3.8.2). Other variables are from US CEX. 'full' columns denote specifications including controls for family size, squared family size, household head age, household head age squared, marital status (binary) as well as categorical race, education and region variables. Robust standard errors in parentheses. Household weights provided by CEX applied. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Parametric estimates of quadratic EECs for the years 1996, 2005 and 2022 are presented in Tables 2 and 3. We begin by discussing the results for land use in Table 2. In all specifications across all years there is a positive association between household income and land-use footprints. Looking at unconditional estimates in 2022, shown in Column (5), additional USD 1,000 of income are associated with a 525 m^2 increase of consumption-based land use impact. At least, this is the marginal association at the 0 income level. As the negative coefficient on income squared suggests, the increase will diminish as income rises. In particular, an additional USD 1,000 of income are associated with an additional 374 m^2 of land use for households with USD 50k of income (525 + 2 × -1.51 × 50), and only an extra 223 m^2 at incomes of USD 100k. In other words, the marginal propensity to convert additional income into additional land use is falling, and Land-EECs are concave. Land use is a normal good (i.e., constantly increasing demand with increasing income, $\eta_{i,t} > 0$) behaving like a necessity ($\eta_{i,t} < 1$).[20]

EECs are concave in all three years, and both with and without covariates. Still, there are some differences across the columns in Table 2. Perhaps most strikingly, it appears that controlling for other household characteristics attenuates both the slope and the curvature of EECs, as both the coefficients for income and income squared are roughly cut in half.

Table 3 shows equivalent results with species loss as dependent variable. While the negative coefficients on income squared in the unconditional models suggest a concave relationship in all years, results become largely inconclusive when adding covariates. Most notably, the positive coefficient in the full specification in 2022 even suggests a convex relationship.

[20] Technically, the quadratic EEC estimates suggest a turning point at around USD 180k after which land-use footprints fall with income. However, this is at the upper end of our sample with very few observations exceeding that income level.

Table 3: Parametric Regressions of quadratic Species-EECs for 1996, 2005 and 2022

	(1) 1996	(2) 1996 full	(3) 2014	(4) 2014 full	(5) 2022	(6) 2022 full
Income (k USD)	2.8e-06***	1.4e-06***	2.4e-06***	1.5e-06***	2.2e-06***	8.4e-07***
	(1.9e-07)	(2.0e-07)	(1.2e-07)	(1.3e-07)	(2.6e-07)	(2.8e-07)
Income squared	-4.4e-09***	1.0e-09	-4.9e-09***	-1.9e-09**	-3.9e-10	3.9e-09**
	(1.5e-09)	(1.4e-09)	(7.9e-10)	(8.0e-10)	(1.9e-09)	(1.9e-09)
Controls included	NO	YES	NO	YES	NO	YES
Num. obs.	3160	3160	3461	3461	2465	2465
R^2	0.38	0.50	0.41	0.49	0.30	0.36
Adjusted R^2	0.38	0.50	0.41	0.49	0.30	0.36

Notes: Estimates from heteroscedasticity-consistent OLS regression following Eq. 5 for Species-EECs. In all specifications dependent variable is consumption-embedded species loss (open+trade) calculated as described in Section 3 (using Exiobase EE-MRIO tables v.3.8.2). Other variables are from US CEX. 'full' columns denote specifications including controls for family size, squared family size, household head age, household head age squared, marital status (binary) as well as categorical race, education and region variables. Robust standard errors in parentheses. Household weights provided by CEX applied. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

5.2 Biodiversity Impact and Income

Summarizing the curvature discussion on parametric EECs from above, we find that:

1) All EECs are upward sloping. This is independent of year, biodiversity indicator, or model specification.
2) Land-EECs are consistently concave, both in unconditioned and conditioned versions.
3) The curvature of Species-EECs is less consistent, with conditioned Species-EECs beeing rather linear and sometimes even convex (e.g. in 2022).

Overall, the curvature of Land-EECs is consistent and robust. They are concave. This is not merely a feature of our second degree polynomial regression specification, as can be seen in Figure 5 which compares the quadratic model fit with one of a more flexible, non-parametric generalized additive model (GAM) (Wood, 2008). Appendix results further support this assessment. In Appendix Section A.2 we examine alternative polynomial specifications in further detail by deploying generalized cross-validation (GCV) and cubic specifications. For Land-EECs the suggested polynomial degree by GCV varies between two and three depending on year and specification (with or without covariates). Particularly in recent 2022, GCV suggests that land-use footprints are quadratic in income. Moreover, cubed terms are negligible small and mostly not significant at any conventional level, especially in recent years (see Table A2). While the exact curvature of Land-EECs changes somewhat over time, and generally becomes less curved when including household covariates, they remain concave. Meanwhile the curvature of Species-EECs is less pronounced, and appears to change over time, with unconditioned Species-EECs becoming linear in 2022 (see Figure 5) and conditioned Species-EECs even appearing convex (see Table 3).[21]

Furthermore, in Section 2 we have shown that upward sloping and concave EECs imply that biodiversity is a normal good acting like a necessity (i.e., $0 < \eta_{i,t} < 1$). Given that Species-EECs tend to be linear while Land-EECs are concave, drawing a conclusion on the relationship between income and biodiversity consumption is not straightforward. However, when considering that land use is the primary driver of biodiversity loss, it is reasonable to conclude that an aggregate EEC for biodiversity (the "Biodiversity Engel Curve") takes on a concave shape as well. Hence, like GHG emissions and air pollutants (Sager, 2019; Levinson and O'Brien, 2019), we can assume consumption-embedded biodiversity to behave like a normal and necessary good. Although not surprising in the light of previously derived EECs, this finding

[21]These conclusions are also supported by GCV scores and cubic specifications of Species-EECs (see Appendix Section A.2).

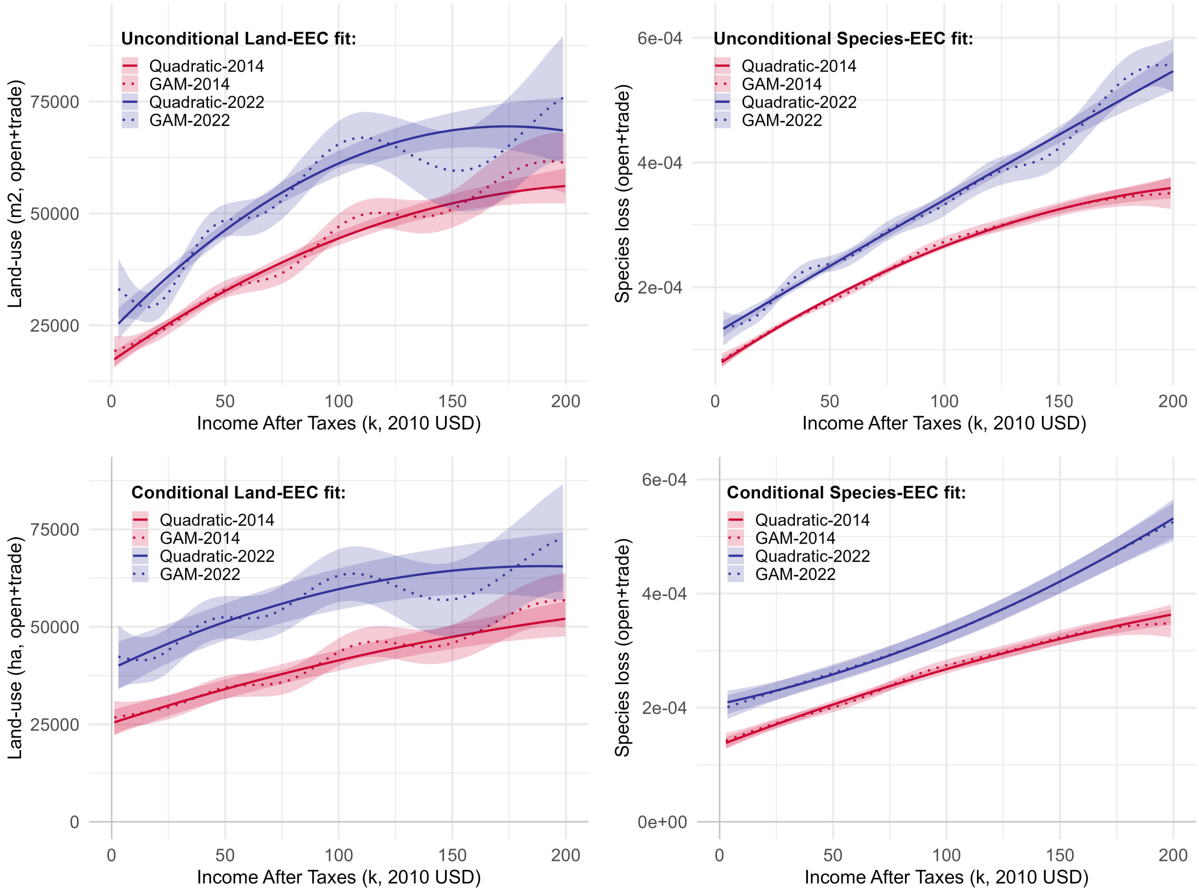


Figure 5: The curvature of biodiversity Engel curves in 2014 and 2022
Notes: Comparison of quadratic fit and non-parametric (Generalized Additive Model, GAM) to describe relationship between real after-tax income (2010 USD) and household biodiversity. 'Conditional' models include household characteristics as covariates.

stands in contrast to the results of Bjelle et al. (2021). The authors conducted a panel regression analysis on the country-level linking GDP per capita to biodiversity footprints of nations for the period 2005 to 2015. Splitting the sample into three regional quantile groups, they find that consumers in high-income countries have an income elasticity for biodiversity above unity. This would suggest that embedded biodiversity behaves like a *luxury* good (i.e., $\eta_{i,t} > 1$). Using micro household data for the US, we can not confirm their finding but instead find evidence pointing in the opposite direction.

