GREEN CONSUMPTION AND INCOME ELASTICITIES: CROSS-COUNTRY EVIDENCE ON ENVIRONMENTAL ENGEL CURVES

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Green consumption and income elasticities: Cross-country evidence on environmental Engel curves*

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Abstract

We examine how income growth reshapes the composition of household consumption between green and non-green goods across countries. Using harmonized data on Environmental Goods and Services (EGS) for 138 countries over 1995–2015, we measure green consumption as expenditure on goods and services explicitly designed to prevent or reduce environmental degradation and estimate a non-linear environmental Engel curve. Green consumption behaves as a luxury at low income levels but progressively transitions toward a necessity as income rises. We further show that income elasticities of green consumption are systematically higher than those of non-green consumption, revealing income-driven composition effects in the consumption basket. These non-homothetic demand patterns imply that income growth systematically shifts household expenditure toward or away from goods intended to reduce environmental pressures, with important policy implications. Applying our estimates to a stylized Climate Fund redistribution, we show that accounting for heterogeneous income elasticities changes its predicted outcome. Relative to the homothetic benchmark with unit elasticities, the response of global green consumption remains limited, whereas the increase in global non-green consumption is substantially larger.

Keywords: Measurement of green consumption; income elasticities; environmental Engel curve; luxury & necessity goods and services; climate policy

JEL Codes: E01, E21; Q5

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1 Introduction

Household CO_2 emissions are ultimately determined by how much households consume, how they allocate consumption across goods and services with heterogeneous environmental content, and the carbon intensity embodied in those consumption choices (Peters, 2008; Ivanova et al., 2016; Levinson and O'Brien, 2019; Ivanova and Wood, 2020; Bjelle et al., 2021). From a demand-side perspective, the environmental implications of economic growth depend not only on aggregate income levels but also on how growth reshapes the composition of household consumption. Evaluating the demand-side environmental implications of income growth and redistributive climate policies therefore requires an explicit understanding of how the composition of the consumption basket responds to income. In this paper, we study this compositional response by distinguishing expenditure on *Environmental Goods and Services*, which we refer to as *green* consumption, from all other consumption, referred to as *non-green*. Because green consumption is defined on the basis of goods and services whose primary purpose is environmental protection and resource management, shifts between green and non-green consumption are relevant in our demand-side framework insofar as they reflect changes in expenditure toward goods and services classified as environmental under the OECD–APEC framework.

As of today, there is scant cross-country evidence on whether income growth systematically alters the composition of consumption between green and non-green goods and services. This question is central to the analysis of environmental transition on the demand side because the implications of income growth depend not only on how much households consume, but also on where additional expenditure is directed. This issue is particularly important because many macroeconomic and climate-policy simulations implicitly abstract from such compositional adjustments. In these frameworks, household demand is often assumed to be homothetic, typically through representative-agent CRRA or CES preferences over an aggregate consumption good, implying unit income elasticities and proportional scaling across consumption categories (Nordhaus, 2017; Weyant, 2017). Under this assumption, income growth and transfers affect the level of consumption but leave the within-country balance between green and non-green consumption unchanged. Yet if preferences are non-homothetic, income changes generate composition effects, whereby the relative demand for green and non-green goods varies systematically with income. Assessing whether such non-homothetic composition effects are empirically relevant is therefore central to understanding how income growth and redistribution reshape consumption composition.

We examine the relationship between income and household green consumption across countries by estimating income elasticities of demand for green and non-green goods and investigating whether income growth induces systematic reallocation within the consumption basket. Characterizing these elasticities is important for three reasons. First, they indicate whether green goods behave as luxury or necessity goods, which is central to understanding affordability constraints in access to green consumption. Second, they inform policy design: when green consumption is constrained by affordability, income-based support and targeted subsidies may be effective; when it behaves more like a necessity, policies aimed at reducing switching costs or expanding infrastructure may become more relevant (Jackson and Papathanasopoulou, 2008; Jacobs and van der Ploeg, 2019; Ottelin et al., 2019; Lévay et al., 2021; Theine et al., 2022). Third, they matter for evaluating redistributive climate policies. When elasticities differ across green and non-green goods, income changes reallocate expenditure within the consumption basket rather than merely rescaling it. The degree of non-homotheticity therefore determines whether transfers preserve within-country consumption composition or instead generate income-driven reallocations between green and non-green goods.

Existing evidence on income elasticities in environmental contexts relies primarily on indirect proxies of environmentally relevant consumption patterns (Peters, 2008; Ivanova and Wood, 2020; Bjelle et al., 2021). Most macroeconomic approaches[1] measure environmental impacts or technology use rather than households' expenditure on explicitly environmental goods and services. This limits our ability to study how income reshapes the composition of demand between green and non-green consumption in a comparable cross-country setting.

We study how disposable income shapes green consumption by estimating income elasticities across 138 countries from 1995 to 2015. To address this question, we introduce a novel, comparable cross-country measure of green consumption based on harmonized classifications of *Environmental Goods and Services* (EGS) introduced by the Organisation for Economic Co-operation and Development (OECD) and the Asia-Pacific Economic Cooperation (APEC). These classifications identify goods and services designed to prevent or reduce pollution and environmental degradation, improve resource and energy efficiency, support renewable energy production, and facilitate environmental monitoring and remediation (OECD, 1999, 2019). We measure green consumption as households' final expenditure on these goods and services. By focusing on households' expenditure on goods and services explicitly designed for environmental purposes, our measure provides a demand-side characterization of green consumption that is comparable across countries.

Our contribution is threefold. First, we introduce a comparable cross-country measure of green consumption based on households' final expenditure on Environmental Goods and Services, combining trade, input-output, and macroeconomic data for 138 countries over 1995 to 2015. Second, using this measure, we estimate non-linear Engel curves for green consumption and document systematic deviations from homotheticity. Green consumption behaves as a luxury at low income levels but progressively transitions toward a necessity as income rises, unlike non-green consumption. This non-homothetic pattern implies that income growth is associated with systematic changes in the composition of consumption between the green and non-green components. Third, we leverage these estimates to examine how assumptions about income elasticities shape the reallocation of expenditure between the green and non-green components of the consumption basket under redistributive policies. Applying our estimates to a stylized global redistributive climate policy, we show that once empirically estimated elasticities are taken into account, the response of global green consumption remains limited, whereas global non-green consumption increases much more strongly than under the homothetic benchmark with unit income elasticities.

