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Trade-offs between social and environmental Sustainable Development Goals

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ABSTRACT

The UN's 17 Sustainable Development Goals (SDGs) aim to improve the lives of people, increase prosperity, and protect the planet. Given the large number of goals, interactions are inevitable. We analyse the interaction between two social goals (related to SDG1 Poverty and SDG10 Inequality) and three environmental goals (related to SDG13 Carbon, SDG15 Land, and SDG6 Water). We use a trade-linked, consumption-based approach to assess interactions in 166 nations, each subdivided into four income groups. We find that pursuing social goals is, generally, associated with higher environmental impacts. However, interactions differ greatly among countries and depend on the specific goals. In both interactions, carbon experiences smaller changes than land and water. Although efforts by high- and low-income groups are needed, the rich have a greater leverage to reduce humanity's footprints. Given the importance of both social and environmental sustainability, it is crucial that quantitative interactions between SDGs be well understood so that, where needed, integrative policies can be developed.

1. Introduction

In response to increasing concern about the long-term sustainability of human societies, the United Nations developed the Sustainable Development Goals (SDGs), a 2030 agenda including 17 goals and 169 targets (United Nations, 2016). Despite criticisms of the framework (Kopnina, 2015), these goals currently dominate the sustainability and policy discussions surrounding development. Some initial progress towards the SDGs was achieved, but our understanding of interactions between SDGs remains limited (Allen et al., 2018). With such a plethora of goals and targets, interaction is inevitable. Possible interactions range from cancellation (achievement of an SDG makes progress on another impossible) to indivisibility (success in an SDG is contingent on success of another) (Nilsson et al., 2016). Correlations between SDGs mostly point towards synergies, but also indicate trade-offs (Pradhan et al., 2017). For some SDGs these interactions are clear, while others are opaque. For example, the environmental impact of increasing equality across income groups could be positive or negative (Rao and Min, 2018). The magnitude of interaction effects is also critical. Although one can assume that increasing incomes above extreme poverty will increase environmental pressures, the magnitude and location of these impacts caused by the global economy are rarely investigated (Hubacek et al., 2017). Given the importance of these goals and their short time horizon, it is critical that policy makers receive relevant and timely information to facilitate potential mitigation or adaptation policies on SDG trade-offs.

Here we quantitatively assess the environmental impacts of ending poverty (related to SDG 1: no poverty), and reducing inequality (related to SDG 10: reduced inequalities). Our choice of social SDGs is motivated by previous findings that individual consumption is the most significant driver of environmental pressures, rather than population (Bradshaw et al., 2010). Furthermore, since poverty and inequality are reflected in consumption volumes (Aguiar and Bils, 2015), any developments suggest concomitant changes in environmental impacts among income groups.

The majority of environmental impacts can be attributed both directly and indirectly (through supply chains) to the consumption by households (Ivanova et al., 2016). Household consumption is a key indicator of wealth and poverty within the SDG framework. Previous work on the environmental impact of household consumption has generally focused solely on a single country or region and a single footprint (López et al., 2017; Sommer and Kratena, 2017; Wiedenhofer

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et al., 2017). Cross-country analyses rarely distinguish income levels (Ivanova et al., 2016), or are limited to one interaction with the environment (Hubacek et al., 2017). In this work, we quantify the effect of reducing extreme poverty and inequality on environmental impacts. We estimate country-specific effects for 166 nations of the world (Fig. A1), covering 6.84 billion people (99% of the total population; UN, 2017). We choose three environmental footprint categories corresponding to carbon (CO_2-equivalents, related to SDG 13: climate action), land (land stress, related to SDG 15: life on land), and water (freshwater scarcity, related to SDG 6: clean water and sanitation). Water and land, as our most vital resources, are scarce (Lambin and Meyfroidt, 2011; Scherer and Pfister, 2016a), and global temperature rise is still accelerating (Smith et al., 2015), which highlights the importance of these three environmental categories.

To perform the analysis, we link the Global Consumption Database of the World Bank (World Bank, 2017c) to EXIOBASE (Stadler et al., 2018). In EXIOBASE, international trade links the production and consumption of countries. This approach is essential, as 20–37% of environmental impacts are related to production for exports (Lenzen et al., 2012; Wiedmann, 2016). Our year of reference is 2010. As the magnitude and pattern of expenditure differs among income groups (see Figs. A2 and A3), we investigate trends within four different income groups.