5.3 Estimating the effect of income redistribution on biodiversity

Comparing the different scopes of Land-EECs and Species-EECs (Section 5.1), we can differentiate how inequality impacts biodiversity by year and driver (land use vs. acidification and climate change). Land-EECs capture the land-use footprints of everyday expenditures. Our results suggest that these are upward-sloping and concave. Species-EECs capture the effects of *climate change* and *terrestrial acidification* on species loss. Their curvature is less pronounced. The relationship between income inequality and land use pressures seems thus more robust. Below, we quantify the magnitude of a "biodiversity-equality trade-off" implied by the concave Land-EECs.

5.3.1 Marginal redistribution

Assuming quadratic forms of Land-EECs, the change in aggregate land use in year t when transferring a marginal unit of income from household j to household i is:

$$\frac{\partial e_{i,t}}{\partial y_{i,t}} - \frac{\partial e_{j,t}}{\partial y_{j,t}} \overset{(5)}{=} -2\beta_{2,t}(y_{j,t} - y_{i,t}) \tag{6}$$

Here, $\frac{\partial e_{i,t}}{\partial y_{i,t}}$ is the change in land use for a marginal income change of household i. Based on Eq. (6), we estimate the average change in total land use in 2022 by a short-term *marginal income transfer* of USD 1,000 from a household at the 75^{th} income percentile (USD 78.2k) to a household at the 25^{th} percentile (USD 24.4k) to be an increase of $80m^2$.[22] Of course, this estimate relies on the assumption that households, on average, move along the estimated Land-EECs when their incomes change (conditional on household characteristics).[23]

Eq. (6) also sheds more light on how the biodiversity-equality trade-off may differ between the short and long run. The expected change in total land use is negatively proportional to $\hat{\beta}_{2,t}$. As discussed in Section 5.1, for impacts of long-run policies unconditonal EECs may be more informative as other household characteristics (like education) may be affected as well by these policies. Since unconditional Land-EECs display a larger absolute $\hat{\beta}_{2,t}$ (in 2022, 1.51 compared to 0.74), we can expect that the trade-off is more pronounced for long-rung redistribution policies.

5.3.2 Perfect equality

In addition to a marginal income transfer, we predict the change in average land use if income was perfectly equally distributed among households. The expected change in average land use at a given income distribution is the difference between the expected mean land use under perfect equality ($\bar{e}_t^E$) and the current mean land-use footprint ($\bar{e}_t$), following Sager (2019) and assuming quadratic EECs:

$$\bar{e}_t^E - \bar{e}_t = \hat{\beta}_{2,t}\left[\bar{y}_t^2 - \frac{1}{N}\sum_{i=1}^{N}(y_{i,t})^2\right] \tag{7}$$

with $\bar{e}_t^E := E[\bar{e}_t | y_1 = ... = y_N = \bar{y}]$. Eq. (7) is subject to the same assumptions that apply for marginal transfers (Section 5.3.1). We estimate that, in the short-term, full redistribution would increase average land use by 3.2% or 1,444 m^2 in 2022 (relative to a mean of 45,625 m^2). Summed across the 131 million US households in 2022, this would amount to an additional 189,164 km^2 of required land, larger than the

[22] Calculated as $-2 \times 0.74 \times (78.2 - 24.4)$.

[23] For instance, if unobserved cultural attributes that vary with income are also related to the consumption of meat or other biodiversity-intense goods, our estimated EECs would be subject to omitted variable bias.

area of many US states including New York (ca. 141,000 km^2) and Virginia (ca. 111,000 km^2). However, such absolute estimates should be interpreted with caution (see Section 3.3).

While we have focused here on the effects on consumption-based land-use pressures, a similar analysis could be conducted with the Species-EECs. In that case a less consistent picture might emerge, due to the less pronounced functional form (see Figure 5). In particular, near-linear unconditional Species-EECs in 2022 would suggest no biodiversity-equality trade-off and the mild convexity of conditional Species-EECs in 2022 might even suggest a biodiversity-equality synergy where less income inequality helps to lower aggregated biodiversity pressure.

6 Discussion & Limitations

Our results suggest that income redistribution may generate adverse impacts on biodiversity through higher land use due to the concavity of Land-EECs in the United States. Our results provide an important reference for a key domain of biodiversity pressure and for an important economy, but should not be taken as conclusive. Rather, the shape of EECs might differ across countries, biodiversity measure and time. By now EECs have been investigated fairly well in the US context and for multiple environmental dimensions. Further research is required to examine whether similar patterns in the nexus of income inequality and environmental degradation can be found for other high-income regions, such as the EU, and for low- and middle-income economies. For instance, previous research suggests that there are significant differences in the income elasticities for biodiversity between high- and low-income countries (Bjelle et al., 2021). While the distributional effects of carbon pricing have been extensively investigated (Dorband et al., 2019; Fremstad and Paul, 2019; Rausch et al., 2011; Sager, 2023), we are not aware of similar analyses for market-based instruments to preserve biodiversity. The EECs for biodiversity derived in this study could function as a starting point for further research to analyze the effects of e.g., biodiversity protection measures or taxation of biodiversity-intensive products on inequality.

Our quantification of the biodiversity-equality trade-off is subject to several assumptions: (i) We conduct a partial equilibrium analysis assuming that external determinants of consumption remain unaffected by redistribution policies. Particularly, we assume that land intensities of products and consumption preferences of households do not change due to income redistribution, thereby not considering social and other-regarding preferences (Akerlof, 1997; Sobel, 2005). (ii) We assume that estimated land-use footprints of households are unbiased, or that any bias that may exist is the same across income levels. This would be violated, for instance, if richer households shift towards more expensive products within the same category, e.g. premium instead of regular pork.[24] (iii) Our analysis requires that the functional form relating consumption-embedded land-use footprints and household income (Eq. (5)) is, on average, accurately modeled by a second-order polynomial regression. Deploying several tests and specifications, we have strong evidence that this is indeed the case as outlined in Section 5.2 and A.2.

There is also potential to further refine the methodology underlying EECs, particularly with respect to the biodiversity indicators. The estimation of Land-EECs and Species-EECs allowed us to separately analyze the impact categories land use on the one hand, and climate change and terrestrial acidification on the other hand. The two impact indicators have different coverage, which is partly complementary. Land footprints of households can be grasped intuitively (area in m^2). They also comprise a refined differentiation among “everyday expenditures” particularly food items, resulting in precisely estimated Land-EEC for “everyday products”. However, computed land footprints cover a lower share of household

[24] Since we assume a homogeneous land-use intensity for the entire (country-specific) pork sector, we would underestimate the concavity of EECs and thus the severity of the biodiversity-equality trade-off.

expenditures as based on the *Diary Survey* and only the direct and indirect consumption of agricultural and forestry products. In contrast, species-loss footprints cover the majority of total household expenditures (as based on interview survey) and represent an impact indicator more directly linked to biodiversity. While our Species-EEC considers pressures through greenhouse gas emissions and terrestrial acidification it does not consider land use as the most important pressure on biodiversity loss. The missing linkage of land use to a biodiversity indicator (like species loss), does not allow to draw direct conclusions from the pressure (land use) to the biodiversity *impact*.[25] By examining both types of Biodiversity-EECs, Land-EEC and Species-EEC, we hope to alleviate this methodological constraint and gain a thorough insight into the relationship between household income and several types of consumption-driven pressures on biodiversity. Nevertheless, for future research it may be worthwhile to estimate EECs for biodiversity by means of a *consolidated biodiversity indicator* embracing the impact of all relevant pressures together in one measure.