The rest of the paper is structured as follows. Section 2 reviews the related literature. Section 3 presents the empirical framework and the construction of the green consumption measure. Section 4 reports the main results. Section 5 discusses the implications of income elasticities for the design of redistributive policies promoting green consumption, and Section 6 concludes.

2 Literature background

2.1 Income, consumption patterns, and the environment

A large literature examines how income shapes household environmentally relevant consumption patterns, including the consumption of goods and services that mitigate environmental pollution.

[1] We intentionally screen out existing microeconomic evidence based on local data, which limits the external validity and cross-country comparability of the estimated income elasticities (Chancel, 2014; Levinson and O'Brien, 2019; Theine et al., 2022).

A central question is whether such consumption behaves as a luxury or a necessity good, that is, whether its income elasticity is greater or lower than unity (Panayotou, 1997; Pearce, 2003; Plassmann and Khanna, 2006; Baiocchi et al., 2010). Early contributions to the income–environment nexus focused on the Environmental Kuznets Curve (EKC), which posits a non-linear relationship between income and various indicators of environmental degradation, with pollution increasing at early stages of development and declining at higher income levels (Grossman and Krueger, 1995). While the EKC literature has generated important insights into long-run income–environment relationships, it primarily focuses on aggregate environmental outcomes and does not explicitly identify the demand-side mechanisms underlying changes in consumption patterns.

More recent work has refined this perspective through the environmental Engel curve (EEC) framework, which shifts the focus from aggregate outcomes to household demand and examines how income shapes consumption patterns with different pollution intensities (Levinson and O'Brien, 2019). Building on Engel's law, the EEC framework allows for non-linear income effects, whereby a given consumption category may behave as a luxury at low income levels and gradually evolve into a necessity as income rises. It thus provides a demand-side interpretation of the income–environment relationship, focusing on how the environmental content of household consumption baskets changes with income. In this framework, income elasticities summarize how environmentally relevant consumption scales with income.

Empirical evidence for the United States supports this view, documenting a concave relationship between income and the pollution intensity of consumption, with income elasticities for lower-polluting consumption patterns declining as income rises (Levinson and O'Brien, 2019). However, direct empirical applications of the EEC framework remain limited (Sager, 2019; Baudino, 2020; Mancini et al., 2022). A key limitation of the existing literature is the lack of harmonized macro-level data that directly capture households' consumption of environmental goods and services in a comparable manner across countries, leading empirical studies to rely on heterogeneous proxies.

2.2 Challenges in measuring green consumption

Despite growing interest in the income–environment relationship, empirical studies face a measurement constraint: green consumption is not directly observed at the macroeconomic level for large international panels. As a result, the literature has relied on indirect proxies that capture different dimensions of environmentally relevant consumption behaviour, but none directly measures households' consumption of environmental goods and services. We group these proxies into three broad categories: consumption-based footprints, energy-use indicators, and green-sector or green-technology proxies.

The most commonly used approach proxies green consumption using ecological or carbon footprint indicators (Tukker and Jansen, 2006; Peters, 2008; Weber and Matthews, 2008; Kerkhof, Nonhebel and Moll, 2009; Ivanova and Wood, 2020). These measures, typically derived from input–output tables (IOTs) or multi-regional input–output (MRIO) models, infer environmentally relevant consumption patterns from observed environmental impacts using top-down or bottom-up approaches (Chakravarty et al., 2009; Chancel and Piketty, 2015; Hubacek et al., 2017; Oswald et al., 2020). When combined with Household Budget Survey (HBS) data, footprint-based indicators relate income or expenditure to the environmental impacts embodied in household consumption and to estimate income or expenditure elasticities across broad consumption categories (Tukker and Jansen, 2006; Peters, 2008; Weber and Matthews, 2008; Isaksen and Narbel, 2017; Oswald et al., 2020; Ivanova and Wood, 2020; Bjelle et al., 2021; Theine et al., 2022). While informative about environmental outcomes,[2] these approaches do not directly measure households' consumption of explicitly environmental goods and services, but rather the environmental footprint associated with consumption.

A key limitation of footprint-based measures is that they capture impacts induced by consumption rather than households' demand-side choices or green preferences *per se*. By construction, they combine final demand with upstream production technologies, energy mixes, and global supply chains, and therefore cannot isolate demand-side behaviour from supply-side characteristics (Girod and De Haan, 2010; Ivanova and Wood, 2020). Because they are usually constructed at relatively aggregated product categories, they also cannot distinguish between high- and low-impact goods within a category or identify environmentally friendly goods within standard consumption baskets (Girod and De Haan, 2010). As a result, footprint-based measures may fail to distinguish the adoption of greener goods from higher overall consumption levels, potentially overstating the environmental burden of high-income households while understating the pollution intensity of lower-income consumption patterns (Gill and Moeller, 2018; Starr et al., 2023; Ivanova and Wood, 2020).

Another strand of the literature approximates green consumption using household energy use and energy-efficiency indicators (Golley and Meng, 2012; Wiedenhofer et al., 2013). These measures capture direct and indirect energy consumption, often linking reductions in energy demand to increased environmental awareness. However, energy-based proxies are strongly influenced by regional characteristics of energy production, infrastructure, and technological efficiency, rather than by households' consumption choices *per se*. As a result, they do not distinguish between intentional pro-environmental behaviour and passive exposure to cleaner energy systems or more efficient technologies. Variations in household energy use may therefore arise differences in technology, regulation, or geographic context rather than the adoption of greener consumption patterns.

