

Implications of the distribution of German household environmental footprints across income groups for integrating environmental and social policy design

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Abstract

The distribution of German household environmental footprints (EnvFs) across income groups is analyzed by using EXIOBASE v3.6 and the consumer expenditure survey of 2013. Expenditure underreporting is corrected by using a novel method, where the expenditures are modeled as truncated normal distribution. The focus lies on carbon (CF) and material (MF) footprints, which for average German households are 9.1 ± 0.4 metric tons CO₂e and 10.9 ± 0.6 metric tons material per capita. Although the lowest-income group has the lowest share of transportation in EnvFs, at 10.4% (CF) and 3.9% (MF), it has the highest share of electricity and utilities in EnvFs, at 39.4% (CF) and 16.7% (MF). In contrast, the highest-income group has the highest share of transportation in EnvFs, at 20.3% (CF) and 12.4% (MF). The highest-income group has a higher share of emissions produced overseas (38.6% vs. 34.3%) and imported resource use (69.9% vs. 66.4%) compared to the average households. When substituting 50% of imported goods with domestic ones in a counterfactual scenario, this group only decreases its CF by 2.8% and MF by 5.3%. Although incomes in Germany are distributed more equally (Gini index 0.28), the German household CF is distributed less equally (0.16). A uniform carbon tax across all sectors would be regressive (Suits index -0.13). Hence, a revenue recycling scheme is necessary to alleviate the burden on low-income households. The overall carbon intensity shows an inverted-U trend due to the increasing consumption of carbon-intensive heating for lower-income groups, indicating a possible rebound effect for these groups. This article met the requirements for a gold – gold JIE data openness badge described at <http://jie.click/badges>.

KEYWORDS

carbon footprint, carbon tax, industrial ecology, inequality, input–output analysis (IOA), uncertainty

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1 | INTRODUCTION

Household consumption is associated with roughly 60% of the global greenhouse gas (GHG) emissions and 50–80% of global resource use (Ivanova et al., 2016; Peters & Hertwich, 2008). In order to reduce these environmental pressures, developed countries, in particular, implement abatement measures, such as energy efficiency and changes in the economic structure (Ang & Su, 2016; Voigt, De Cian, Schymura, & Verdolini, 2014). Germany, for example, reduced its GHG emissions, from 1.25 (fourth largest global emitter in 1990) to 0.91 (seventh in 2015) billion tons¹ CO₂e (UNFCCC, 2019). Although Germany has achieved an absolute decoupling between economic growth and production-based GHG emissions, there has been no decoupling between its economy and consumption-based emissions (carbon footprint) (Sanyé-Mengual, Secchi, Corrado, Beylot, & Sala, 2019). Increasing supply-chain emissions overseas are largely due to manufacturing outsourcing to nations with lower average production costs, and often also higher carbon intensities (Wiedmann & Lenzen, 2018), particularly China (Davis & Caldeira, 2010; Peters, Davis, & Andrew, 2012).

Germany's national climate change mitigation strategy relies heavily on production-based measures, such as industrial emissions permit trading, energy efficiency, and renewable energy policies (Renn & Marshall, 2016; Tanaka, 2011). Consumption-based policies complement these measures to curb the emissions increase from household consumption due to rising affluence, for example, by shifting consumption toward commodities with lower environmental impacts (Baranzini et al., 2017; Böhringer, Bye, Fæhn, & Rosendahl, 2012a; Minx et al., 2013). However, these policies, for example, a carbon tax applied to household consumption, tend to be regressive as they might impact low-income groups more severely than higher-income ones (Büchs, Bardsley, & Duwe, 2011). Consequently, their distributive implications need to be considered as a main linkage between environmental and social policy design (Beck, Rivers, Wigle, & Yonezawa, 2015; Wang, Hubacek, Feng, Wei, & Liang, 2016).

Increasing inequality is a global phenomenon (Milanovic, 2013; Piketty & Saez, 2014) that is also observable in Germany. Despite being a relatively equitable country, Germany has experienced a gradual increase in income Gini index from 0.26 in 2000 to 0.29 in 2012 (Grabka, Goebel, & Schröder, 2015). While implementing a carbon tax could help Germany achieve its climate target (Lutz & Meyer, 2010), the distribution of embodied GHG emissions in the groups' household consumption has to be assessed beforehand to understand how environmental and social objective can be reconciled (Neuhoff, Bach, Diekmann, Beznoska, & El-Laboudy, 2013) and to identify consumption levels that stay within the global physical limits (Tukker et al., 2016).

1.1 | Inequality of environmental footprints across income groups

The study of environmental footprints (EnvFs), using global supply-chain data from production stage to the point of final consumption, provides the information about environmental pressure embodied in trade (Jiborn, Kander, Kulionis, Nielsen, & Moran, 2018; Peters & Hertwich, 2008; Tukker, Wood, & Giljum, 2018b). Carbon (CF), land (LF), material (MF), and water footprint (WF) are considered as the major EnvFs (Steinmann et al., 2018). Identifying the main consumption sectors and production sources and regions of GHG emissions and resource use helps policymakers to target these supply-chain hotspots appropriately (Wood et al., 2019). Identifying regional hotspots is also necessary due to the differences in emission and resource intensities of imports (López, Arce, Kronenberg, & Rodrigues, 2018).

Previous studies showed that expenditure and income are the strongest driving forces of household EnvFs (Baiocchi & Minx, 2010; Ivanova et al., 2017; Weber & Matthews, 2008). Understanding how EnvFs vary with income is critical to avoid increasing economic inequality due to environmental policies, upholding the United Nation Sustainable Development Goals (SDGs) of Responsible Consumption and Production, Climate Action, and Reduced Inequalities (Costanza et al., 2016; Scherer et al., 2018).

While income-specific CF studies for Germany (Miehe, Scheumann, Jones, Kammen, & Finkbeiner, 2016), other European countries (Duarte, Mainar, & Sánchez-Chóliz, 2012; Isaksen & Narbel, 2017; Kerkhof, Moll, Drissen, & Wilting, 2008; López, Arce, Morenate, & Monsalve, 2016; Steen-Olsen, Wood, & Hertwich, 2016), and other large economies (Hubacek, Baiocchi, Feng, & Patwardhan, 2017; Perobelli, Faria, & Vale, 2015; Wiedenhofer et al., 2017) have been conducted, inequality in other major household EnvFs, such as MF, is not that well studied (López, Arce, Morenate, & Zafrilla, 2017; Shigetomi, Nansai, Kagawa, & Tohno, 2016). LF and WF are not largely discussed in the income-specific studies, since they are largely dominated by food products (Steen-Olsen, Weinzettel, Cranston, Ercin, & Hertwich, 2012). People do not tend to consume more food due to rising income, hence the LF and WF inequalities are not as stark (Dorband, Jakob, Kalkuhl, & Steckel, 2019).

While a breakdown of footprints by emitting industries and producing regions is available in the current income-specific studies (López et al., 2016, 2017), these studies do not take into account the "greener" consumption choices made by higher income groups, for example, buying eco-labeled products that have lower environmental impacts. Environmentally conscious consumers tend to have a higher income than the average and are willing to pay higher prices for those products (Pedersen & Neergaard, 2005).

Several studies have modeled the impact of individual actions to reduce consumption-based emissions (Duarte et al., 2015; Moran et al., 2018; Wood et al., 2018a). However, to the best of our knowledge, there are no studies that have modeled the impact of these actions for different income

¹ All tons used throughout this article refers to metric tons.

groups. High-income groups show a propensity to consume local products (Auger, Devinney, Louviere, & Burke, 2010), which could reduce their EnvFs.

1.2 | Goal and scope of the study

This paper assesses the distribution of household EnvFs across income groups in Germany in detail, focusing on the CF and MF. The case study of Germany enriches the literature in the income-specific household EnvFs, whose income inequality (Gini index 0.28) is lower than those of Spain (0.34) (López et al., 2016) and Japan (0.33) (Koide et al., 2019), but higher than that of Norway (0.26) (Steen-Olsen et al., 2016). Results and discussion on LF and WF are available in Supporting Information S1.