Moreover, the general and well-known assumptions and limitations of EE-MRIO analysis (Kitzes, 2013; Wiedmann, 2009; Steen-Olsen et al., 2016), also apply to our study: (i) EE-MRIO analysis assumes *homogeneity of product groups and of prices*. Specifically, each sector produces a single, homogeneous good or service, at least in terms of its environmental impact, which is sold at the same price to consumers and different producers. Thus, we can not capture variations in biodiversity intensity between products within the same sector.[26] (ii) Input-output analysis generally assumes *linear production functions* for all sectors, i.e., that the output in a sector is produced with a constant, fixed proportion of input from other sectors. (iii) Input-output tables do not capture *non-market flows*, such as unpaid work and black market trading, and their associated environmental impacts, such as burning firewood and deforestation of self-owned woodland. Their exclusion would lead to underestimate the biodiversity footprint of households. However, such activities are mostly relevant in low-income countries with a large portion of “off the books” activities (Kitzes, 2013).(iv) In general, the development of a EE-MRIO databases is prone to introduce uncertainties and biases arising from disparities between countries in data collection and evaluation of environmental impacts.

Finally, we emphasize that, while we do indeed find evidence of a biodiversity-equality trade-off working through consumer demand, this does not necessarily mean that we must sacrifice equality objectives for sustainability goals. In particular, our approach assumes that households move along the estimated EECs (homogeneous preferences) and that biodiversity intensities and retail prices remain constant. Thus, adverse environmental impacts could be mitigated if policy makers create incentives for lowering biodiversity intensity of production (supply side) or for a shift towards more sustainable consumption baskets (demand side).

7 Conclusion

In this paper, we estimate descriptive and parametric Environmental Engel Curves (EEC) for land use (Land-EEC) as well as for the impacts of climate change and terrestrial acidification on species

[25] If the effect of land use on species loss was uniform (linear), moving from land use (in ha) to a land-use impact indicator would not affect the shape of estimated EECs and only the measurement unit, but also have little added-value. However, the impact of land use on species loss is regionally specific and varies with the type of use (crop production, pasture, forestry, infrastructure, etc.) (Marques et al., 2017; Verones et al., 2020). Thus, if e.g., poorer households consume more products that use (direct and indirect) “land-inputs” from regions where land use has a relatively large impact on species loss, EECs for land-use related species loss would be more concave than our Land-EECs. For instance, looking at the country-level, Verones et al. (2017) have shown that net importers of an impact category (land, acidification, water) can become net exporters (and vice versa) when moving from (traditional) pressures to impact footprints.

[26] For instance, it is estimated that a high-quality USD 200 shoe has four times the biodiversity footprint than a USD 50 shoe. Consequently, if with *rising income* goods with a *lower biodiversity per USD ratio* (but in the same product-lass, e.g., shoes) are increasingly demanded, the concavity of EECs would be underestimated (as suggested by findings of Girod and De Haan (2010) for household GHG emissions).

loss (Species-EEC) to gain a deeper understanding on the relationship between income, inequality and consumption-related biodiversity loss.

We observe that EECs have *shifted downwards* between 1996 and 2014, so that biodiversity impacts of consumption from households at all income levels were lower in 2014 than in 1996. This finding aligns with previous studies for the US, which also found downward shifting EECs for GHG emissions (Sager, 2019) and local air pollutants (Levinson and O'Brien, 2019) during a similar period. We attribute this shift to technological advances, which outweigh the upward pressure on Biodiversity-EECs from a shift towards more biodiversity-intensive products. Interestingly, EECs seem to have *shifted upwards* after 2014 until 2022. Similarly, we find that average biodiversity footprints of US households declined between 1996 and the early 2010s but increased thereafter until the end of the sampling period in 2022. Our analysis suggests that this increase is the result of higher biodiversity pressure from the scale and composition of consumption, which outweighs technological progress over the final decade.

Regarding the shape of EECs, we find that both Land-EECs and Species-EECs are *upward sloping*, suggesting that embedded biodiversity consumption is a normal good (income elasticity > 0). Land-EECs are additionally concave, implying that consumption-embedded land-use impacts are akin to a necessity (income elasticity < 1). In contrast, the curvature of Species-EECs is less pronounced and varies by year and model. Since land use is the primary driver of biodiversity loss, we conclude that embedded biodiversity behaves like a necessity. While this finding is in line with EECs for GHG emissions and air pollutants (Sager, 2019; Levinson and O'Brien, 2019), it stands in contrast to the estimated income elasticities for *biodiversity* (> 1) from country-level panel regression analysis by Bjelle et al. (2021).

Based on estimated parametric EECs, we explore the effects of income redistribution on aggregate biodiversity footprints of US consumers. Since the curvature of Land-EECs is more consistent and pronounced, we expect this relationship to be driven by consumption-embedded land use. Using quadratic estimates of Land-EECs, we find a *biodiversity-equality trade-off* such that progressive income redistribution may inadvertently lead to larger biodiversity impacts in aggregate. More specifically, we predict that in 2022, a *marginal income* transfer of USD 1000 from a US household at the 75^{th} income percentile to a household at the 25^{th} percentile would increase aggregate land use by $80m^2$. Aggregate land use would increase by +3.2% respectively $1{,}444m^2$ on average per household in the case of *perfect income equality.* This result is similar to a predicted surge in aggregate CO_2 by Sager (2019) of +2.3% for the same scenario in 2009 (+1.8% for CH4, +1.3% for N2O).

With these findings, we aim to contribute to the debate around the biodiversity-equity nexus by formalizing an empirically grounded micro-founded mechanism linking these two important topics. Our findings show that income redistribution can have inadvertent repercussions for aggregate biodiversity pressure from consumption. For a given biodiversity target, this provides a rational for additional conservation policies both international and national: While income redistribution is primarily shaped by domestic policy, it also affect biodiversity in other countries via global value chains, highlighting the need for international cooperation, such as through the U.N. Convention on Biological Diversity. In addition, effective national policies to mitigate biodiversity pressure could alter and potentially overcome the trade-off between inequality reduction and environmental preservation we have quantified above.

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Appendix

A.1 Data and Methodology on Data and Methodology

A.1.1 Environmentally-Extended Input-Output Analysis

Hereafter, we briefly describe the deployment of environmentally-extended Leontief input-output analysis (Leontief, 1970) to obtain biodiversity intensities for various product-classes and years. For a more detailed discussion of environmentally-extended multi-regional input-output analysis the reader is refereed to Kitzes (2013). In addition, Tukker and Dietzenbacher (2013) and Inomata and Owen (2014) give a comprehensive overview of databases covering their construction as well as limitations.

Leontief Input-Output Analysis

We start with the transaction matrix $\boldsymbol{Z}_{(\boldsymbol{N}\times\boldsymbol{N})}$ with element $z_{i,j}$ indicating the total inputs (in EUR) from country-sector i to country-sector j, e.g. the Euro amount of German machinery that is used in the production of US motor vehicles. $\boldsymbol{Z}$ is of dimension $N \times N$ with $N = P * O = 9800$ ($P = 200$ Exiobase product-types and $O = 49$ number of regions). Conducting an element-wise division of $\boldsymbol{Z}$ by the transpose of the total output vector $\boldsymbol{x}_{(\boldsymbol{N}\times\boldsymbol{1})}$ yields the *direct requirements matrix* $\boldsymbol{A}_{(\boldsymbol{N}\times\boldsymbol{N})}$ with $a_{i,j}$ indicating how much input of country-sector i is required to produce EUR 1 of output in sector j:[27]

$$\boldsymbol{A} = \boldsymbol{Z} \circ \boldsymbol{x}^{\boldsymbol{T}}, \text{ with } \circ : \text{element-wise division operator} \tag{IO.1}$$

The Leontief transformation to get the *total requirements matrix*:

$$\boldsymbol{L} = (\boldsymbol{I} - \boldsymbol{A})^{-1}, \text{ with } \boldsymbol{I} : \text{Identity matrix} \tag{IO.2}$$

Element $l_{i,j}$ of matrix $\boldsymbol{L}$ indicates how much direct and indirect input of country-sector i is required to supply EUR 1 of final demand by sector j. By the last step, we make sure that the *entire value chain* is taken into account when calculating country-sector input requirements and, in the next step, corresponding biodiversity intensities (i.e., not only direct biodiversity footprints of country-sectors are considered, but also indirect). This is particularly important when considering that approx. 30% of biodiversity threats result from consumer demand outside of the country in which they occur (Moran et al., 2016) and that the US is a net importer of biodiversity (Chaudhary and Kastner, 2016; Irwin et al., 2022; Lenzen et al., 2012a).