Measures based on green technology adoption, renewable energy use, or the consumption of environmentally friendly products are also employed as proxies for green consumption patterns (Sexton and Sexton, 2014; Qiao and Dowell, 2022). While such indicators capture structural shifts associated with the expansion of green markets, they often reflect supply-side developments driven by environmental regulation or public support rather than households' consumption choices. In particular, green technology indicators tend to measure investment and adoption decisions, frequently supported by public policies rather than goods and services that enter standard household consumption baskets. This limits their relevance for analysing household-level green consumption patterns. Moreover, studies focusing on specific environmentally friendly products, such as electric vehicles (Sexton and Sexton, 2014; Qiao and Dowell, 2022), are typically restricted to particular locations or product categories due to data constraints and therefore fail to capture households' overall consumption baskets.

Altogether, while these proxies provide useful information on environmental outcomes or market developments, they do not offer a direct, comprehensive measure of households' green consumption across countries.

2.3 Evidence on income–green consumption elasticities

Against this backdrop, it is unsurprising that empirical studies on the relationship between income and green consumption yield mixed findings. Household-level analyses typically combine Household Budget Surveys with environmental impact indicators, while cross-country studies rely on aggregate

[2] See Heinonen et al. (2020) for a recent review of consumption-based carbon footprint measures.

environmental measures constructed from national accounts or input–output frameworks. Most of this literature therefore estimates income or expenditure elasticities of environmental impacts rather than elasticities of demand for explicitly environmental goods and services.

One strand of the literature reports high values for income or expenditure elasticities of carbon footprints among higher-income groups, implying that income growth at the top of the distribution is associated with more pollution-intensive consumption patterns (Wiedenhofer et al., 2017; Otto et al., 2019). In this setting, the values of income and expenditure elasticities capture the marginal propensity to emit that depends on both the country and the environmental indicator considered (Hübler, 2017). Such findings are documented for the UK (Baiocchi et al., 2010), India (Pachauri, 2004; Parikh et al., 2009), the United States (Chancel, 2022; Starr et al., 2023), China (Golley and Meng, 2012), and several European countries (Kerkhof, Benders and Moll, 2009; Ala-Mantila et al., 2014; Chancel, 2014; Isaksen and Narbel, 2017; Ivanova and Wood, 2020; Hardadi et al., 2020; Theine et al., 2022).

In contrast, another strand of the literature finds that high-income households exhibit a lower marginal propensity to emit than low- and middle-income households, such that additional income is more likely to be allocated toward less pollution-intensive goods and services (Hubacek et al., 2017; Grunewald et al., 2017; Gill and Moeller, 2018; Rojas-Vallejos and Lastuka, 2020; Lévay et al., 2021). These findings are consistent with a "green shift" in household demand as income rises, whereby higher-income consumers increasingly move toward cleaner consumption categories. This shift is commonly attributed to stronger environmental preferences, policy incentives, and greater access to environmental goods and services. It may operate through several channels, including the consumption of less pollution-intensive product categories (Gill and Moeller, 2018), the purchase of higher-quality goods within a category (Kerkhof, Nonhebel and Moll, 2009), and the ability to afford more expensive, technology-intensive, and resource-efficient green goods and services (Rojas-Vallejos and Lastuka, 2020). It is also consistent with a "pioneer consumer" effect, whereby high-income households drive early demand for environmentally friendly products and contribute to their diffusion (Vona and Patriarca, 2011).

Taken together, the mixed empirical findings and the limitations of existing proxies underscore the need for a measure of green consumption that is directly grounded in consumption expenditures and comparable across countries. To address this gap, we construct a consumption-based measure of green consumption using product-level definitions and classifications of Environmental Goods and Services developed by the OECD and APEC. This approach allows us to estimate income–green consumption elasticities in a large cross-country panel using a measure directly anchored in expenditure on explicitly classified environmental goods and services. Our measure should therefore be understood as complementary to footprint-based indicators rather than as a substitute for them.

3 Empirical framework

3.1 Baseline specification

The baseline specification estimates the relationship between per-capita green consumption and per-capita disposable income, while controlling for unobserved heterogeneity. We rely on a log–log specification with country and year fixed effects, which allows the estimated coefficients to be interpreted as elasticities. The baseline specification is given by

$$g_{it} = \beta_y y_{it} + \beta_{yy} y_{it}^2 + \mathbf{\Theta C}_{it} + \alpha_i + \lambda_t + \epsilon_{it}, \tag{1}$$

where lowercase letters denote the logarithms of the corresponding variables, and subscripts i and t refer to country i and year t, respectively. The variable g_{it} denotes per-capita green consumption, while y_{it} denotes disposable income per capita. We include the squared term y_{it}^2 to allow for non-linearities in the income–green consumption relationship, such that the coefficients β_y and β_{yy} jointly determine the income elasticity of green consumption. The terms α_i and λ_t capture country and year fixed effects, respectively, and ϵ_{it} denotes the error term.

The vector of controls, $\mathbf{C}_{it}$, includes the logarithm of the urban population, sectoral value-added in agriculture and fishing, manufacturing, and services (Grunewald et al., 2017), as well as the share of renewable energy in total energy consumption. Urbanisation captures systematic differences in consumption behaviour between urban and rural households, reflecting heterogeneity in infrastructure, lifestyles, and access to consumption opportunities (Gill and Moeller, 2018). Sectoral value-added shares control for cross-country differences in economic structure that may affect the availability and diffusion of green goods and services through production spillovers and input–output linkages. The share of renewable energy consumption serves as a proxy for a country's position in the energy transition and captures persistent differences in production and consumption systems, as well as latent pro-environmental preferences that may influence green consumption independently of income.

Finally, we augment $\mathbf{C}_{it}$ with the inflation rate ($IRATE$) and a Green Price Index (GPI), which jointly control for price effects. While harmonized cross-country price indices for environmental goods and services are not available, the GPI provides a reduced-form proxy for price dynamics specific to the environmental sector, whereas inflation captures economy-wide price movements. Including both variables allows us to account for changes in the relative prices of environmental and non-environmental goods. Controlling for these price effects is essential to isolate the income–green consumption relationship from variation driven by price movements rather than by households' underlying consumption choices.