The methodology to calculate the EnvFs and the inequality parameters is available in Section 2. We report the consumption pattern changes across income and product groups (Section 3.1) and emitting industries (Section 3.2). Section 3.2 also provides a simulation of substituting imports from the carbon-intensive nations with domestic goods. Footprint intensities across income groups are assessed in Section 3.3. The distribution of the EnvFs is evaluated using Gini indices in Section 3.4. Additionally, carbon tax scenarios (without and with revenue recycling) are simulated to observe the economic impacts on different income groups in Section 3.5. The reliability of the results is discussed in Section 4, while their policy implications are discussed in Section 4.1. The limitations of the selected method and the research scope are addressed in Section 4.2, and we provide an outlook on the future research in Section 5.

2 | DATA AND METHODOLOGY

In order to assess the environmental pressure of global supply chains, multi-regional input–output (MRIO) approach was chosen as it enables us to evaluate the burdens borne by different countries due to the imported products for household consumption (Hubacek, Feng, Minx, Pfister, & Zhou, 2014; López et al., 2016). Consumer expenditure survey (CES) was utilized to obtain the final consumption data for each income group.

The two main problems in conducting income-specific footprinting studies are (a) to bridge the CES dataset to the classification of the MRIO table, and (b) to account for the expenditure underreporting, which causes considerable differences between household demand in the System of National Accounts (SNA) and the CES dataset. This study improved the existing method applied in bridging the expenditures by correcting the underreporting in the same classification and price as in the CES, prior to the bridging process (Min & Rao, 2017). The hitherto applied correction methods are conducted after bridging the survey data (Steen-Olsen et al., 2016), which is already a major uncertainty source (Min & Rao, 2017).

Underreporting is attributable to (a) recall bias, where respondents are less likely to report infrequent purchases correctly; (b) non-responses, where they are reluctant to report purchases that are socially undesirable; and (c) imputation errors, where the estimated values to fill missing data are lower than the actual values (Deaton, 2005). It is typically biased toward certain product categories, such as alcohol and tobacco, illicit services, or medical emergencies (Blattman, Jamison, Koroknay-Palicz, Rodrigues, & Sheridan, 2016; Steen-Olsen et al., 2016). The uncertainties reported in the CES are mostly lower than the underreporting gaps (DESTATIS, 2015).

To better quantify the underreporting, this study modeled the expenditure uncertainty as truncated normal distribution. This distribution is often used to simulate uncertainties from censored datasets (Cragg, 1971), where a dependent variable is below or above a certain value, but it is unknown by how much (Hsu & Liu, 2008). Using this distribution, the CES and SNA expenditure datasets are assigned as the lower and upper bounds, respectively. Consequently, the new mean expenditures will be between these bounds.

2.1 | Expenditure data sources

The Federal Statistical Office of Germany provides the household consumption in the SNA according to the COICOP (Classification of Individual Consumption by Purpose) classification in purchaser's price and NACE classification in both basic and purchaser's price (DESTATIS, 2015). It also provides CES data aggregated for each income group, EVS 2013. Since this study focuses only on the Gini index, using the aggregate data (instead of the micro-data) is adequate since the mean expenditure for each product and income group is available in this dataset (Wiedenhofer et al., 2017). Applying micro-data requires imputing empty values and removing outliers, which could lead to larger errors if these procedures are not conducted properly (Marcus, Siegers, & Grabka, 2013).

We further disaggregated food expenditure data according to the food consumption survey (Heuer, Krems, Moon, Brombach, & Hoffmann, 2015). The disaggregation procedure and the statistical description of the expenditure datasets are available in Supporting Information S1-1 and S2, providing the mean, number of sampled households, and uncertainty levels (standard errors) for 98 expenditure categories of 11 income groups and the average households.

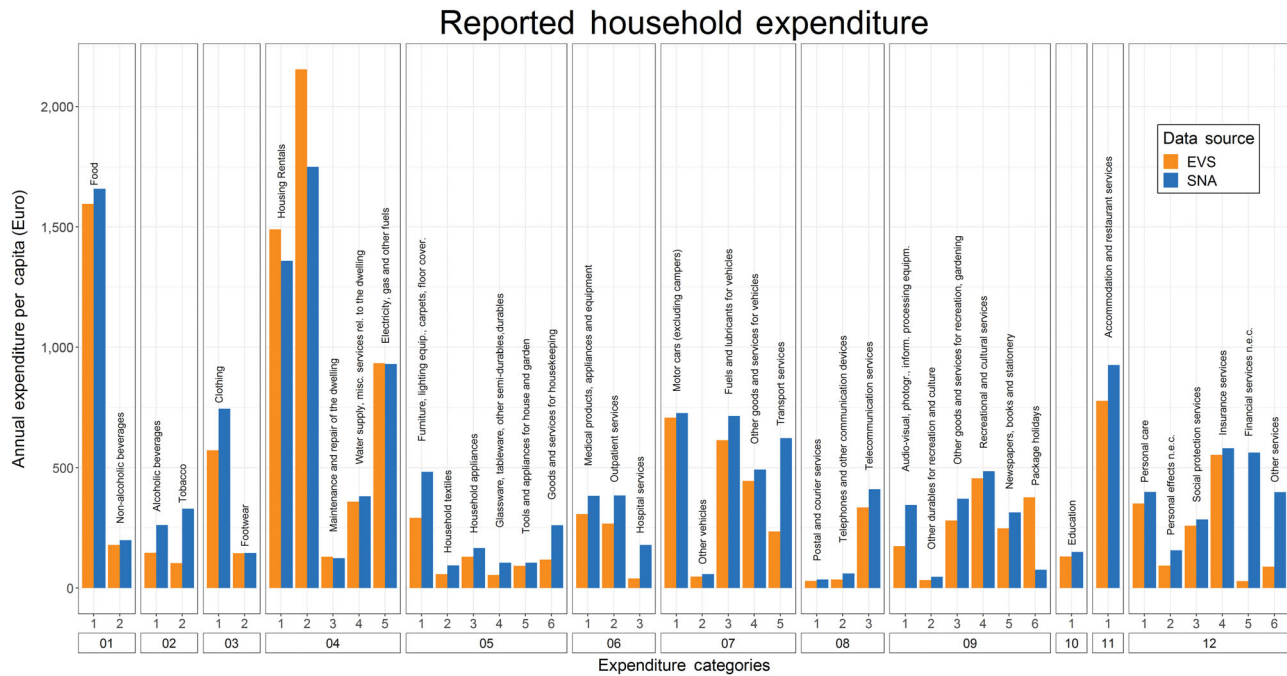


FIGURE 1 Reported annual household expenditure per capita for each (aggregate) expenditure category in COICOP classification, according to the survey (EVS) and national account (SNA). The orange bars report the annual expenditures based on the EVS, while the blue ones report those based on the SNA. Underlying data used to create this figure can be found in Supporting Information S2

Despite being reported in COICOP classification and purchaser's price, the expenditure figures from EVS and SNA are considerably different, with a substantial gap of 15.3% in total (Figure 1). Different spending categories show different underreporting rates, with the exception of housing rental (04.1 and 04.2) and package holidays categories (09.6) reporting higher expenditures in the EVS survey. These exceptions happen since the sampled households might have recorded their expenditures not thoroughly consistent with the COICOP classification, for example, they reported the expenditures on financial services (12.5) for housing mortgages to the housing rental categories (04.1 and 04.2) (Marcus et al., 2013).

2.2 | Calculating household environmental footprints and their uncertainties

The income-group-specific EnvFs were calculated using EXIOBASE v3.6 year 2013 in product-by-product construct that contains interindustrial commodity flows of 200 products in 49 regions (Stadler et al., 2018). Its high resolution is preferred in assessing environmental impacts to avoid lumping together major countries or sectors with different impact intensities (Inomata & Owen, 2014; Tukker et al., 2018a).

We addressed the underreporting problem by simulating multiple sets of expenditures for the average households within the range between EVS and SNA dataset. Using the underreporting data for each category (Figure 1), expenditure uncertainties were propagated in a Monte Carlo simulation (MCS), where we obtained 1,000 samples of both correspondence matrix and demand vector for each income group to then calculate the income-specific EnvFs (Min & Rao, 2017). To determine the expenditure ranges of other income groups, the underreporting is assumed to be distributed in proportion to the expenditure. The procedure to obtain a set of correspondence matrix and demand vectors is illustrated in Figure 2.