Environmental Extension - Open Economy and Trade of Final Products

From the environmental account data, we extract the vector of total land-use $\boldsymbol{f}_{(\boldsymbol{N}\times\boldsymbol{1})}$ with element f_i indicating the total land-use of country-sector i (in km^2). Then we obtain the *direct impact intensities* (or *direct impact coefficients*) $\boldsymbol{s}_{(\boldsymbol{n}\times\boldsymbol{1})}$ (in km^2/EUR) by:

$$\boldsymbol{s} = \boldsymbol{f} \circ \boldsymbol{x} \tag{IO.3}$$

Element s_i of vector $\boldsymbol{s}$ indicates how much land is directly used in sector i to produce EUR 1 output in this sector (direct intensity). Further, we get the vector of *total biodiversity intensities* $\boldsymbol{b}_{(\boldsymbol{n}\times\boldsymbol{1})}$ (also called *extension multipliers* or *total requirements factors of consumption*) with:

[27] In contrast to Sager (2019), we did not exclude the private household sectors. This is mainly because the sector functions as an input sector for COICOP categories. Moreover, in Exiobase the ‘Final consumption expenditure by household’ for the sector ‘Private households with employed persons (95)’ is positive for all years.

$$\boldsymbol{b} = \boldsymbol{L}'\boldsymbol{s} \tag{IO.4}$$

Vector $\boldsymbol{b}$ contains the *total biodiversity intensities* for all 9800 Exiobase *country-sectors* with element b_i indicating the land-use intensity (in km^2/EUR) of the final demand provided by country-sector i. Since consumption items (UCC) are later matched to intensities of *general sector-types* (e.g. chemicals) and not to those of particular country-sectors (e.g. chemicals from Germany), we derive a total emission intensity for each sector-type. This is done by computing the weighted average of all intensities of the same sector-type. More particularly, the intensity of a country-sector i is weighted by the share of the sector in the provision of total final demand of US households. For instance, the land intensity of the sector-type 'chemicals' is the weighted average of land intensities of all 49 chemical sectors (US, German, Indian, etc.) in accordance with their shares in the provision of final 'chemical' products consumed by US households. By doing so, we obtain a vector of *total biodiversity intensities* ($\boldsymbol{i^{Exio,O+T}}$) for all 200 Exiobase product-types considering global value chains as well as global supply chains (hereafter called *open+trade*).

Biodiversity Intensities for Closed Economy & No Trade Scenario

We construct two further vectors of *total biodiversity intensities*. For the first, we simply extract the intensities of *US sectors* from the vector of *total biodiversity intensities* $\boldsymbol{b}$. Hence, global value chains are considered due to previous steps but no trade in final products as no weighted average of intensities is computed, giving us the vector $\boldsymbol{i^{Exio,open}}$ (*open, but no trade*). The second considers only emissions of US sectors and assumes a closed economy supply chain (*closed*, $\boldsymbol{i^{Exio,closed}}$). To obtain $\boldsymbol{i^{Exio,closed}}$ we limit the direct requirements matrix $\boldsymbol{A}$ and the vector of total land-use $\boldsymbol{f}$ to US sectors only. Accordingly, we get matrix $\boldsymbol{A^{US}_{(200\times200)}}$ with $a^{US}_{i,j}$ indicating how much input of US-sector i is required to produce EUR 1 of output in US-sector j, and vector $\boldsymbol{f^{US}_{(200\times1)}}$ with direct intensities of US-sectors. Subsequently, we follow the same steps as described above in equations IO.2 to IO.4 but using matrix $\boldsymbol{A^{US}}$ and vector $\boldsymbol{f^{US}}$.

In addition to computing land intensities for Exiobase product-types, we also compute them for "Classification of individual consumption by purpose" (COICOP) categories, which are used as standardized consumption categories in European consumer surveys. Ivanova and Wood (2020) constructed a bridge table specifying for each COICOP category how much input it receives from which Exiobase sector (as a share between zero and one). For instance, COICOP category *food* contains 6% dairy products, 5% wheat, etc. By multiplying the bridge table $\boldsymbol{r_{(C\times P)}}$ (with $C = 64$: number of COICOP categories) with the vector of total emission intensities for Exiobase product-types ($\boldsymbol{i^{Exio}_{(P\times1)}}$), we obtain the same types of land intensities for COICOP categories as for Exiobase product-types.

Species-loss intensities (climate change & terrestrial acidification) of Exiobase and COICOP sectors are obtained analogously using different factor vectors ($\boldsymbol{f}^{CC}$ and $\boldsymbol{f}^{Acid}$).

A.1.2 US CEX - Household Income and Expenditure Data

The US consumer expenditure survey (CEX) is a nationwide survey conducted by the U.S. Bureau of Labor Statistics (BLS) collecting expenditures and income data as well as demographic characteristics, on a household level (BLS, 2018). Expenditures are identified by a universal classification code (UCC). The CEX consists of two separate surveys, the Diary and the Interview Survey, which cover together the entire range of consumer expenditures. However, Diary and Interview portions use different household samples and, in parts, cover different consumption items which is why they can not be merged into one dataset on the household level. While both portions overlap in large parts, neither one is designed to present a full account of expenditures. Accordingly, some consumption items are collected by the Interview or the Diary Survey only.

For the Interview Survey households are interviewed in four consecutive quarters. Afterwards they drop out of the survey pool. In each interview households report their expenditures of the last preceding 3 months on mostly large and recurring goods and services that they are expected to recall for a 3 months period or longer. In general, reported expenditures are either relatively large like major appliances, automobiles and property, or occur on a quite regular basis like utilities and rent. The Interview Survey collects *detailed data* on 60% to 70% of total household expenditures. Furthermore, *global estimates* for additional 20% to 25% percent of total expenditures are collected including food and other selected items such as tobacco products and alcoholic beverages. Taken together the Interview Survey covers 80% to 95% of all household expenditures.

The diary survey collects *detailed data* on small and frequently purchased items which might be difficult to recall in detail for a 3 months period. Therefore, households are interviewed in two consecutive one-week periods. Surveyed items include beverage and food expenses at home and in eating places (e.g. steak, juice, vegetables, etc.), clothing items, nonprescription drugs, personal care services and products, as well as housekeeping services and supplies.

Due to the different structure of Interview and Diary Survey, the yearly consumption expenditures of a household i on item k (i.e., $c_{i,k,t}$ in Eq. (4)) have to be estimated differently. For the interview survey, data is collected in quarter-yearly survey waves. Yearly income (after- and before-tax) and other socio-demographics are contained in FMLI files, while expenditure data is contained in MTBI files. Since expenditures are surveyed for the precedent three months, we aggregate the expenditures of four quarters to obtain yearly expenses on UCCs. Moreover, since households are taken into the survey continuously over the year and are interviewed in four consecutive quarters, for many households the first and the last interview lies in different years (e.g. 2006 and 2007). Therefore, households are assigned to the year in which their second interview was conducted. For the Diary Survey income data and other socio-demographics are accessible in FMLD files, while expenditure are provided in EXPD files. For the Diary Survey households report their expenditures on small and frequently purchased items in two consecutive one-week periods. To attain estimates of households yearly expenditures on a consumption item k, we aggregate the expenses for item k in the surveyed two-week period and multiply it with 26.07 ($= \frac{365 \frac{days}{year}}{7 \frac{days}{week} \times 2}$). In case the two-week period includes the last week of December and the first week of January, households are assigned to the year when the last data collection took place.

A.1.3 Diary sample income imputation after 2014

In the CEX Diary surveys, the after-tax variable is only available through 2014, as detailed tax information was no longer collected afterwards. From 2015 on, we thus impute after-tax household income using a multiple imputation approach based on random forest models (using the 'missForest' R package). In each year, the model is trained on data from the CEX Interview sample, where both after-tax income and all predictor variables are available, and then used to predict the missing after-tax income variable in the CEX Diary sample. Included predictors are: before-tax income, its' square and cube, age and marital status of the reference person, region, family size, number of members below 18, number of members above 64, amount paid to social security contributions, and amount received from social security. To benchmark this approach, we artificially drop 50% of after-tax income observations in the 2014 sample, and then run the same imputation procedure. As shown in Figure A1, this achieves a very strong fit between imputed and true values of the artificially missing observations (with an R^2 of 0.97).

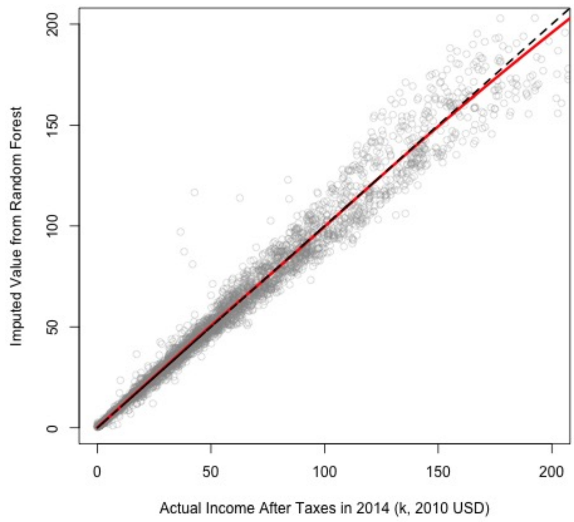

Figure A1: Comparison of imputed values for random 50% of sample vs. actual after-tax income in 2014

A.2 Model Selection – Determining Polynomial Degree for Household Income

In this section, we deepen the discussion on the curvature of our estimated EECs. In addition to non-parametric generalized additive models (see Section 5.2 and Figure 5), we deploy generalized cross-validation (GCV) and models with varying polynomial degrees for household income variable in our main specification in Eq. 5 (Craven and Wahba, 1978). Cross-validation is a model validation technique for evaluating how well findings from a statistical analysis generalize on new observations (out-of-sample method) (James et al., 2013). In general, it involves splitting the sample repeatedly into training and test data set for estimating the mean-squared error (MSE) which is the squared difference between predicted and real outcome. The MSE can be decomposed into a variance and bias component. Thus, cross-validation addresses, among others, potential bias-variance trade-offs one is confronted with when including more explanatory variables, like polynomials, into the estimation (Fahrmeir et al., 2013). In the particular case of leave-one-out cross validation (LOOCV), the splitting process is repeated n-times, with only one observation in the test and $n-1$ observations in the training set in each run. This approach has several advantages, particularly, it is less biased. One obvious downside is the computational demand (James et al., 2013). Generalized cross-validation (GCV) helps to overcome this problem by deploying a fast and computational effective approximation algorithm for LOOCV (Wood, 2008).