Given Equation 1, the income elasticity of green consumption is:

$$\varepsilon_{it} \equiv \frac{\partial g_{it}}{\partial y_{it}} = \beta_y + 2\,\beta_{yy}\,y_{it} \tag{2}$$

where the elasticity varies with the level of disposable income through the quadratic term in y_{it}. The income elasticity of green consumption allows for a direct classification of the good. When $\varepsilon_{it} < 1$, green consumption behaves as a necessity good, whereas $\varepsilon_{it} > 1$ indicates a luxury good. The income threshold separating these two regimes, what we call the income turning point $ITP_{\text{lux/nec}}$, is given by the level of disposable income for which $\varepsilon_{it} = 1$ and solving for y. In the same fashion, the separating necessity goods from inferior $ITP_{\text{nec/inf}}$, is obtained by setting $\varepsilon_{it} = 0$ and solving for y. Together, these turning points are defined as

$$ITP_{\text{lux/nec}} = \frac{1-\beta_y}{2\beta_{yy}} \quad \text{and} \quad ITP_{\text{nec/inf}} = -\frac{\beta_y}{2\beta_{yy}}$$

Importantly, given that our specification is quadratic and estimated at the country level, the reported coefficients should be interpreted as macro-elasticities. In non-linear demand systems such as QUAIDS, aggregation across heterogeneous households may introduce distribution-dependent terms in the aggregate Engel relationship. However, theoretical and empirical evidence suggests that such aggregation biases are typically modest under realistic income distributions (Denton and Mountain, 2004). Recent work shows that macro-level income elasticities capture demand patterns relevant for structural change and environmental outcomes (Comin et al., 2021; Caron and Fally, 2022).

3.2 Measuring green consumption

Definition of environmental goods and services. We follow the definition of green goods proposed by the Organisation for Economic Co-operation and Development (OECD) and the Asia-Pacific Economic Cooperation (APEC). Environmental Goods and Services (EGS) are defined as goods and services whose primary purpose is the prevention, reduction, and elimination of pollution and other forms of environmental degradation, as well as the sustainable management of natural resources. This includes technologies, products, and services that reduce environmental risks, minimise pollution and resource use, enable energy and material efficiency, support renewable energy production, and facilitate environmental monitoring, remediation, and conservation (OECD, 2008, 2019).

Strategy. Aggregate household consumption is observed consistently across countries and years, but not at a sufficiently disaggregated product level to identify environmental goods and services directly within national accounts. We therefore adopt an indirect strategy to recover green consumption at the country–year level by combining BACI trade data (Gaulier and Zignago, 2010), Exiobase3rx production, trade and household final demand data (Bjelle et al., 2019), and household real consumption from Penn World Tables v9.1 (Feenstra et al., 2015). [3]

Total household consumption C is decomposed into green (G) and non-green (B) components such that $C = G+B$. The green basket G corresponds to expenditure on environmental goods and services (EGS), whereas the non-green basket B captures all remaining consumption. [4] Because direct consumption data at the required level of product disaggregation are unavailable, we rely on product-level production and trade data classified as environmental goods and services to infer an implied measure of green consumption basket, G, that approximates the environmental content of domestic consumption. More precisely, we construct country–year shares of environmental goods and environmental services in total consumption, denoted ω_{eg} and ω_{es} respectively, and apply these shares to aggregate household consumption.

The use of shares is important because the underlying data sources are not fully consistent in levels. A share-based accounting approach ensures consistency with aggregate household consumption while allowing the composition of consumption between green and non-green goods and services to vary across countries and over time. Green consumption is therefore reconstructed as:

$$G = \omega_{eg} \cdot C + \omega_{es} \cdot C. \tag{3}$$

The aggregate environmental goods and services share is given by $\omega_{egs} = \omega_{eg} + \omega_{es}$. This approach separates the identification of the environmental composition of consumption from the level of aggregate household consumption, ensuring consistency with national accounting identities and cross-country comparability.

Implementation. The implementation focuses on constructing country–year specific environmental consumption shares, distinguishing environmental goods from environmental services. We

[3] We isolate household real consumption by applying the share of household consumption from Penn World Tables to real consumption.

[4] EGS and NEGS denote conceptual product categories. The variables G and B refer to their empirical counterparts constructed at the country–year level and used in the estimations.

rely on the OECD–APEC framework, which provides a harmonised, product-based classification of environmental goods and services (EGS) compatible with international statistical standards. Environmental goods are identified using the Combined List of Environmental Goods (CLEG), defined at the 6-digit Harmonized System (HS) level (Sauvage, 2014). Environmental services are identified using the APEC list based on the Central Product Classification (CPC 2.1) (Sauvage and Timiliotis, 2017; Nordås and Steenblick, 2021). Together, these classifications comprise 248 HS codes and 76 CPC codes, corresponding to 248 environmental goods and 76 environmental services. We first construct the share of environmental goods consumption, ω_{eg}, using product-level production and trade data. Because each Exiobase3rx product category [5] aggregates multiple HS6 codes, relying only on the standard HS–CPA–Exiobase3rx concordance would impose a fixed environmental goods structure across countries and over time. This would mechanically attribute cross-country variation in green consumption to expenditure levels rather than to changes in consumption composition. To recover meaningful country–year variation, we therefore use BACI trade data to compute country–year specific import and export shares of environmental goods. These shares are then used to weight aggregate production and trade flows in Exiobase3rx, yielding an implied measure of environmental goods consumption based on domestic production and net trade. Specifically, environmental goods consumption is reconstructed as $G^{eg} = P^{eg} - X^{eg} + M^{eg}$, and the corresponding share is obtained as $\omega_{eg} = \frac{G^{eg}}{C_{EXIO}}$.

We then construct the share of environmental services consumption, ω_{es}. Because services are not covered by BACI trade data, we cannot apply the same trade-based strategy as for goods. Instead, environmental services are identified using the APEC classification and mapped onto Exiobase3rx service categories through the CPC–ISIC–CPA concordance. We compute, for each service category, the share corresponding to activities classified as environmental and apply this share to household final demand in Exiobase3rx. Environmental services consumption is then expressed as a share of total household consumption, such that $\omega_{es} = \frac{G^{es}}{C_{EXIO}}$. Time variation in ω_{es} is therefore more limited than for ω_{eg} and mainly reflects structural changes in service composition.