One thousand samples within the range of the average German household expenditures for each category were drawn to be assigned for bridging the expenditures in COICOP to NACE classification, based on a truncated normal distribution (Figure 2, Step 1). The probability density function (PDF) and parameters are formulated in Equation (1), where μ , σ , a , and b are the mean, the standard deviation, the lower and upper limits of the expenditure, respectively. Upper limits are determined based on the underreporting of each category. Detailed procedure to determine these parameters are provided in Figure S1.1 in Supporting Information S1.

$$\text{If } a \leq x \leq b \quad f(x; \mu, \sigma, a, b) = \frac{\phi\left(\frac{x-\mu}{\sigma}\right)}{\sigma\left(\Phi\left(\frac{b-\mu}{\sigma}\right) - \Phi\left(\frac{a-\mu}{\sigma}\right)\right)} \quad (1)$$

$$\text{else } f(x; \mu, \sigma, a, b) = 0$$

The process of bridging expenditures from COICOP to NACE classification

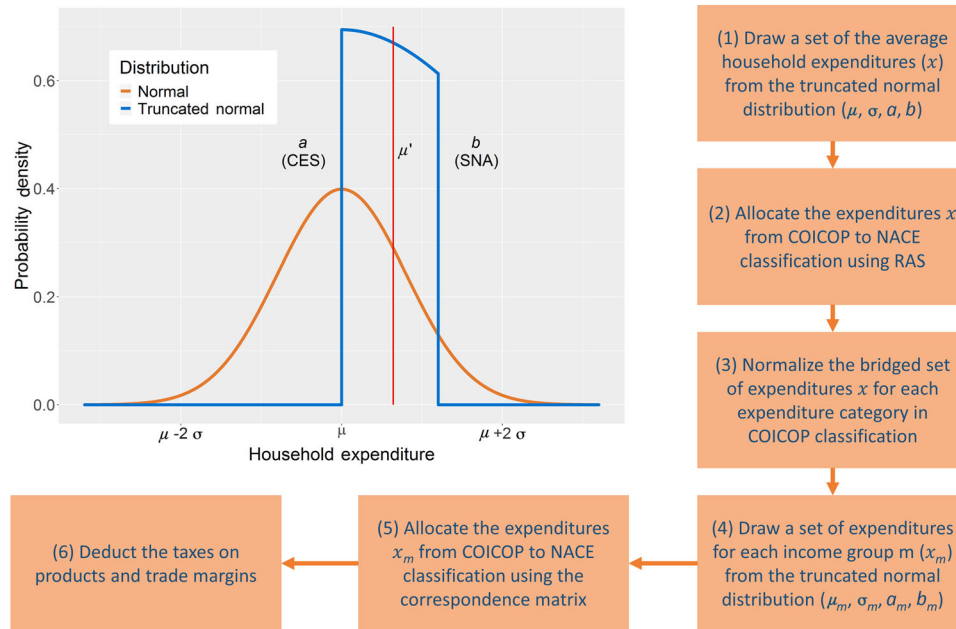


FIGURE 2 Algorithm for performing a Monte Carlo simulation (MCS) to calculate the income-specific EnvFs. One thousand samples of the average household expenditures were propagated based on a truncated normal distribution, to be allocated from COICOP to NACE classification (bridging). The allocated expenditures are then normalized to obtain 1,000 samples of correspondence matrix. These matrices were used to bridge 1,000 samples of demand vector for each income group, also propagated based on a truncated normal distribution. Finally, these demand vector samples were converted from purchaser's price to basic price

$$\phi(\xi) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}\xi^2\right) \quad \Phi(x) = \frac{1}{2} \left(1 + \frac{2}{\sqrt{\pi}} \int_0^{\frac{x}{\sqrt{2}}} e^{-t^2} dt \right).$$

The expenditure datasets in the SNA (X_i) were disaggregated from 42 to 103 COICOP categories based on the shares of the average expenditure in EVS dataset (\bar{x}_j) (Equation (2)). In the categories where the respondents incorrectly assigned purchases that belong to the other categories according to the SNA classification (e.g., including transportation into vacation categories), the expenditures were adjusted by disaggregating the aggregate purchases of these categories. The expenditures of housing rent (04.1 and 04.2), financial services (12.5), and other services (12.6) in SNA dataset were aggregated into one category, and transportation (07.5), vacation (09.6), and accommodation and restaurant (11.1) as another. Then the expenditures for these seven categories were disaggregated based on the expenditure shares in EVS dataset (Equation (3)). This new expenditure dataset (x'_j) is addressed as the adjusted SNA.

$$\text{If } i \notin \{04.1, 04.2, 12.5, 12.6\} \text{ or } \{07.5, 09.6, 11.1\} \quad x'_j = \frac{\bar{x}_j}{\sum_j \bar{x}_j} \times X_i \quad (2)$$

$$\text{else} \quad x'_j = \frac{\bar{x}_j}{\sum_j \bar{x}_j} \times \sum_i X_i. \quad (3)$$

We allocated the household expenditures in the EVS to the final demand vector (Y) in EXIOBASE, both in purchaser's price, using the RAS procedure (Figure 2, Step 2). While the household expenditure in basic price from EXIOBASE is similar to that from the SNA, with a 1.7% gap, we applied the tax and margin rates from the SNA to obtain the basic price, since the rates from EXIOBASE are much lower and therefore not suitable for use (Statistical Bureau, 2019).

Compared to the IPFP-RAS (iterative proportional fitting procedure) that randomizes expenditure allocation share within a set of constraints (Min & Rao, 2017), this procedure allocates the expenditures as close as possible to the values in the target vector (Miller & Blair, 2009). The initial

correspondence matrix was built based on the UN correspondence between COICOP and NACE classification, with several changes to obtain a closer match between the bridging result and EXIOBASE; for example, package holidays were also assigned to the hospitality, transportation, and recreational services.

When applied to the adjusted SNA expenditure data, the RAS procedure could result in small gap between the bridged expenditure and EXIOBASE datasets in purchaser's price, at around 1.5% for most categories. The correspondence matrix R was obtained by dividing the bridged expenditure to each NACE sector k by the total expenditure of the COICOP category j (Figure 2, Step 3), provided in Equation (4). The details of the RAS procedure and the expenditure bridging results are provided in Supporting Information S1-2 and S2.

$$R = \begin{bmatrix} R_{11} & \cdots & R_{1k} \\ \vdots & \ddots & \vdots \\ R_{j1} & \cdots & R_{jk} \end{bmatrix} = \begin{bmatrix} \frac{x_{11}}{\sum_j x_{j1}} & \cdots & \frac{x_{1k}}{\sum_j x_{jk}} \\ \vdots & \ddots & \vdots \\ \frac{x_{j1}}{\sum_j x_{j1}} & \cdots & \frac{x_{jk}}{\sum_j x_{jk}} \end{bmatrix}. \quad (4)$$

After obtaining 1,000 different samples of correspondence matrix, 1,000 new samples of expenditures for each income group were drawn to obtain demand vectors to estimate the income-specific EnvFs, also based on a truncated normal distribution (Figure 2, Step 4). To determine the distribution ranges, the underreporting is assumed to be distributed proportionally based on the expenditure for each product group. For example, income group i whose expenditure of product group j (x_{ij}) is twice the average (μ_j) will have a maximum underreporting of twice the difference between the average expenditure in the EVS (\bar{x}_j) and adjusted SNA datasets (x'_j). Consequently, its upper limit (b_{ij}) is twice the expenditure in the adjusted SNA. In the case where the underreporting is lower than 1.96 times the standard error ($\sigma_{x,ij}$), it is the expenditure plus 1.96 times the standard error. The upper limit is defined in Equations (5) and (6).

$$\text{If } (x'_j - \bar{x}_j) > 1.96 \sigma_{x,ij} b_{ij} = \frac{x_{ij}}{\mu_j} \cdot x'_j \quad (5)$$

$$\text{else } b_{ij} = x_{ij} + 1.96 \sigma_{x,ij}. \quad (6)$$

These expenditures in COICOP were then bridged into NACE classification using the correspondence matrix (Figure 2, Step 5). The uncertainty level was defined as the standard deviation of MCS results. After bridging process, we converted this reclassified expenditure vector from purchaser's price into basic price (Min & Rao, 2017) by deducing the taxes and assigning trade margins as the expenditure for trade sectors (Figure 2, Step 6). The income-specific EnvFs per capita were calculated using Equation (7).

$$\text{EnvF}_m = C \cdot S \cdot L \cdot Y_m + \text{DE}_m \quad (7)$$

Y_m is the final demand vector of income group m in basic price. L represents the multi-regional Leontief-inverse matrix, S is the stressor matrix containing physical emissions per monetary unit of output, and DE_m is the direct emissions/resource use vector of income group m . We allocated 54% of direct household emissions for the heating fuel, with 3% from solid fuel, 44% from heating oil, and 53% from gas, and the rest (46%) was allocated to gasoline fuel (DESTATIS, 2016). C is the characterization factor matrix containing midpoint indicators ReCiPe 2008, where CF is measured as the global warming potential over a 100-year time horizon (GWP100), relative to CO_2 (Steinmann et al., 2018).