Table A1 and A3 present GCV scores for Land-EECs respectively Species-EECs with varying polynomial degrees up to order four for household income variable in different years. “full" columns denote specifications including other household characteristics as specified in 5. A lower score implies a lower estimated MSE.

For Land-EECs we find the lowest scores between a third (until 2005) and a second (2022) polynomial for all specifications. We further pursue these suggestions by examining quadratic and cubic regression results in Table 2 respectively A2. While squared income coefficients are mostly economically and statistically significant in quadratic specifications, this does not hold for neither squared nor cubed terms in cubic specifications (except in 1996). Particularly in 2022, GCV scores and regression outcomes point towards a quadratic specification.

A similar pattern holds for Species-EECs. While cubic (1996–2014), quadratic (’2022 full’) and linear

Table A1: GCV scores of Land-EECs with varying polynomial degree for household income

	1996		2014		2022	
Polynomial	Land	Land full	Land	Land full	Land	Land full
1	6.2903e+13	5.7510e+13	3.8557e+13	3.5738e+13	1.5140e+14	1.4599e+14
2	6.2777e+13	5.7536e+13	3.8342e+13	3.5728e+13	1.5051e+14	1.4584e+14
3	6.2635e+13	5.7439e+13	3.8322e+13	3.5722e+13	1.5057e+14	1.4590e+14
4	6.5206e+13	5.8632e+13	3.9299e+13	3.6722e+13	1.5229e+14	1.4744e+14

Notes: Generalized cross-validation (GCV) scores for Land-EECs with varying polynomial degrees (1–4) for household income variable for the years 1996, 2014 and 2022. "full" columns denote specifications including other household characteristics as specified in Eq. 5.

Table A2: Parametric Regression of cubic Land-EEC for the Years 1996, 2014 and 2022

	(1)	(2)	(3)	(4)	(5)	(6)
	1996	1996 full	2014	2014 full	2022	2022 full
Income (k USD)	201.44	-37.81	239.08***	99.97	532.44***	320.06***
	(137.18)	(133.74)	(64.86)	(61.47)	(111.03)	(119.27)
Income squared	5.77**	5.89**	0.70	0.88	-1.60	-1.24
	(2.62)	(2.57)	(0.87)	(0.84)	(1.30)	(1.28)
Income cubed	-0.03***	-0.03**	0.00*	0.00	0.00	0.00
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Controls included	NO	YES	NO	YES	NO	YES
Num. obs.	3996	3996	4836	4836	4959	4959
R^2	0.11	0.19	0.09	0.16	0.04	0.08
Adjusted R^2	0.11	0.19	0.09	0.16	0.04	0.07

Notes: Estimates from heteroscedasticity-consistent OLS regression following Eq. 5 for Land-EECs in 1996, 2005, 2022. In all specifications dependent variable is consumption-embedded land-use (m2, open+trade) calculated as described in Section 3 (using Exiobase EE-MRIO tables v.3.8.2). Other variables are from US CEX. 'full' columns denote specifications including controls for family size, squared family size, household head age, household head age squared, marital status (binary) as well as categorical race, education and region variables. Robust standard errors in parentheses. Household weights provided by CEX applied. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A3: GCV scores of Species-EECs with varying polynomial degree for household income

	1996		2014		2022	
Polynomial	Species	Species full	Species	Species full	Species	Species full
1	1.8992e-04	1.5374e-04	1.2386e-04	1.0615e-04	5.3680e-04	5.0043e-04
2	1.8912e-04	1.5380e-04	1.2171e-04	1.0592e-04	5.3722e-04	4.9863e-04
3	1.8892e-04	1.5371e-04	1.2166e-04	1.0578e-04	5.3687e-04	4.9878e-04
4	2.0882e-04	1.7168e-04	1.2642e-04	1.1659e-04	5.4797e-04	5.2286e-04

Notes: Generalized cross-validation (GCV) scores for Species-EECs with varying polynomial degrees (1–4) for household income variable for the years 1996, 2014 and 2022. "full" columns denote specifications including other household characteristics as specified in Eq. 5.

(2022 unconditioned) have the lowest GCV scores in respective years and specifications, including cubed income terms rarely yield robust results (except in '2014 full').

Table A4: Parametric Regressions of cubic Species-EEC for the Years 1996, 2014 and 2022

	(1)	(2)	(3)	(4)	(5)	(6)
	1996	1996 full	2014	2014 full	2022	2022 full
Income (k USD)	2.1e-06***	8.3e-07**	2.0e-06***	9.6e-07***	3.0e-06***	1.4e-06**
	(3.9e-07)	(3.6e-07)	(2.7e-07)	(2.6e-07)	(5.7e-07)	(5.6e-07)
Income squared	8.0e-09	1.0e-08*	1.1e-09	6.2e-09*	-1.2e-08	-3.0e-09
	(6.4e-09)	(5.9e-09)	(4.0e-09)	(3.7e-09)	(8.2e-09)	(8.0e-09)
Income cubed	-5.6e-11*	-4.2e-11	-2.3e-11	-3.0e-11**	4.2e-11	2.4e-11
	(2.9e-11)	(2.7e-11)	(1.5e-11)	(1.4e-11)	(3.1e-11)	(3.1e-11)
Controls included	NO	YES	NO	YES	NO	YES
Num. obs.	3160	3160	3461	3461	2465	2465
R^2	0.38	0.50	0.41	0.49	0.30	0.36
Adjusted R^2	0.38	0.50	0.41	0.49	0.30	0.36

Notes: Estimates from heteroscedasticity-consistent OLS regression following Eq. 5 for Species-EECs. In all specifications dependent variable is consumption-embedded species loss (open+trade) calculated as described in Section 3 (using Exiobase EE-MRIO tables v.3.8.2). Other variables are from US CEX. 'full' columns denote specifications including controls for family size, squared family size, household head age, household head age squared, marital status (binary) as well as categorical race, education and region variables. Robust standard errors in parentheses. Household weights provided by CEX applied. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

A.3 Additional Tables

Table A5: Average Biodiversity Footprints of Households by Years

Year	After-tax Income (k 2010 USD)	Land use (ha, closed)	Land use (ha, open)	Land use (ha, open+trade)	Species loss (closed)	Species loss (open)	Species loss (open+trade)
1996	47.45	3.61	4.32	4.76	1.90e-04	2.25e-04	2.36e-04
2005	64.60	2.85	3.48	4.30	1.83e-04	2.28e-04	2.46e-04
2014	57.17	2.32	2.73	3.26	1.42e-04	1.72e-04	1.87e-04
2019	60.22	2.63	3.17	3.64	1.44e-04	1.73e-04	1.86e-04
2022	59.25	3.15	3.77	4.56	1.84e-04	2.28e-04	2.53e-04

Note: Average household biodiversity footprints (Land use in ha, Species loss) by years assuming either a closed economy (closed), global value chains but no trade in final products (open), or global value chains and trade in final products (open+trade). species-loss footprints include impacts from climate change and acidification. Household weights provided by CEX applied.