Finally, we define the overall environmental consumption share as $\omega_{egs} = \omega_{eg} + \omega_{es}$ and construct green consumption as $G = (\omega_{eg} + \omega_{es}) \cdot C$, where C denotes real household consumption from the Penn World Tables, expressed in constant 2011 USD. Dividing by population yields green consumption per capita, G_{pc}. This EGS-based construction provides a harmonized and macro-consistent cross-country panel of green consumption that captures variation in the environmental goods and services component of aggregate demand. It should not be interpreted as a measure of the net environmental impacts embodied in household consumption, for which comparable cross-country lifecycle data are not available at this level of disaggregation. Full construction details are provided in Appendix A.

3.3 Data

Explanatory variables. Disposable income per capita is constructed from expenditure-side real GDP at chained PPP, sourced from the Penn World Tables (Feenstra et al., 2015), net of Taxes

[5] Exiobase3rx is the most disaggregated version of Exiobase3rx containing Multi-Regional Environmentally Extended Input-Output Tables including households' final consumption by product category, for 200 product categories, across 214 countries, from 1995 to 2015. Each product belongs to one of the seven consumption categories available in Exiobase3rx. Among consumption categories, one is dedicated to services.

on Income, provided by GRD 2021 (UNU-WIDER, Version 2021.). [6] Control variables are drawn from the World Bank and include the share of the urban population, sectoral value-added shares (agriculture and fishing, manufacturing, and services), the share of renewable energy consumption, the inflation rate measured as the annual growth rate of the consumer price index, and a Green Price Index (GPI) capturing aggregate price dynamics in the environmental sector.

To account for aggregate price dynamics affecting green consumption, we construct a Green Price Index (GPI) using product-level trade data from BACI. Environmental goods are identified based on the CLEG classification mapped to the HS92 nomenclature over the period 1995–2015. For each environmental good, prices are proxied by BACI unit values, defined as the ratio of trade value to traded quantity. For each HS92 environmental good and country, we define a base-year price using the median unit value observed in 2011. Using the median rather than the mean limits the influence of extreme unit values and measurement noise arising from compositional changes, reporting errors, or quality heterogeneity in trade data. Current-period prices are then expressed relative to this base-year benchmark.

Formally, the GPI is constructed as a Laspeyres-type deflator aggregating product-level prices using contemporaneous trade quantities as weights. For each country i and year t, the index is defined as the ratio of the value of environmental goods evaluated at current prices to the value of the same quantities evaluated at base-year prices. This yields a country–year-specific deflator, denoted $\mathrm{GPI}_{g,i,t}$, capturing changes over time in the average price of traded environmental goods. The GPI is not intended to measure household-level prices or relative prices between green and non-green goods. Rather, it serves as a reduced-form macroeconomic control capturing broad price movements in environmental goods markets. Its inclusion allows us to verify that the estimated relationship between disposable income and green consumption is not mechanically driven by aggregate price dynamics affecting environmental goods.

Alternative dependent variables. In addition to the baseline measure of green consumption per capita, G_{pc}, we construct alternative consumption measures used exclusively for robustness checks (Section C). These include an alternative green consumption measure, $G_{M_{pc}}$, and a complementary measure of non-green consumption per capita, B_{pc}. The alternative green consumption measure, $G_{M_{pc}}$, is constructed under the assumption that green imports reflect access to and consumption of environmental goods. For each country–year, we compute the share of environmental goods in total imports using BACI trade data mapped to the OECD–APEC Environmental Goods classification. This import share is then applied to household real consumption from the Penn World Tables to obtain an import-based alternative measure of green consumption per capita. While this measure abstracts from domestic production and exports, it provides a transparent robustness check based on trade exposure to environmental goods. Non-green consumption per capita, B_{pc}, is defined residually from the accounting identity $C = G + B$, such that $B = C - G$. This residual construction ensures full accounting consistency and allows us to test whether the non-linear income pattern identified for green consumption also characterizes the complementary component of the consumption basket.

[6] Despite this adjustment, disposable income remains highly correlated with GDP per capita: the Pearson correlation is 0.994 and the Spearman rank correlation is 0.999.

3.4 Descriptive Statistics

Our sample covers $N = 138$ countries over the period 1995–2015 ($T = 21$), yielding a balanced panel of 2,898 country–year observations. Table 1 reports summary statistics for the main variables used in the analysis and highlights substantial cross-country heterogeneity in both disposable income and green consumption per capita. While green consumption represents, on average, a modest share of household expenditure, its distribution is highly dispersed, suggesting that the income–green consumption relationship is unlikely to be linear and motivating the use of flexible income specifications in the empirical analysis.

Figure 1a reports cumulative green consumption over the period 1995–2015 and highlights strong distributional heterogeneity. The highest cumulative levels are observed in high-income countries—particularly the United States, Japan, and several European economies—reflecting both earlier adoption and persistently higher green consumption. Middle-income countries such as China, Brazil, and India also account for sizeable cumulative volumes, while low-income countries display much lower levels, consistent with persistent barriers to green consumption.

Figure 1b depicts the evolution of green consumption over time by income group and highlights heterogeneous dynamics across countries. Green consumption grows steadily in high-income countries, while upper-middle- and lower-middle-income countries experience steeper increases, with levels more than doubling over the period. As a result, the growth of global green consumption is increasingly driven by middle-income countries rather than by high-income countries alone, consistent with a catch-up process in which rising incomes support the adoption of greener consumption patterns. Low-income countries display a more discontinuous but upward trend; however, given their initially low levels, this growth translates into limited absolute increases.

The figure also indicates that the expansion of global green consumption is accompanied by a decline in cross-country concentration between 1995 and 2015. While the Green Consumption Index, normalized to unity in 1995, documents a sustained increase in aggregate green consumption, the Herfindahl–Hirschman Index exhibits a downward trend, indicating a progressive diffusion of green consumption across countries. Combined with the faster growth observed among initially low-consumption countries, these patterns are consistent with conditional β-convergence in green consumption, whereby countries starting from lower initial levels tend to experience higher subsequent growth rates. Unreported dispersion measures further point to the presence of σ-convergence, as the cross-country distribution of green consumption becomes less concentrated over time. These dynamics show that green consumption is not only increasing globally but also converging across countries, albeit in a gradual and uneven manner.