2.3 | Measuring inequality of household environmental footprints

EVS unfortunately lacks data for households with income higher than 18,000 Euro/month. Yet G-SOEP, another survey that covers high-income households, records an even lower average expenditure than EVS (Marcus et al., 2013). There has been an effort to estimate the overall expenditure of top 5% and 1% of German households more accurately by combining EVS and G-SOEP datasets (Bach, Beznoska, & Steiner, 2016).

Due to this limitation, the EnvFs for top income households were estimated using EnvF elasticities and their estimated private expenditure (Bach et al., 2016) to calculate the EnvF Gini indices appropriately. We assumed that these households have the same elasticity as the average households. The EnvF elasticities are defined as the percentage changes in EnvFs with respect to a 1% increase in the household expenditure (Baiocchi, Minx, & Hubacek, 2010; Ivanova et al., 2016), calculated using Equation (8).

$$\ln \text{EnvF}_i = A_i + \varepsilon_i \ln Y \quad (8)$$

Y is the household expenditure per capita, $EnvF$ represents $EnvF$ indicator i per capita, ϵ is the average household footprint elasticity of $EnvF$ i , and A is a constant. We applied weighted least squares (WLS) regression to represent different sample sizes in each income group more appropriately (Wooldridge, 2010). After calculating the $EnvF$ s of top income households, the $EnvF$ Gini indices were calculated as the measures of the $EnvF$ distribution across income groups (Wiedenhofer et al., 2017) using Equation (9).

$$G = 1 - \sum_{m=1}^n (P_m - P_{m-1}) (C_m + C_{m-1}) \quad (9)$$

G represents the $EnvF$ Gini index, C_m is the cumulative share of household $EnvF$ from income group 1 to m compared to the national household $EnvF$, and P_m is the population share of income group m .

2.4 | Assessing distributional effects of carbon tax schemes

To address the issue of distributional effects of policy instruments to curb the consumption of carbon-intensive products, this study also provided a simulation of carbon tax scenarios in a static IO model. It should be noted that we only calculated the price signal, that is, the proportion of the tax payment due to the unchanged consumption compared to the income (Feng et al., 2010; Jiang & Shao, 2014).

Demand or output changes due to the price changes, which are often modeled in equilibrium or macroeconomic model (Kirchner, Sommer, Kratena, Kletzan-Slamanig, & Kettner-Marx, 2019), were not considered. The distributional effects of the tax burden across income groups were measured using Suits index (Equation (10)). A Suits index of -1 implies that the poorest pays all the tax, while 1 means that the richest pays everything (Suits, 1977).

$$S = 1 - \sum_{m=1}^n (I_m - I_{m-1}) (T_m + T_{m-1}) \quad (10)$$

S represents the Suits index, T_m is the cumulative share of tax burden from income group 1 to m , and I_m is the cumulative share of net income from income group 1 to m .

3 | RESULTS

The average $EnvF$ s of German households in 2013 were 9.1 ± 0.4 tons CO_2e and 10.9 ± 0.6 tons material per capita, with the average expenditure per capita of $1,410 \pm 70$ Euro/month (Figure 3). The highest-income group, whose household income is 10,000–18,000 Euro/month (percentile 95–98), has an average CF of 14.8 ± 0.9 tons CO_2e per capita. Meanwhile, the lowest one, whose income is under 900 Euro/month (bottom 4%), is responsible for 5.4 ± 0.2 tons CO_2e per capita. The CF of middle-income groups, those between the 20th and 80th percentile (Easterly & Levine, 2001), ranges between 8.4 ± 0.4 and 10.3 ± 0.5 tons CO_2e per capita. The highest-income group consumes 17.5 ± 1.3 tons material per capita, while the lowest one consumes 7.6 ± 0.4 tons material per capita.

3.1 | Environmental footprints of German households by product group

The transportation share of CF increases with the expenditure. It accounts only 10.4% for the lowest-income group, but almost twice (20.3%) for the highest-income group due to increasing private transportation (Figure 4). Since the higher-income groups have a higher opportunity cost of travel time than the lower ones (due to their higher income), they have a higher incentive to use private transportation that is faster and more convenient (Buehler, 2011). Meanwhile, the electricity and utilities share shrinks substantially from 39.4% to 29.1%, as well as the food share from 19.9% to 9.2%.

The transportation share of MF increases greatly from 3.9% to 12.4%, while that from food decreases from 37.6% to 20.7%. This decline follows Engel's law, affirming a negative relationship between the income and food expenditure share, since people do not tend to consume more food due to rising income (Dorband et al., 2019). The electricity and utilities share also shrinks steadily from 16.7% to 10.6%. The share changes in MF do not necessarily imply a shift of environmental burden, since MF aggregates all types of materials, irrespective of their impact (Wiedmann et al., 2015). Differentiating materials in assessing household MF distribution thus is desirable (López et al., 2017; Shigetomi et al., 2016).