Table A6: Land use and Species loss intensities (per 2010 USD, open + trade) for Exiobase sectors and COICOP categories in 1996 and 2022

			Land (m2/USD)		**CC + acidif. (species-loss/USD)**	
Nr	Type	Description	1996	2022	1996	2022
1	Exiobase	Paddy rice	4.68	2.65	3.60e-08	3.57e-08
2	Exiobase	Wheat	44.68	48.40	1.73e-08	1.31e-08
3	Exiobase	Cereal grains nec	23.96	11.54	1.52e-08	9.17e-09
4	Exiobase	Vegetables, fruit, nuts	2.44	1.87	3.06e-09	1.68e-09
5	Exiobase	Oil seeds	33.13	20.67	6.70e-09	4.25e-09
6	Exiobase	Sugar cane, sugar beet	7.51	3.14	1.63e-08	8.65e-09
7	Exiobase	Plant-based fibers	6.62	2.40	1.60e-08	6.68e-09
8	Exiobase	Crops nec	2.78	0.09	8.17e-09	2.14e-09
9	Exiobase	Cattle	68.84	42.62	6.91e-08	2.88e-08
10	Exiobase	Pigs	1.05	0.19	9.05e-09	4.55e-09
11	Exiobase	Poultry	3.99	0.82	1.46e-08	6.62e-09
12	Exiobase	Meat animals nec	34.79	68.43	4.06e-07	1.20e-06
13	Exiobase	Animal products nec	3.12	1.31	5.98e-09	2.38e-09
14	Exiobase	Raw milk	20.16	12.35	3.22e-08	1.58e-08
15	Exiobase	Wool, silk-worm cocoons	0.60	0.15	1.23e-08	1.10e-08
16	Exiobase	Manure (conventional treatment)	0.00	0.00	0.00e+00	0.00e+00
17	Exiobase	Manure (biogas treatment)	0.00	0.00	0.00e+00	0.00e+00
18	Exiobase	Products of forestry, logging and related services (02)	73.40	26.22	3.70e-09	5.33e-10
19	Exiobase	Fish and other fishing products; services incidental of fishing (05)	0.93	0.06	4.05e-09	1.19e-09
20	Exiobase	Anthracite	1.23	0.11	4.79e-08	1.34e-08
21	Exiobase	Coking Coal	0.11	0.05	3.80e-08	1.04e-08
22	Exiobase	Other Bituminous Coal	0.15	0.40	3.78e-08	2.47e-08
23	Exiobase	Sub-Bituminous Coal	0.11	0.05	3.79e-08	1.06e-08
24	Exiobase	Patent Fuel	0.94	0.05	1.02e-07	1.04e-08
25	Exiobase	Lignite/Brown Coal	0.11	0.05	3.80e-08	1.04e-08
26	Exiobase	BKB/Peat Briquettes	0.84	0.22	6.20e-08	2.91e-08
27	Exiobase	Peat	0.00	0.00	0.00e+00	0.00e+00
28	Exiobase	Crude petroleum and services related to crude oil extraction, excluding surveying	0.27	0.05	2.51e-08	1.06e-08
29	Exiobase	Natural gas and services related to natural gas extraction, excluding surveying	0.25	0.07	5.35e-08	1.03e-08
30	Exiobase	Natural Gas Liquids	0.25	0.07	5.33e-08	1.03e-08
31	Exiobase	Other Hydrocarbons	0.20	0.11	2.15e-08	6.14e-09
32	Exiobase	Uranium and thorium ores (12)	0.28	0.02	1.26e-08	6.02e-09
33	Exiobase	Iron ores	0.15	0.07	1.19e-08	2.87e-09
34	Exiobase	Copper ores and concentrates	0.08	0.02	1.87e-08	4.59e-09
35	Exiobase	Nickel ores and concentrates	0.00	0.00	0.00e+00	0.00e+00
36	Exiobase	Aluminium ores and concentrates	0.08	0.04	1.33e-08	2.04e-09
37	Exiobase	Precious metal ores and concentrates	0.29	0.11	1.50e-08	1.22e-08

38	Exiobase	Lead, zinc and tin ores and concentrates	0.09	0.03	1.99e-08	1.24e-08
39	Exiobase	Other non-ferrous metal ores and concentrates	0.11	0.05	1.37e-08	3.18e-09
40	Exiobase	Stone	0.11	0.03	1.14e-08	2.21e-09
41	Exiobase	Sand and clay	0.20	0.05	1.39e-08	3.15e-09
42	Exiobase	Chemical and fertilizer minerals, salt and other mining and quarrying products n.e.c.	0.71	0.43	1.92e-08	8.58e-09
43	Exiobase	Products of meat cattle	62.85	37.98	6.31e-08	2.82e-08
44	Exiobase	Products of meat pigs	0.79	0.29	6.65e-09	3.35e-09
45	Exiobase	Products of meat poultry	2.57	0.98	9.26e-09	4.33e-09
46	Exiobase	Meat products nec	1.03	0.62	9.66e-09	7.03e-09
47	Exiobase	products of Vegetable oils and fats	16.65	9.23	9.63e-09	5.00e-09
48	Exiobase	Dairy products	9.16	5.93	1.89e-08	9.88e-09
49	Exiobase	Processed rice	11.81	5.53	6.27e-08	2.97e-08
50	Exiobase	Sugar	4.37	1.86	1.10e-08	5.02e-09
51	Exiobase	Food products nec	4.76	3.11	7.75e-09	3.98e-09
52	Exiobase	Beverages	1.83	1.27	6.42e-09	3.17e-09
53	Exiobase	Fish products	3.91	1.79	1.21e-08	5.11e-09
54	Exiobase	Tobacco products (16)	0.74	0.50	4.27e-09	2.17e-09
55	Exiobase	Textiles (17)	0.92	0.67	1.03e-08	5.15e-09
56	Exiobase	Wearing apparel; furs (18)	0.76	0.59	1.06e-08	4.65e-09
57	Exiobase	Leather and leather products (19)	2.03	1.60	1.08e-08	6.11e-09
58	Exiobase	Wood and products of wood and cork (except furniture); articles of straw and plaiting materials (20)	28.64	10.50	7.64e-09	2.62e-09
59	Exiobase	Wood material for treatment, Re-processing of secondary wood material into new wood material	0.00	0.00	0.00e+00	0.00e+00
60	Exiobase	Pulp	14.18	7.03	8.93e-09	3.97e-09
61	Exiobase	Secondary paper for treatment, Re-processing of secondary paper into new pulp	0.00	0.00	0.00e+00	0.00e+00
62	Exiobase	Paper and paper products	4.81	2.71	9.06e-09	4.82e-09
63	Exiobase	Printed matter and recorded media (22)	0.95	0.16	4.78e-09	1.19e-09
64	Exiobase	Coke Oven Coke	0.14	0.05	9.70e-08	3.03e-08
65	Exiobase	Gas Coke	0.00	0.00	0.00e+00	0.00e+00
66	Exiobase	Coal Tar	0.00	1.15	0.00e+00	2.51e-09
67	Exiobase	Motor Gasoline	0.28	0.12	2.92e-08	9.75e-09
68	Exiobase	Aviation Gasoline	0.32	0.11	2.86e-08	9.63e-09
69	Exiobase	Gasoline Type Jet Fuel	0.26	0.00	2.90e-08	0.00e+00
70	Exiobase	Kerosene Type Jet Fuel	0.28	0.41	2.97e-08	1.13e-08
71	Exiobase	Kerosene	0.33	0.67	3.17e-08	1.22e-08
72	Exiobase	Gas/Diesel Oil	0.30	0.22	2.99e-08	1.14e-08
73	Exiobase	Heavy Fuel Oil	0.26	0.11	2.98e-08	9.59e-09
74	Exiobase	Refinery Gas	0.26	0.11	2.92e-08	9.64e-09
75	Exiobase	Liquefied Petroleum Gases (LPG)	0.29	0.12	2.99e-08	9.75e-09

76	Exiobase	Refinery Feedstocks	0.26	0.11	2.90e-08	9.62e-09
77	Exiobase	Ethane	0.27	0.11	2.96e-08	9.60e-09
78	Exiobase	Naphtha	0.26	0.11	2.95e-08	9.59e-09
79	Exiobase	White Spirit	SBP	0.26	0.11	2.91e-08
9.65e-09						
80	Exiobase	Lubricants	0.36	0.22	2.06e-08	7.56e-09
81	Exiobase	Bitumen	0.26	0.10	2.78e-08	8.88e-09
82	Exiobase	Paraffin Waxes	0.26	0.12	2.87e-08	9.50e-09
83	Exiobase	Petroleum Coke	0.26	0.11	2.85e-08	9.56e-09
84	Exiobase	Non-specified Petroleum Products	0.26	0.11	2.83e-08	9.51e-09
85	Exiobase	Nuclear fuel	0.18	0.14	1.42e-08	2.06e-09
86	Exiobase	Plastics, basic	0.40	0.39	9.16e-09	4.49e-09
87	Exiobase	Secondary plastic for treatment, Re-processing of secondary plastic into new plastic	0.00	0.00	0.00e+00	0.00e+00
88	Exiobase	N-fertiliser	0.40	0.18	1.07e-08	1.18e-08
89	Exiobase	P- and other fertiliser	0.61	1.49	2.08e-08	1.04e-08
90	Exiobase	Chemicals nec	0.88	2.01	1.04e-08	8.37e-09
91	Exiobase	Charcoal	11.85	11.11	3.35e-08	2.88e-08
92	Exiobase	Additives/Blending Components	0.51	0.43	8.35e-09	4.61e-09
93	Exiobase	Biogasoline	0.54	0.42	8.45e-09	4.51e-09
94	Exiobase	Biodiesels	0.59	0.51	8.69e-09	4.74e-09
95	Exiobase	Other Liquid Biofuels	0.52	0.43	8.27e-09	4.47e-09
96	Exiobase	Rubber and plastic products (25)	1.15	1.40	7.16e-09	4.62e-09
97	Exiobase	Glass and glass products	0.54	0.29	1.01e-08	5.69e-09
98	Exiobase	Secondary glass for treatment, Re-processing of secondary glass into new glass	0.00	0.00	0.00e+00	0.00e+00
99	Exiobase	Ceramic goods	0.96	0.64	1.89e-08	9.89e-09
100	Exiobase	Bricks, tiles and construction products, in baked clay	0.70	0.19	1.09e-08	4.19e-09
101	Exiobase	Cement, lime and plaster	0.40	0.14	3.07e-08	1.57e-08
102	Exiobase	Ash for treatment, Re-processing of ash into clinker	0.00	0.00	0.00e+00	0.00e+00
103	Exiobase	Other non-metallic mineral products	0.42	0.33	1.09e-08	8.75e-09
104	Exiobase	Basic iron and steel and of ferro-alloys and first products thereof	0.26	0.17	1.67e-08	6.69e-09
105	Exiobase	Secondary steel for treatment, Re-processing of secondary steel into new steel	0.00	0.00	0.00e+00	0.00e+00
106	Exiobase	Precious metals	0.52	0.22	9.59e-09	4.56e-09
107	Exiobase	Secondary preciuos metals for treatment, Re-processing of secondary preciuos metals into new preciuos metals	0.00	0.00	0.00e+00	0.00e+00
108	Exiobase	Aluminium and aluminium products	0.31	0.18	1.26e-08	4.99e-09