Taken together, the descriptive evidence shows that green consumption is strongly associated with income levels with potential non-linearities. Faster growth in initially low-consumption countries contributes to a gradual convergence of green consumption patterns, consistent with a catch-up process. However, these patterns do not identify whether income systematically drives green consumption growth or whether income elasticities vary along the income distribution, motivating a formal estimation of income elasticities.

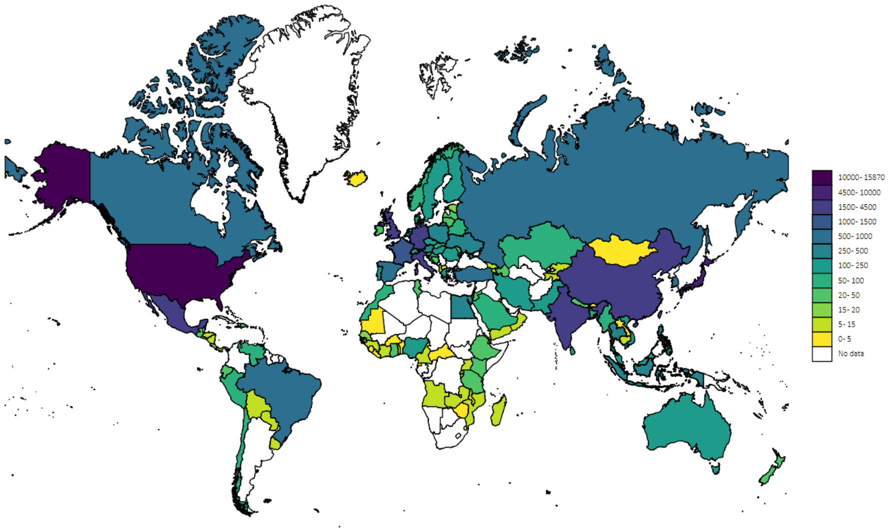
Table 1: Summary statistics

Variable	Description	Unit	Mean	Std. Dev.	Min	Max
		Key variables				
G_{pc}	Green consumption per capita	Constant 2011 US$	364.63	506.70	0.48	3,384.62
Y_{pc}	Disposable income per capita	Constant 2011 US$	14,095.35	14,861.91	180.04	97,761.47
		Green consumption shares				
G/C	Share of green consumption in total consumption	Percent	4.50	3.93	0.12	53.86
G/Y	Share of green consumption in disposable income	Percent	2.48	2.51	0.03	30.80
		Control variables				
GPI	Green Price Index	Index	74.85	64.56	1.84	491.18
$IRATE$	Inflation rate	Percent	7.67	13.64	-61.75	100.00
AGR	Agriculture value added	Billions (2011 US$)	33.31	132.02	0.01	2,650.62
MAN	Manufacturing value added	Billions (2011 US$)	92.55	334.81	0.01	5,618.63
$SERV$	Services value added	Billions (2011 US$)	307.98	1,057.22	0.12	12,607.43
URB	Urban population	Millions	21.22	63.11	0.01	775.35
REN	Renewable energy consumption	Percent of total energy use	34.35	30.80	0.00	96.62
		Alternative measures for robustness checks				
$G_{M_{pc}}$	Green consumption per capita based on EG imports	Constant 2011 US$	468.12	441.09	1.11	3,046.38
B_{pc}	Non-green consumption per capita	Constant 2011 US$	5,499.58	4,808.18	102.95	27,800.19
GDP_{pc}	Real GDP per capita	Constant 2011 US$	15,494.65	16,772.60	188.94	98,008.13

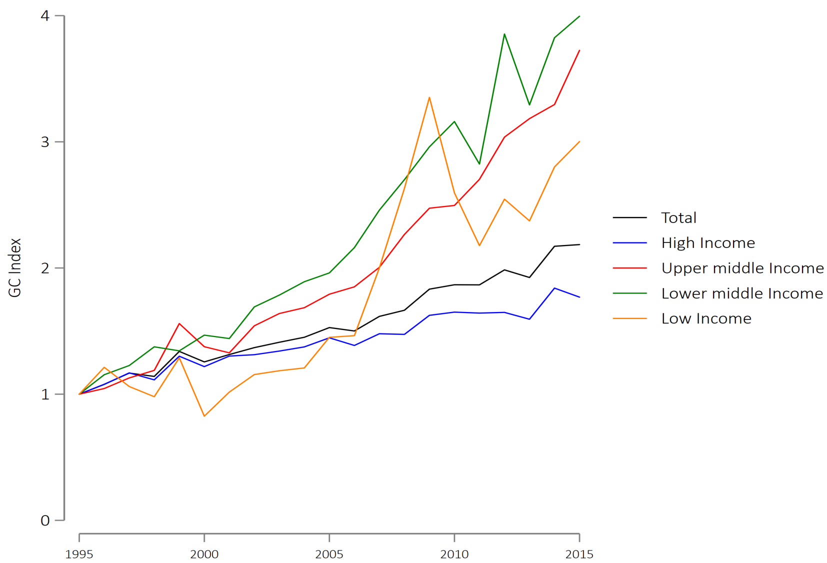
Notes: The balanced panel covers $N = 138$ countries over the period $t \in [1995, 2015]$, yielding 2,898 observations. The dependent variable in the baseline specifications is green consumption per capita (G_{pc}). Alternative measures ($G_{M_{pc}}$, B_{pc}, and GDP_{pc}) are used exclusively in robustness analyses. The main explanatory variable is disposable income per capita (Y_{pc}), included quadratically in the estimations. The variables C, G and Y denote real consumption in constant 2011 US$, green consumption and disposable income at the national level. Control variables include sectoral value added (agriculture, manufacturing, services), urban population, renewable energy consumption, inflation, and a Green Price Index (GPI). The GPI captures aggregate price dynamics in the environmental sector and does not correspond to observed prices of specific environmental goods or services.