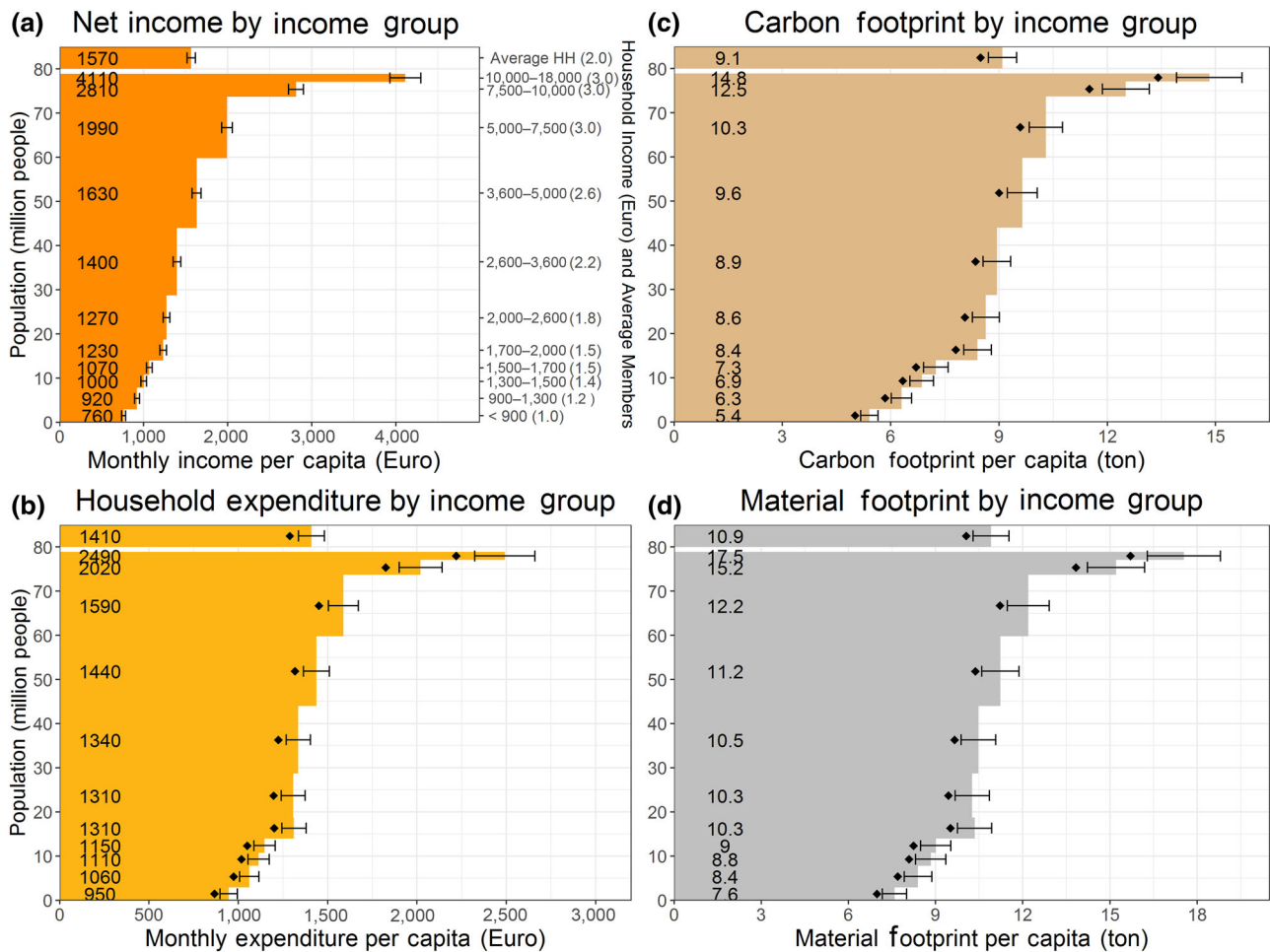


FIGURE 3 Monthly net income, expenditure, and EnvFs of German households. (a) Monthly net income (orange, in Euro per capita). (b) Monthly adjusted private expenditure (yellow, in Euro per capita). (c) German household CF (brown, in ton CO₂e per capita). (d) German household MF (gray, in ton material per capita). The y-axis represents population arranged by increasing income. The top bars represent the average households. The dots represent the expenditure and EnvF results without underreporting correction. Underlying data used to create this figure can be found in Supporting Information S3

3.2 | Environmental footprints of German households by emitting industry and region

Based on time-series EXIOBASE v3.6, environmental burdens embodied in German imports have increased slightly from 1995 to 2015 (Stadler et al., 2018). Major burdens in imports come from non-renewable material, electricity, and transportation, mostly to produce manufactured goods (Wood et al., 2018b). The annual changes in the embodied impacts of German households are available in Supporting Information S1-3 and S2.

In 2013, the CF of German households was mostly driven by direct emissions and domestic electricity (Figure 5a: 2.54 and 1.59 ton CO₂e on average, respectively). GHG emissions of the lowest-income group decline by around half in most sectors, except for the agriculture sectors and domestic electricity. The highest-income group contributes to a higher share of emissions from overseas (38.6%) than the lowest (33.6%). Their embodied emissions from all household consumption, stemming both from domestic transport sectors or those in the American continent, are more than twice the average (1.07 and 0.46 ton CO₂e, respectively). Their emissions coming from electricity sectors in China and the Rest of the World (RoW) for imported goods are almost twice the average (0.59 and 0.43 ton CO₂e, respectively).

The major sources of MF are the aggregate mining and energy supply sectors (Figure 5b: 3.70 ton and 2.48 ton material on average, respectively). The metal resource use of the lowest-income group is only half the average (0.27 ton material), lower compared to the other resources. The highest-income group consumes a slightly larger share of imported resources (69.9%) than the lowest (61.1%). Their domestic resource use is roughly 1.5 times the average (5.30 ton material), while its resource use coming from China and RoW is almost twice as large (2.80 ton and 4.60 ton, respectively). These results suggest an increasing burden outsourced to developing countries due to the expenditure rise (López et al., 2016, 2017).

We also simulated the effect of shifting the country of origin for 50% of the clothing and household goods on EnvFs. Details of the substitution procedure and results are available in Supporting Information S1-5 and S3. This situation impacts the magnitude of total household EnvFs

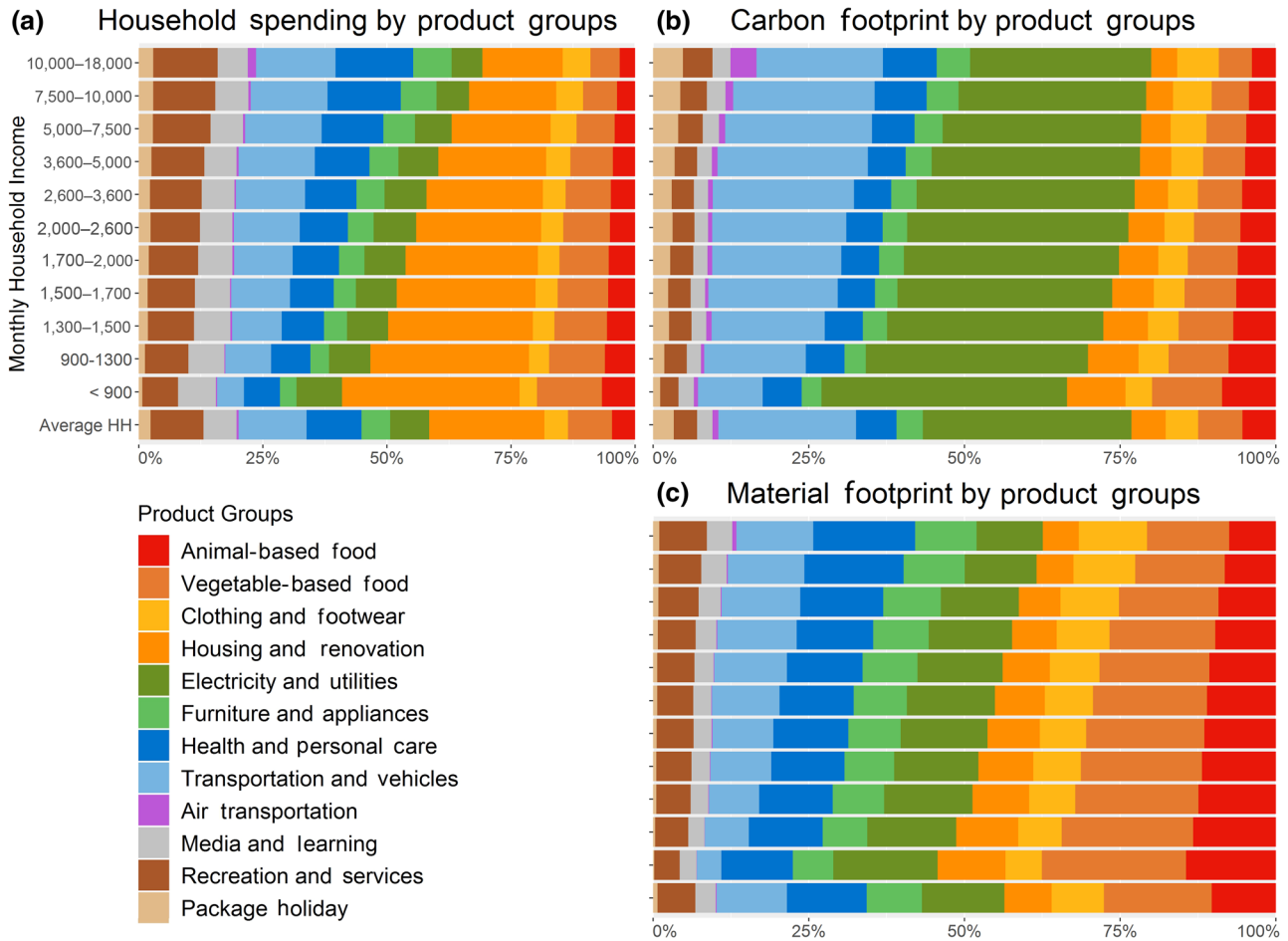


FIGURE 4 Breakdown of income-specific household expenditure and EnvFs, reclassified into 12 product groups. (a) Breakdown of expenditure. (b) Breakdown of carbon footprint (CF). (c) Breakdown of material footprint (MF). The lowest bar represents the income group of average German households, then bars are arranged by increasing income. Reclassification details of product groups are available in Supporting Information S2. Underlying data used to create this figure can be found in Supporting Information S3

marginally; the lowest-income group increases its household CF and MF by 3.2% and 5.3%, while the highest-income group decreases its CF and MF by 2.8% and 5.3%, respectively. This result implies that reducing excess consumption has a larger environmental impact for higher-income groups, instead of merely shifting the product origin.