109	Exiobase	Secondary aluminium for treatment, Re-processing of secondary aluminium into new aluminium	0.00	0.00	0.00e+00	0.00e+00
110	Exiobase	Lead, zinc and tin and products thereof	0.29	0.15	8.92e-09	4.64e-09
111	Exiobase	Secondary lead for treatment, Re-processing of secondary lead into new lead	0.00	0.00	0.00e+00	0.00e+00
112	Exiobase	Copper products	0.42	0.22	9.75e-09	3.54e-09
113	Exiobase	Secondary copper for treatment, Re-processing of secondary copper into new copper	0.00	0.00	0.00e+00	0.00e+00
114	Exiobase	Other non-ferrous metal products	0.81	0.35	1.04e-08	3.55e-09
115	Exiobase	Secondary other non-ferrous metals for treatment, Re-processing of secondary other non-ferrous metals into new other non-ferrous metals	0.00	0.00	0.00e+00	0.00e+00
116	Exiobase	Foundry work services	0.27	0.18	1.22e-08	4.36e-09
117	Exiobase	Fabricated metal products, except machinery and equipment (28)	0.27	0.40	6.50e-09	6.36e-09
118	Exiobase	Machinery and equipment n.e.c. (29)	0.27	0.28	4.38e-09	4.00e-09
119	Exiobase	Office machinery and computers (30)	0.25	0.50	3.25e-09	3.76e-09
120	Exiobase	Electrical machinery and apparatus n.e.c. (31)	0.35	0.36	5.25e-09	4.86e-09
121	Exiobase	Radio, television and communication equipment and apparatus (32)	0.24	0.26	3.84e-09	2.49e-09
122	Exiobase	Medical, precision and optical instruments, watches and clocks (33)	0.21	0.28	3.50e-09	2.85e-09
123	Exiobase	Motor vehicles, trailers and semi-trailers (34)	0.41	0.31	4.95e-09	2.78e-09
124	Exiobase	Other transport equipment (35)	0.26	0.27	4.37e-09	3.51e-09
125	Exiobase	Furniture; other manufactured goods n.e.c. (36)	2.06	1.11	6.50e-09	4.06e-09
126	Exiobase	Secondary raw materials	0.65	0.37	1.44e-08	3.53e-09
127	Exiobase	Bottles for treatment, Recycling of bottles by direct reuse	0.00	0.00	0.00e+00	0.00e+00
128	Exiobase	Electricity by coal	0.06	0.03	2.78e-07	9.20e-08
129	Exiobase	Electricity by gas	0.07	0.04	7.69e-08	9.71e-08
130	Exiobase	Electricity by nuclear	0.05	0.02	7.11e-10	3.30e-10
131	Exiobase	Electricity by hydro	0.06	0.03	1.26e-09	8.16e-10
132	Exiobase	Electricity by wind	0.06	0.03	2.56e-09	5.17e-10
133	Exiobase	Electricity by petroleum and other oil derivatives	0.14	0.10	1.96e-07	4.06e-08
134	Exiobase	Electricity by biomass and waste	0.09	0.04	1.86e-09	3.02e-08
135	Exiobase	Electricity by solar photovoltaic	0.02	0.02	4.65e-07	3.20e-08
136	Exiobase	Electricity by solar thermal	0.06	0.05	8.22e-10	6.27e-10
137	Exiobase	Electricity by tide, wave, ocean	0.00	0.00	0.00e+00	0.00e+00
138	Exiobase	Electricity by Geothermal	0.08	0.03	1.06e-09	4.10e-10

139	Exiobase	Electricity nec	0.10	0.04	5.14e-09	3.59e-09
140	Exiobase	Transmission services of electricity	0.07	0.03	1.54e-09	1.14e-09
141	Exiobase	Distribution and trade services of electricity	0.08	0.03	8.96e-10	3.92e-10
142	Exiobase	Coke oven gas	0.05	0.11	3.46e-08	9.27e-09
143	Exiobase	Blast Furnace Gas	0.09	0.11	9.13e-08	1.09e-08
144	Exiobase	Oxygen Steel Furnace Gas	0.00	0.00	0.00e+00	0.00e+00
145	Exiobase	Gas Works Gas	0.06	0.12	1.77e-08	5.31e-09
146	Exiobase	Biogas	0.09	0.05	3.33e-08	3.63e-08
147	Exiobase	Distribution services of gaseous fuels through mains	0.06	0.11	2.31e-08	7.41e-09
148	Exiobase	Steam and hot water supply services	0.15	0.06	5.41e-07	6.80e-07
149	Exiobase	Collected and purified water, distribution services of water (41)	0.15	0.08	5.23e-09	2.32e-09
150	Exiobase	Construction work (45)	1.14	0.44	4.22e-09	1.85e-09
151	Exiobase	Secondary construction material for treatment, Re-processing of secondary construction material into aggregates	0.00	0.00	0.00e+00	0.00e+00
152	Exiobase	Sale, maintenance, repair of motor vehicles, motor vehicles parts, motorcycles, motor cycles parts and accessoiries	0.02	0.01	6.77e-10	1.56e-10
153	Exiobase	Retail trade services of motor fuel	0.66	0.35	2.91e-09	3.88e-09
154	Exiobase	Wholesale trade and commission trade services, except of motor vehicles and motorcycles (51)	0.04	0.01	6.48e-10	1.70e-10
155	Exiobase	Retail trade services, except of motor vehicles and motorcycles; repair services of personal and household goods (52)	0.02	0.01	1.89e-10	1.51e-10
156	Exiobase	Hotel and restaurant services (55)	1.27	0.10	3.30e-09	5.21e-10
157	Exiobase	Railway transportation services	0.14	0.30	1.13e-08	3.39e-09
158	Exiobase	Other land transportation services	0.08	0.04	2.72e-09	7.54e-10
159	Exiobase	Transportation services via pipelines	0.14	0.67	7.16e-08	2.81e-08
160	Exiobase	Sea and coastal water transportation services	0.22	0.28	2.78e-08	7.09e-09
161	Exiobase	Inland water transportation services	0.13	0.03	2.48e-08	1.03e-08
162	Exiobase	Air transport services (62)	0.21	0.09	1.87e-08	6.64e-09
163	Exiobase	Supporting and auxiliary transport services; travel agency services (63)	0.08	0.02	1.94e-09	8.83e-10
164	Exiobase	Post and telecommunication services (64)	0.07	0.02	1.39e-09	3.22e-10
165	Exiobase	Financial intermediation services, except insurance and pension funding services (65)	0.14	0.02	1.99e-09	3.92e-10
166	Exiobase	Insurance and pension funding services, except compulsory social security services (66)	0.08	0.02	9.32e-10	3.35e-10