Figure 1: Global patterns of green consumption, 1995–2015

(a) Cumulative green consumption



(b) Dynamics of green consumption by income group



Notes: Panel (a) reports cumulative green consumption over 1995–2015, expressed in billions of constant 2011 US\$. Panel (b) displays the Green Consumption (GC) Index by income group, normalized to 1 in 1995 within each group.

4 Results

4.1 Main results

Table 2 reports the coefficients and the estimated income–green consumption elasticities. Comparing the specifications on the basis of the log-likelihood highlights the importance of accounting for unobserved country heterogeneity. Specifications without country fixed effects, reported in Columns (1) and (3), display substantially lower log-likelihood values (–3,638.0 and –3,477.6, respectively), indicating a markedly poorer fit, even when additional structural controls are included. By contrast, specifications with country fixed effects, reported in Columns (2) and (4), achieve much higher log-likelihood values (–1,674.6 and –1,672.4), underscoring the role of time-invariant country-specific factors in shaping green consumption. Adding sectoral composition and renewable-energy controls in the presence of country fixed effects yields only marginal improvements in fit, indicating that their explanatory power is largely absorbed by the fixed effects.

The comparison based on estimated income elasticities further clarifies the differences across specifications. In Column (1), which omits country fixed effects, the mean elasticity is close to unity (0.999), and nearly half of the observations display elasticities above one, implying widespread luxury-good behaviour that is likely inflated by unobserved cross-country heterogeneity. Introducing country fixed effects in Column (2) substantially reduces both the mean elasticity (0.768) and the share of luxury-good observations (16.4%). Column (3), which adds structural controls without fixed effects, produces implausibly low elasticities, suggesting over-correction when unobserved heterogeneity is not properly accounted for. Finally, Column (4), which combines country fixed effects with structural controls, yields a balanced and economically plausible pattern, with a mean elasticity of 0.909 and about one-third of observations exhibiting elasticities above unity. Taken together, these results indicate that Column (4) provides the most credible characterization of the non-linear income–green consumption relationship and therefore serves as the preferred baseline specification.

Focusing on our preferred specification (Column 4), which includes the full set of control variables as well as both country and year fixed effects, we highlight four main results. First, the first-order effect of disposable income is positive and statistically significant, while the second-order term is negative and statistically significant. Together, these estimates indicate a concave relationship between disposable income and green consumption, consistent with the environmental Engel curve framework. It implies that the responsiveness of green consumption to income declines as income levels rise.

Second, the price-related controls support the interpretation of the estimated income effects. The coefficient on the Green Price Index (GPI) is negative and weakly statistically significant, while the inflation rate ($IRATE$) enters negatively and significantly. This pattern is economically intuitive: inflationary pressures reduce real purchasing power and disproportionately affect demand for green goods and services, which tend to be more income-sensitive. The inclusion of these price controls confirms that the estimated income–green consumption relationship is not mechanically driven by aggregate price dynamics but reflects genuine income-driven changes in consumption behaviour.

Third, the implied income elasticities indicate that green consumption behaves as a luxury good at lower income levels and gradually transitions toward a necessity good as income increases. [7] In Column (4), approximately 35% of the observations are associated with income elasticities

[7]Country-specific income elasticities are reported in Appendix B (Tables B1–B4).

greater than unity, primarily concentrated among low- and lower-middle-income countries. By contrast, for most high-income countries, income elasticities remain positive but fall below one, indicating that increases in disposable income translate into less-than-proportional increases in green consumption.

Fourth, the estimated income turning point—around USD 4,800 in constant 2011 prices—lies within the range of lower-middle-income economies. Below this threshold, affordability constraints appear to play a dominant role in limiting the adoption of green goods and services. Above it, green consumption becomes progressively integrated into household consumption baskets, and its dynamics become less dependent on income growth, suggesting a growing role for non-income factors such as preferences, social norms, and public policy.

We perform a series of robustness checks, reported in Appendix C. First, instrumenting disposable income using the Bartik-inspired shift–share design described in Appendix C.1 yields results close to those of the baseline specification: the income–green consumption relationship remains concave, the mean estimated elasticity remains close to the baseline fixed-effects estimate (0.897, compared with 0.909 in the baseline), and the share of observations with elasticities above unity is nearly identical (33.47%, compared with 34.6%). Second, using an alternative import-based measure of green consumption also yields a concave income–green consumption relationship. The mean estimated elasticity increases relative to the baseline specification (1.058 in the LSDV specification compared with 0.909 in the baseline), and the share of observations with elasticities above unity rises accordingly (58.49% compared with 34.6%). This pattern is consistent with the idea that, when green consumption is proxied through imports, access to environmental goods is more strongly conditioned by income. Third, estimating the same specification for non-green consumption is particularly important for interpreting the baseline results. Estimated elasticities are substantially lower, with a mean elasticity of 0.658 in the LSDV specification and only 2.76% of observations displaying elasticities above unity. This is consistent with the view that most non-green goods are necessity goods. Fourth, replacing disposable income with GDP per capita yields similar turning points and elasticity distributions, indicating that the main result does not depend on the income measure used. Finally, excluding the United States and China, first separately and then jointly, leaves both the estimated turning points and the distribution of elasticities almost unchanged.

Across these specifications, the baseline result remains unchanged. Although the level of estimated elasticities varies with the measure of green consumption, the income measure, and the consumption category considered, the estimated relationship between income and green consumption remains non-linear and concave. Taken together, these results indicate that the baseline findings are not driven by endogeneity, the construction of the green consumption measure, the choice of income measure, or the influence of large-country outliers. They also show that the pattern identified for green consumption is not observed for non-green consumption, whose estimated elasticities remain below unity in nearly all observations. Overall, they confirm that the estimated relationship between income and green consumption is characterized by elasticity values above unity over a substantial part of the income distribution, unlike non-green consumption.