Based on other studies, EU countries could reduce 35% of their CF by reallocating production resource optimally (Fujii & Managi, 2015), although 10% clothing demand reduction decreases the CF only by 0.3% (Wood et al., 2018a). Therefore, focusing efforts on household goods might have higher impacts, especially since their embodied emissions and material use have risen rapidly (Wood et al., 2018b).

3.3 | Environmental footprint intensities of German household income groups

Since each income group has a different consumption basket, the overall EnvF intensities (in footprint/EUR) also differs for each group. Detailed results on carbon and material intensities for all spending categories are available in Supporting Information S2. On average, the overall EnvF intensities of German households are 0.54 kg CO₂e and 0.65 kg material per Euro spent. They exhibit a declining trend for incomes 3600–5000 Euro/month and beyond (Figure 6, brown thick lines: 0.56 kg CO₂e/Euro and 0.65 kg material/Euro).

The overall carbon intensity of German households exhibits an inverted-U trend, in contrast to that of, for example, Spanish households that shows a constantly declining trend (Duarte et al., 2012). This intensity pattern reflects the environmental Kuznet's curve (EKC), as German lower-income households gradually consume more energy-intensive basic products (Grossman & Krueger, 1995). However, further disaggregation shows that this inverted-U trend on carbon intensity is observed only in housing category.

The carbon intensity of housing increases until the income group 3600–5000 Euro/month (Figure 6a, 0.67 kg CO₂e/Euro) and decreases steadily afterward. Meanwhile, the carbon intensity of transportation declines rapidly after the income group 1700–2000 Euro/month (0.96 kg CO₂e/Euro),



FIGURE 5 Breakdown of German household environmental footprints (EnvFs) per capita by emitting industry and producing region for three representative income groups: low (LI), average, and high (HI). The bubble size represents the footprint size coming from that specific industry and region. The color represents the ratio of that footprint compared to the average footprint coming from the same industry and region. The circle area is proportional to the footprint size. (a) Breakdown of German CF (kg CO₂e) per capita by emitting industry. The y-axis represents industries: Agriculture and food production, electricity and utilities, material extraction and goods, fuel and transportation, other services, and direct emissions. (b) Breakdown of German MF (kg) per capita by producing region. The y-axis represents industries: Plant-based agriculture, animal-based agriculture, energy supply, aggregate mining, metal mining, and other sectors. Underlying data used to create this figure can be found in Supporting Information S3

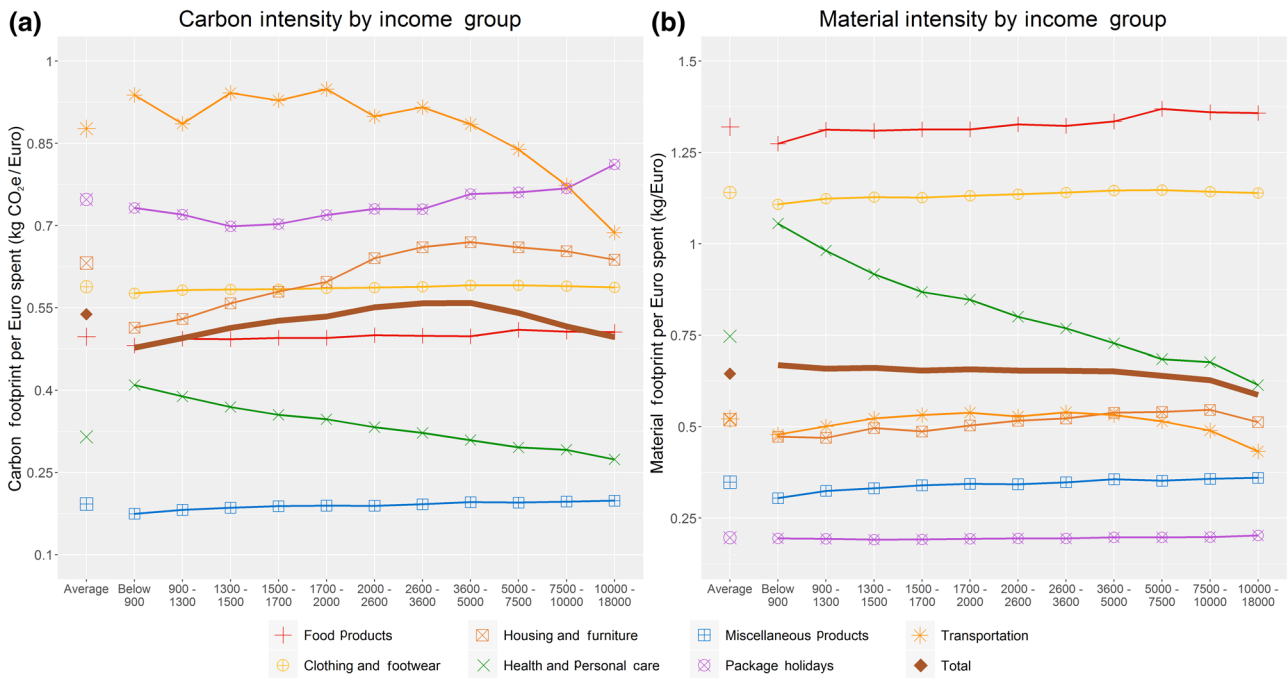


FIGURE 6 Environmental footprints (EnvFs) intensities of German households by income group. The y-axis represents the EnvF per Euro spent, while the x-axis represents the income range. (a) Carbon intensities, or CF per Euro spent by income group. (b) Material intensities, or MF per Euro spent by income group. Product groups are reclassified into six aggregate groups, classification available in Supporting Information S2. Underlying data used to create this figure can be found in Supporting Information S3

since people tend to spend their additional income on more expensive vehicles rather than fuel (Choo & Mokhtarian, 2004). This shift also causes an inverted-U trend in the material intensity of transportation (Figure 6b).

Both carbon and material intensities of health and personal care declines rapidly as the higher-income groups spend a smaller share of health-care budget on pharmaceuticals. The decline might be overestimated due to the assumption of price homogeneity (Majeau-Bettez, Strømman, & Hertwich, 2011), as EXIOBASE aggregates both fine and bulk chemicals, unlike WIOD (Timmer, Dietzenbacher, Los, Stehrer, & de Vries, 2015) or Eora (Lenzen, Kanemoto, Moran, & Geschke, 2012, 2013).

3.4 | Inequality of environmental footprints in German households

The CF and MF elasticities of German households are estimated at 1.04 ($R^2 = 0.95$) and 0.90 ($R^2 = 1.00$), respectively. Most micro-studies also show a relatively linear correlation between the expenditure and CF (Girod & de Haan, 2010; Isaksen & Narbel, 2017), which justify the use of aggregate data to estimate the CF of the top income groups. The CF elasticity in Norway is 1.14 (Steen-Olsen et al., 2016).

CF elasticity in Germany is lower than that in Norway due to the higher direct emissions from heating, which are generally inelastic (Jones & Kammen, 2011). Space heating in Norway is mostly from electricity (Steen-Olsen et al., 2016). The Gini indices of the household CF and MF in Germany are 0.16 and 0.14, respectively. Compared to the income Gini index of 0.29, the Gini indices of the household EnvFs are lower; supporting the argument that the consumption inequality is not as distinctive as income inequality (Krueger & Perri, 2005). Detailed calculation of the Gini indices is available in Supporting Information S1-5 and S3.

3.5 | Static simulation of carbon tax scenario

We simulated a scenario with an industry-wide global carbon tax of 50 EUR/ton in a static IO model, assuming no impacts of price changes on commodity flows. This proposed value is in the middle range of the currently proposed carbon tax rates, ranging between 40 to 80 USD/ton (Klener et al., 2018; Stiglitz et al., 2017). The Suits index for a uniform carbon tax proposal in Germany is estimated at -0.13 , implying a regressive tax. Charging a carbon tax at 50 Euro/ton leads to additional expenditure of the lowest-income group by 2.9%, yet only by 1.5% for the highest (Figure 7a).