2. Methods

2.1. Household expenditures

Fig. A4 shows the conceptual framework of the main analysis. The World Bank distinguishes four income groups for household expenditures of 106 products and services in 91 countries in 2010 (World Bank, 2017c). The income groups use international dollars, considering the purchasing power parity, and are split by absolute monetary boundaries: lowest ≤ \$2.97, low = \$2.97–8.44 \$, middle = \$8.44–23.03, and higher ≥ \$23.03 per capita per day. Per-capita expenditures are multiplied with the population of each income group to obtain total expenditures per income group. To link the World Bank database to EXIOBASE, the expenditures are reclassified to the 200 products and services of EXIOBASE. First, a concordance matrix (C) is built, which indicates if a class from the World Bank is (partially) contained in a class of EXIOBASE (1) or not (0). Second, a bridge matrix (B) is estimated that translates the classes from one system to the other:

$$f_2 \approx f_{2,100} = B_{100}{}^T \bullet f_1$$

where f_1 is the total expenditures or final demand vector from the World Bank and f_2 is the total final demand vector in the classification of EXIOBASE. The index of 100 indicates the maximum number of iterations during which B is estimated. A first guess of B (B_1) is derived from C with the additional information about the distribution of total expenditures among the EXIOBASE classes (d_2), a vector whose sum equals 1:

$$B_i = (C\hat{\cdot d_2})^{-1} \bullet C \bullet \hat{d}_2$$

where the hat (ˆ) denotes a diagonal matrix of a vector. Subsequently, B is iteratively updated to further harmonise the two classification systems using a variant of the RAS algorithm (Stone, 1961):

$$B_{i+1} = \hat{r}_i \bullet A_i \bullet \hat{s}_i$$

where

$$A_i = \hat{f}_1 \bullet B_i$$

$$s_i = d_2 \oslash d_{2,i} = d_2 \oslash (f_{2,i} / (\vec{1}^T \bullet A_i \bullet \vec{1}))$$

$$r_i = f_1 \oslash f_{1,i} = f_1 \oslash (A_i \bullet \hat{s}_i \bullet \vec{1})$$

where $\oslash$ is Hadamard (element-wise) division and $\vec{1}$ is a column vector of 1′s. B is calibrated without distinguishing income groups in either classification, and then applied to reclassify the World Bank's detailed expenditures to EXIOBASE's product system.

We estimate expenditures per income group for additional 74 countries (24% of the analysed population but 82% of the expenditures) by assuming a lognormal distribution of incomes (Bílková and Malá, 2012; Easterly, 2009). The income Gini index (Central Intelligence Agency, 2017; World Bank, 2017b) (G) allows to calculate the standard deviation (σ) of that distribution (Bílková and Malá, 2012):

$$\sigma = 2 \bullet erf^{-1}(G)$$

where erf^{-1} is the inverse error function. The Lorenz curve with the resulting standard deviation, calculated with the function "Lc.lognorm" in R package "ineq" (Zeileis, 2014), provides the cumulative income shares. Income shares are then multiplied with the mean per-capita expenditures (World Bank, 2017d) and a sample population of 10,000 to get individual incomes, which are subsequently split into income groups at a precision of 2 decimal percentages. Since the income boundaries are expressed in international dollars, but expenditures in US dollars, we multiply the thresholds with the country's price level ratio (World Bank, 2017e). Gaps in expenditures are first filled with estimates from a linear regression with the country's GDP (World Bank, 2017a) (adjusted $R^2 = 0.89$). Remaining gaps in income Gini indices and expenditures are filled with values from nearby countries. Population data is obtained from the United Nations (UN, 2017). EXIOBASE provides expenditure patterns for 32 of the additional countries without differentiating incomes (Tukker et al., 2013; Wood et al., 2015). In contrast to countries covered by the Global Consumption Database, expenditure patterns of countries covered by EXIOBASE are assumed not to differ among income groups. For the remaining 43 countries (9% of the analysed population), the expenditure patterns are assumed to be equal to nearby countries. Which countries follow which approach is listed in Appendix B.

To validate our approach of using the Gini index to derive income contributions of EXIOBASE countries, we compare our estimates of income quintiles with the income quintiles given in the World Bank's Development Indicator Database. The estimates and reference values are provided in Appendix C, along with the Pearson correlation coefficients for a total of 40 countries for which the required data is available in the year 2010. The correlation coefficient ranges from 0.9965 to 0.9999, demonstrating the robustness of our method.

For visualization and interpretation, products are aggregated to seven consumption categories. 1) Food includes plant-based and animal products as well as restaurant services. 2) Housing includes real estate services, forestry and wood products, construction materials, water, and waste. 3) Energy includes electricity, housing fuels, and hot water. 4) Transport includes vehicles, transport services, and transportation fuels. 5) Clothing includes wearing apparel, furs, and products from wool, textile, and leather. 6) Manufactured goods include machinery, equipment, and other manufactured goods. 7) Services include education, health, recreational, and other services.

2.2. Environmentally extended multi-regional input-output analysis

We use the product-by-product version 3.4 of EXIOBASE (Stadler et al., 2018) based on the industry technology assumption for environmentally extended multi-regional input-output analyses (EE-MRIO). It allows to connect national consumption to production anywhere in the world, and covers 200 product groups per country and 49 countries or regions. The impacts of a country's consumption sourcing products from different locations are then evaluated by:

$$H = Q \bullet B \bullet (I - A)^{-1} \bullet F + D$$

where H is the impact matrix with income groups as columns. Q is the characterization matrix that describes the impacts per unit of emission