167	Exiobase	Services auxiliary to financial intermediation (67)	0.10	0.02	9.37e-10	3.10e-10
168	Exiobase	Real estate services (70)	0.34	0.03	1.93e-09	6.52e-10
169	Exiobase	Renting services of machinery and equipment without operator and of personal and household goods (71)	0.13	0.08	2.12e-09	5.28e-10
170	Exiobase	Computer and related services (72)	0.14	0.03	1.71e-09	4.24e-10
171	Exiobase	Research and development services (73)	0.26	0.16	3.21e-09	1.25e-09
172	Exiobase	Other business services (74)	0.17	0.17	2.03e-09	1.34e-09
173	Exiobase	Public administration and defence services; compulsory social security services (75)	0.33	0.12	3.51e-09	1.16e-09
174	Exiobase	Education services (80)	0.33	0.08	3.63e-09	1.22e-09
175	Exiobase	Health and social work services (85)	0.41	0.31	2.72e-09	1.53e-09
176	Exiobase	Food waste for treatment: incineration	0.50	0.10	9.97e-09	1.63e-09
177	Exiobase	Paper waste for treatment: incineration	0.21	0.08	9.71e-09	1.51e-09
178	Exiobase	Plastic waste for treatment: incineration	0.12	0.07	4.10e-08	3.13e-09
179	Exiobase	Intert/metal waste for treatment: incineration	0.15	0.11	3.88e-08	3.16e-09
180	Exiobase	Textiles waste for treatment: incineration	0.15	0.06	4.22e-08	3.37e-09
181	Exiobase	Wood waste for treatment: incineration	0.19	0.06	1.04e-08	1.36e-09
182	Exiobase	Oil/hazardous waste for treatment: incineration	0.30	0.05	2.58e-08	2.54e-09
183	Exiobase	Food waste for treatment: biogasification and land application	2.21	0.47	1.36e-08	3.66e-09
184	Exiobase	Paper waste for treatment: biogasification and land application	2.24	0.91	2.13e-08	1.05e-08
185	Exiobase	Sewage sludge for treatment: biogasification and land application	0.15	0.08	7.92e-09	1.54e-09
186	Exiobase	Food waste for treatment: composting and land application	0.53	0.15	1.16e-08	2.58e-09
187	Exiobase	Paper and wood waste for treatment: composting and land application	0.14	0.07	9.18e-09	1.30e-09
188	Exiobase	Food waste for treatment: waste water treatment	0.18	0.08	1.69e-08	3.12e-09
189	Exiobase	Other waste for treatment: waste water treatment	0.18	0.08	8.14e-09	1.12e-09
190	Exiobase	Food waste for treatment: landfill	0.19	0.07	1.49e-07	6.70e-08
191	Exiobase	Paper for treatment: landfill	0.12	0.08	2.31e-07	2.55e-08
192	Exiobase	Plastic waste for treatment: landfill	0.22	0.07	2.17e-08	5.41e-09
193	Exiobase	Inert/metal/hazardous waste for treatment: landfill	0.16	0.08	7.10e-09	1.39e-09
194	Exiobase	Textiles waste for treatment: landfill	0.12	0.07	2.40e-08	7.40e-09
195	Exiobase	Wood waste for treatment: landfill	0.12	0.07	6.86e-08	2.80e-08
196	Exiobase	Membership organisation services n.e.c. (91)	0.30	0.08	2.72e-09	1.04e-09

197	Exiobase	Recreational, cultural and sporting services (92)	0.23	0.08	2.65e-09	6.46e-10
198	Exiobase	Other services (93)	0.14	0.08	2.42e-09	1.22e-09
199	Exiobase	Private households with employed persons (95)	0.66	0.47	6.44e-09	9.80e-10
200	Exiobase	Extra-territorial organizations and bodies	0.00	0.00	0.00e+00	0.00e+00
201	COICOP	Food	7.71	6.08	9.88e-09	5.78e-09
202	COICOP	Bread and cereals	7.22	5.72	9.98e-09	5.28e-09
203	COICOP	Meat	10.53	6.43	1.69e-08	1.10e-08
204	COICOP	Fish and seafood	3.91	1.79	1.21e-08	5.11e-09
205	COICOP	Milk. cheese and eggs	9.27	5.99	1.91e-08	9.94e-09
206	COICOP	Oils and fats	12.26	7.42	1.56e-08	8.17e-09
207	COICOP	Fruit	2.44	1.87	3.06e-09	1.68e-09
208	COICOP	Vegetables	2.44	1.87	3.06e-09	1.68e-09
209	COICOP	Sugar. jam. honey. chocolate and confectionery	7.42	4.61	1.53e-08	7.86e-09
210	COICOP	Food products n.e.c.	4.76	3.11	7.77e-09	3.98e-09
211	COICOP	Non-alcoholic beverages	3.30	2.19	7.08e-09	3.57e-09
212	COICOP	Alcoholic beverages	3.30	2.19	7.08e-09	3.57e-09
213	COICOP	Tobacco	0.74	0.50	4.27e-09	2.17e-09
214	COICOP	Clothing	0.84	0.63	1.04e-08	4.90e-09
215	COICOP	Footwear	1.24	0.97	1.07e-08	5.21e-09
216	COICOP	Actual rent	0.34	0.03	1.93e-09	6.52e-10
217	COICOP	Imputed rent	0.34	0.03	1.93e-09	6.52e-10
218	COICOP	Maintenance and repair of the dwelling	3.13	1.47	5.67e-09	2.96e-09
219	COICOP	Water supply and miscellaneous services reacting to the dwelling	0.21	0.08	4.94e-08	1.59e-08
220	COICOP	Electricity	0.06	0.03	2.94e-08	1.98e-08
221	COICOP	Gas	0.19	0.09	4.60e-08	1.08e-08
222	COICOP	Liquid fuels	0.47	0.37	1.64e-08	6.55e-09
223	COICOP	Solid fuels	27.79	10.19	1.01e-08	3.41e-09
224	COICOP	Heat energy	0.15	0.06	5.41e-07	6.80e-07
225	COICOP	Furniture and furnishings	2.05	1.10	6.58e-09	4.05e-09
226	COICOP	Carpets and other floor coverings	1.82	1.06	8.21e-09	4.56e-09
227	COICOP	Repair of furniture. furnishings and floor coverings	1.44	0.77	4.58e-09	2.86e-09
228	COICOP	Household textiles	0.92	0.67	1.03e-08	5.15e-09
229	COICOP	Household appliances	0.27	0.31	4.90e-09	4.58e-09
230	COICOP	Glassware. tableware and household utensils	1.14	0.90	1.10e-08	6.17e-09
231	COICOP	Tools and equipment for house and garden	1.10	0.66	6.49e-09	4.97e-09
232	COICOP	Non-durable household goods	1.16	1.61	9.68e-09	6.74e-09
233	COICOP	Domestic services and household services	0.29	0.20	3.44e-09	6.66e-10

234	COICOP	Medical products, appliances and equipment	0.81	1.83	9.68e-09	7.82e-09
235	COICOP	Out-patient services	0.41	0.31	2.72e-09	1.53e-09
236	COICOP	Hospital services	0.41	0.31	2.72e-09	1.53e-09
237	COICOP	Purchase of vehicles	0.31	0.25	4.03e-09	2.33e-09
238	COICOP	Spare parts and accessories for personal transport equipment	0.42	0.25	4.22e-09	2.33e-09
239	COICOP	Fuels and lubricants for personal transport equipment	0.34	0.26	2.78e-08	9.82e-09
240	COICOP	Maintenance and repair of personal transport equipment	0.07	0.06	1.43e-09	9.36e-10
241	COICOP	Other services in respect of personal transport equipment	0.17	0.13	3.68e-09	1.82e-09
242	COICOP	Passenger transport by railway	0.14	0.30	1.13e-08	3.39e-09
243	COICOP	Passenger transport by road	0.08	0.03	2.60e-09	7.73e-10
244	COICOP	Passenger transport by air	0.24	0.22	2.18e-08	7.98e-09
245	COICOP	Passenger transport by sea and inland waterway	0.22	0.28	2.78e-08	7.09e-09
246	COICOP	Combined passenger transport	0.18	0.15	2.63e-08	8.67e-09
247	COICOP	Other purchased transport services	0.21	0.30	3.04e-08	8.51e-09
248	COICOP	Communication	0.15	0.14	2.62e-09	1.41e-09
249	COICOP	Audio-visual, photographic and information processing equipment	0.25	0.26	3.48e-09	2.51e-09
250	COICOP	Other major durables for recreation and culture	0.33	0.15	2.89e-09	9.93e-10
251	COICOP	Other recreational items and equipment, gardens and pets	1.26	0.67	6.41e-09	3.39e-09
252	COICOP	Recreational and cultural services	0.24	0.08	2.66e-09	7.02e-10
253	COICOP	Newspapers, books and stationery	0.95	0.16	4.78e-09	1.19e-09
254	COICOP	Package holidays	0.56	0.05	2.49e-09	7.38e-10
255	COICOP	Pre-primary and primary education. Secondary education. Post-secondary education. Tertiary education and Education not defined by level	0.32	0.09	3.52e-09	1.17e-09
256	COICOP	Catering services	1.27	0.10	3.30e-09	5.21e-10
257	COICOP	Accommodation services	1.27	0.10	3.30e-09	5.21e-10
258	COICOP	Personal care	0.40	0.31	2.89e-09	1.78e-09
259	COICOP	Jewellery. clocks and watches	1.27	0.75	5.21e-09	3.54e-09
260	COICOP	Other personal effects	0.95	0.25	5.79e-09	1.92e-09
261	COICOP	Social protection	0.55	0.39	5.63e-09	1.03e-09
262	COICOP	Insurance	0.13	0.04	1.44e-09	4.96e-10
263	COICOP	Other financial services n.e.c.	0.14	0.02	1.89e-09	3.84e-10
264	COICOP	Other services n.e.c.	0.14	0.06	1.59e-09	6.40e-10

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