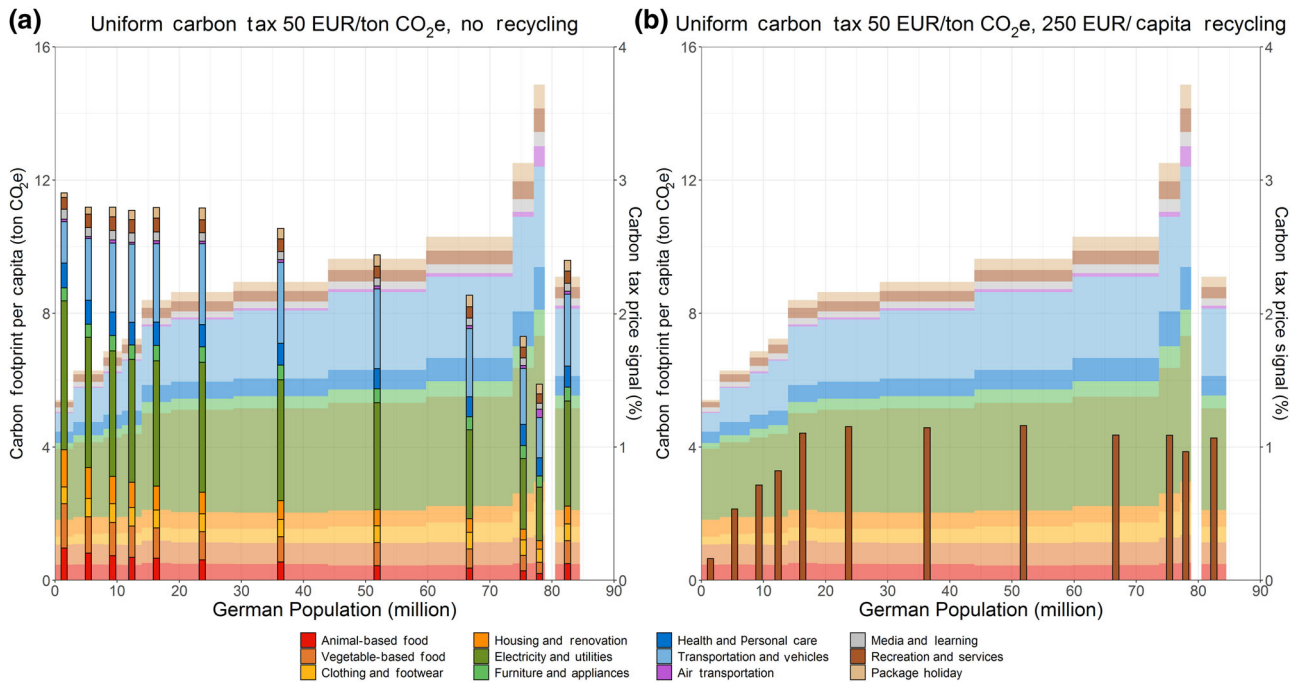


FIGURE 7 Scenario simulation for uniform carbon tax at 50 Euro/ton CO₂e. (a) Scenario without revenue recycling. (b) Scenario with revenue recycling. In this subfigure, the price signal rate is aggregated. Wide transparent bars (left axis) represent household CF per capita by product group. Thin solid bars (right axis) represent price signal rates, measured as proportion of the carbon tax paid compared to the net total income. Underlying data used to create this figure can be found in Supporting Information S3

However, the carbon tax scheme could be made progressive if a part of the tax revenue is recycled to the households (Vogt-Schilb et al., 2019). By redistributing 250 Euro per capita annually in a lump sum payment for all households, the Suits index changes into 0.04 while the government still earns 42% of the carbon tax revenue. In this revenue recycling scheme, the tax shares for middle and high-income groups are relatively similar at around 1%, while those for low-income groups are lower than 1% (Figure 7b). The detailed calculations of Suits indices for both scenarios are available in Supporting Information S3.

4 | DISCUSSION

The average household CF per capita calculated in this study is lower compared to other top-down studies (11.9–14.3 ton CO₂e/capita) (Ivanova et al., 2016; Mieke et al., 2016), but closer to the bottom-up studies (9.0–9.7 ton CO₂e/capita) (Greiff, Teubler, Baedeker, Liedtke, & Rohn, 2017; Schubert, Wolbring, & Gill, 2013). This result is lower due to the update in the direct emissions inventories in EXIOBASE v3.6 (Stadler et al., 2018). According to this version, the average household EnvFs are 9.5 tons CO₂e and 11.5 tons material per capita. The official figure of national CF is higher, at 11 ton CO₂e in 2016 (Weiß & Welke, 2017) since it captures total national final demand, including government spending and gross capital formation.

Compared to the results without underreporting correction (Figure 3, dotted), the differences for each EnvF of the average German households are approximately just 5–8%. These differences are rather small when taking into account the large expenditure gap between the EVS and SNA datasets (15.3%). The EnvFs gaps were reduced since we corrected the underreporting using a truncated normal model.

In the case study of Spain, the estimated household CF per capita of middle-income group is 6.5 tons CO₂e, (López et al., 2016) although based on WIOD, the average is 8.55 tons CO₂e per capita (Roibás, Loiseau, & Hospido, 2018; Timmer et al., 2015). This 24% CF gap might partly come from an expenditure allocation mismatch, since the recorded underreporting is just 13.4% (Instituto Nacional de Estadística, 2018).

In this study, we addressed this mismatch by adjusting the household consumption data (Equations (2) and (3)) to obtain an accurate initial correspondence matrix. Addressing this mismatch is important since the expenditure data in the CES is inconsistent with the SNA classification (Min & Rao, 2017). We observed that the uncertainty contribution from the distribution of intensities is less than 1%, similar to previous research (Min & Rao, 2017). The initial assumption of allocation (correspondence matrix) is the main determining factor of the RAS procedure results (the footprint intensities) (Wiebe & Lenzen, 2016).

Applying a uniform method in bridging expenditures and addressing underreporting enables a more reliable cross-country comparison of the EnvF Gini indices. The straightforwardness of the method used here makes it easily replicable for OECD countries with large underreporting, for example, Mexico (OECD, 2019).

4.1 | Policy implications

Examining different EnvFs helps policymakers understand the potential impacts of different environmental excise taxes (Ekins, Pollitt, Summerton, & Chewpreecha, 2012), assess resource nexuses (Vivanco, Wang, & Hertwich, 2018), or benchmark national consumption against the planetary boundaries (Hoekstra & Wiedmann, 2014; Rockström et al., 2009; Steffen et al., 2015). Their comprehensiveness and detail offer an alternative to the ecological footprint (EF) that quantifies an aggregate national ecological capacity instead of a set of specific environmental pressure indicators (Giampietro & Saltelli, 2014; Lin, Wackernagel, Galli, & Kelly, 2015). Being an aggregate indicator, EF excludes other important pressures, such as material scarcity (van den Bergh & Grazi, 2014).

The consumption levels with pressures within the planetary boundaries (Rockström et al., 2009) are estimated at 2.5 tons CO₂e and 8 tons material per capita (Hoekstra & Wiedmann, 2014; Tukker et al., 2016). The German household CF exceeds the boundary by a factor of 2.2 for the lowest-income group and 5.8 for the highest (Figure 3), and only the former consumes materials within the limit.

This study is relevant for policymakers to design fairly distributed mitigation plans (Dennig, Budolfson, Fleurbaey, Siebert, & Socolow, 2015; Klenert et al., 2018), which is particularly important for Germany to realize its ambitious climate targets. The national target aims at cutting 55% of its GHG emissions by 2030 (compared to 1990), sourcing its entire electricity from renewable energy (RE) by 2050, and cutting 80% of its GHG emissions by 2050 (BMU, 2016). However, Germany's emission reduction in 2018 was only 30.8% (BMU, 2018). To stay on track of its 2030 target, it should have reduced 40% of its emissions by 2020 (Klaus, Vollmer, Werner, Lehmann, & Mischen, 2010).

Electricity in Germany is dominantly generated by coal (39.4% in 2017) (Fraunhofer, 2018), responsible for 89% of the GHG emissions from household electricity production (Stadler et al., 2018). This sector is a crucial hotspot for emission reduction, since Germany is facing a great challenge to achieve its emission target. Critics have argued that the ongoing energy transition (*Energiewende*) in Germany is ineffective since the coal share in electricity generation remains high. Although the RE has lowered the price of electricity in Germany (merit-order effect) (Cludius, Hermann, Chr, & Graichen, 2016), coal share remains high due to the delay in installing sufficient gas-fired power plants for back-up capacities due to the uncertainty in carbon pricing (Dillig, Jung, & Karl, 2016) and the acceleration of the nuclear phase-out (Leipprand & Flachsland, 2018).

Currently, Germany administers a 24% electricity surcharge (EEG, *Erneuerbare-Energien-Gesetz*) to fund RE investments (Thalman & Wehrmann, 2018). Yet charging a flat rate for electricity is not equitable and harms low-income groups even more than the uniform carbon tax does, due to its larger share in lower-income groups (Figure 4). Worse, the surcharge is also flat for all types of electricity generation, irrespective of their GHG emissions, thus discouraging private RE investment due to the lack of monetary incentives (Aslani, Naaranoja, & Zakeri, 2012).

Findings on the CF by industry and region (Figure 5) indicate that high-income groups show greater burden shifting to China and other developing countries. Carbon leakage happens since countries with lower average production costs, which are the destination of outsourcing activities, tend to have higher carbon intensities than those of importing countries. Since the destination countries of outsourcing activities were typically the non-Annex-I countries, which had no absolute emission reduction targets in the Kyoto Protocol (Babiker, Reilly, & Jacoby, 2000; Bohringer, 2003), the imported products were produced at a less stringent emission restriction. Although these countries have also pledged their commitment to jointly reduce their emissions at the Paris Agreement, their submitted Nationally Determined Contributions (NDC) are still largely insufficient to achieve the global target of 2°C (Robiou du Pont & Meinshausen, 2018). Levying carbon tariffs on imports (Böhringer, Carbone, & Rutherford, 2012b) is important to reduce carbon leakage.

Reducing material consumption, especially on higher-income groups, has been suggested to alleviate environmental burdens domestically and overseas, as a part of the degrowth movement (Kallis, 2011; Martínez-Alier, Pascual, Vivien, & Zaccai, 2010). Material consumption has a finite contribution to the quality of life (QoL) and once fulfilled, QoL is driven by non-material factors, such as freedom, leisure, education, and democracy (Vita, Hertwich, Stadler, & Wood, 2018). According to a UK household study, there is a potential to reduce household emissions by 37%, while providing a decent standard of living for everybody (Druckman & Jackson, 2010). A short analysis on the discourse of degrowth is provided in Supporting Information S1-9, examining the arguments on this debate.

Compared to the income Gini index of 0.29, the Gini index of the household CF in Germany is lower (0.16). However, the CF inequality in Germany is higher than that in Spain despite having a lower income Gini index. The Gini indices of the household income and CF in Spain are 0.34 and 0.12 (López et al., 2016), respectively. Despite having a higher income Gini index (0.32), Japan has a similar level of CF inequality (0.16) as Germany (Koide et al., 2019). The CF inequality in Spain might be lower due to the different heating requirements (Duarte et al., 2012). However, it is also possible that the bridging process and underreporting lower the calculated CF Gini index in Spain (Min & Rao, 2017). Revenue recycling is necessary to alleviate inequality from the carbon tax (Figure 7) (Beck et al., 2015; Klenert et al., 2018).

The initial increase of carbon intensities in the lower-income groups (Figure 6) happens due to the increasing share of direct emissions from heating (Kerkhof, Benders, & Moll, 2009), since the primary reason for not heating is financial (Ivanova et al., 2018). This increase ought to be

anticipated, as "recycling" the entire revenue in a lump sum might lead to a rebound effect in these groups due to the heating fuel consumption increase (Chitnis, Sorrell, Druckman, Firth, & Jackson, 2014). Partial transfers to reduce heating costs are preferable, while the rest of the revenue could be used for government investment in renewable energy instead (Klenert et al., 2018).

Since heating in Germany mainly comes from direct burning of heating oil or gas (Decker & Menrad, 2015), a shift toward low-carbon heating systems, such as heat pumps using decarbonized electricity (Michelsen & Madlener, 2016) or district heating (Ehrlich, Klamka, & Wolf, 2015), is urgently required. Electricity mix remains the key determiner, since heat pumps are estimated to reduce the heating emissions by only 25% using the current mix in Germany, but up to 90% using a low-carbon mix (Bayer, Saner, Bolay, Rybach, & Blum, 2012).

Consumption-based taxation is applicable for reducing not only GHG emissions, but also resources use. Increasing resource consumption aggravates environmental impacts from material extraction, such as soil degradation, water pollution, and material scarcity (Weterings, Bastein, Tukker, Rademaker, & de Ridder, 2013). Material differentiation in calculating MF is valuable to set equitable virgin material extraction taxes (Söderholm, 2011).

4.2 | Limitation of the method and the research scope

Our simulation propagates household expenditures only from a truncated normal distribution. Since underreported expenditures are often skewed right, applying an asymmetric distribution, such as Weibull or Gamma distribution (Rehm et al., 2010), might also be applicable. In addition to simulating different distribution models using micro-data, machine learning procedures could be applied in the EnvFs studies to impute missing expenditures (Farhangfar, Kurgan, & Dy, 2008; Froemelt, Dürrenmatt, & Hellweg, 2018; Froemelt, Buffat, & Hellweg, 2020).

This study also limits its scope to only income since the main objective of this study is to observe Gini indices of EnvFs. Other studies include other socio-economic parameters such as household size and dwelling size (Liu, Daily, Ehrlich, & Luck, 2003; Minx et al., 2013; Newton & Meyer, 2012), regional electricity mix (Tukker, Cohen, Hubacek, & Mont, 2010), or regional distinctions such as urban-rural typology, population density, and climate (Jones & Kammen, 2014; Marcotullio, Sarzynski, Albrecht, & Schulz, 2014; Minx et al., 2013; Wiedenhofer, Lenzen, & Steinberger, 2013).

While correcting underreporting specifically per aggregate sectors, the methodology applied in this study does not endogenize emissions and resource uses from the previous capital formation induced by household consumption (Minx et al., 2011). Although the household CF share from housing and services is relatively low (Figure 4), the CF of their capital formation is significant, at more than 25% of the total capital formation CF (Södersten, Wood, & Hertwich, 2018a). Employing capital-embodied MRIO tables assesses total household EnvFs more comprehensively (Berrill, Miller, Kondo, & Hertwich, 2020; Chen et al., 2018; Font Vivanco, 2019; Miller et al., 2019). Inducing previous consumptions of fixed capital into the interindustry matrix results in 11% increase in the global GHG emissions embodied in the final consumption (Södersten, Wood, & Hertwich, 2018b).

This research also excludes other uncertainty sources. Possible sources include uncertainties from the trade data and its harmonization within MRIO (Lenzen, Wood, & Wiedmann, 2010; Rodrigues, Moran, Wood, & Behrens, 2018), uncertainties from the technical coefficient matrices (Willing, 2012), and uncertainties from the accounting scheme of GHG emissions and resources use and their allocation methods (Usubiaga & Acosta-Fernández, 2015).

5 | OUTLOOK ON FUTURE RESEARCH

This study provides a novel, yet straightforward improvement to estimate the actual EnvF ranges for each income group through correcting underreporting prior to the bridging process. This procedure could enhance the current approach in micro-data studies (Büchs & Schnepf, 2013; Minx et al., 2013; Newton & Meyer, 2012), using a bootstrapping procedure of redrawing new expenditure values to observe the correlation between the socio-economic parameters and the household EnvFs. Constructing the initial correspondence matrix properly is also useful in constructing a more reliable footprint calculator (Dubois et al., 2019; Salo, Mattinen-Yuryev, & Nissinen, 2019; West, Owen, Axelsson, & West, 2016) by lowering the errors from the allocation mismatch.

The bridging process used in this study is also applicable for improving macroeconomic models. Compared to the static IO models, these models simulate changes in the economic structure. They take into account feedback effects such as demand quantity and price changes (Kirchner et al., 2019). Future research using these models is relevant for policymakers to simulate the effects of other revenue recycling schemes, such as cutting income tax (Klenert et al., 2018) or value-added tax (Kirchner et al., 2019).

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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SUPPORTING INFORMATION

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