Figure 2 displays a clear downward trend in income–green consumption elasticities over time, with pronounced heterogeneity across income groups. Overall, green consumption becomes progressively less sensitive to changes in disposable income. [8] High- and upper-middle-income countries exhibit the steepest declines in elasticity, particularly during the late 1990s and early 2000s, before

[8] Income elasticities of green and non-green consumption, reported by country and income group for the years 1995, 2005, and 2015, are provided in Appendix B.2 (Tables B1–B4).

Table 2: Green consumption as a function of disposable income

	(1)	(2)	(3)	(4)
y	2.860***	2.392***	2.509***	2.619***
	(0.218)	(0.739)	(0.246)	(0.775)
y^2	-0.104***	-0.091**	-0.123***	-0.095**
	(0.013)	(0.043)	(0.014)	(0.043)
GPI	-0.068**	-0.019	-0.044*	-0.019*
	(0.027)	(0.012)	(0.025)	(0.011)
$IRATE$	-0.723***	-0.277*	-0.388***	-0.268*
	(0.115)	(0.149)	(0.119)	(0.149)
Sectoral composition of the economy	NO	NO	YES	YES
Share of renewables in energy production	NO	NO	YES	YES
Country FE	NO	YES	NO	YES
Year FE	YES	YES	YES	YES
R-squared	0.694	0.349	0.726	0.350
Adjusted R-squared	0.691	0.343	0.723	0.343
Log-likelihood	-3,638.0	-1,674.6	-3,477.6	-1,672.4
Mean estimated income elasticity $\hat{\varepsilon}$	0.999	0.768	0.300	0.909
Share of observations where $\hat{\varepsilon} > 1$	46.5%	16.4%	0.3%	34.6%
$ITP_{\text{lux/nec}}$ (in constant 2011$)	7,799.2	2,171.8	456.7	4,858.7
$ITP_{\text{nec/inf}}$ (in constant 2011$, thousands)	964.8	542.4	26.4	920.8

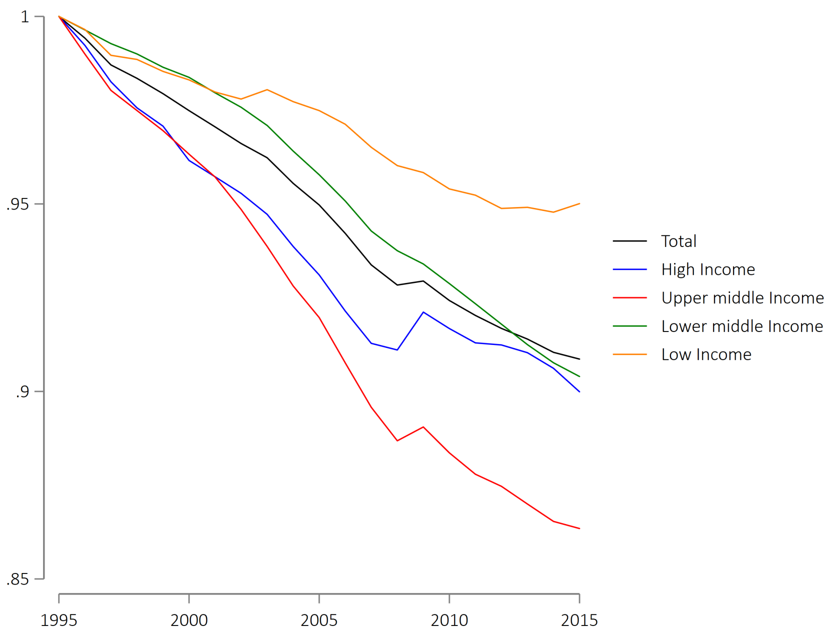
Note: $N = 2,898$. Dependent variable: natural logarithm of per capita green consumption, $g_{i,t}$. All the variables are in natural logarithms except the inflation rate and GPI variables. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Robust standard errors are in parentheses. See text for the computations of income turning points $ITP_{\text{lux/nec}}$ and $ITP_{\text{nec/inf}}$.

stabilizing at values below unity. This pattern is consistent with a transition of green consumption from a luxury good to a necessity good as income levels rise.

Across income groups, the pace and extent of this transition differ substantially. In high-income countries, elasticities fall rapidly and converge toward levels well below unity, indicating that green consumption becomes weakly responsive to income dynamics. Upper-middle-income countries follow a similar but slightly delayed trajectory, indicating a gradual convergence toward the consumption patterns observed in richer economies. Lower-middle-income countries also display a declining trend, albeit at a slower pace, indicating that income constraints remain relevant for longer in shaping green consumption. By contrast, in low-income countries the decline in elasticities is modest, and disposable income remains a key determinant of green consumption due to persistent affordability constraints.

Despite the long-run downward trend, a short-lived rebound in income elasticities is observed around 2009. This rebound does not indicate a strengthening of green consumption *per se*, but rather reflects a temporary increase in its income sensitivity. In this period, green consumption behaves more strongly as a luxury good, becoming disproportionately responsive to income changes. This pattern is consistent with the macroeconomic context of the Global Financial Crisis. When households experience negative income shocks, they adjust their consumption baskets by prioritizing essential goods and screening out discretionary expenditures. In this adjustment process, green goods and services—being relatively more expensive and non-essential—are among the first categories to be reduced. As a result, marginal changes in income translate into larger proportional changes in green consumption, mechanically increasing estimated income elasticities. The rebound is therefore best interpreted as evidence that, under adverse macroeconomic conditions, green consumption temporarily reverts to a luxury good. As economic conditions normalize,

Figure 2: Dynamics of income–green consumption elasticities



Notes: The figure reports the dynamics of income–green consumption elasticities normalized to one in 1995, both by income group and for the full sample. Average elasticity values in 2015 are 0.86 (total), 0.65 (high income), 0.82 (upper-middle income), 1.00 (lower-middle income), and 1.24 (low income). Elasticities are based on estimates reported in Table 2, Column 4.

income elasticities resume their downward trajectory, confirming that in high-income economies green consumption becomes progressively less dependent on income and increasingly shaped by structural, institutional, and behavioural determinants.

Overall, these dynamics are consistent with the Engel curve framework and reinforce our main results, which document a declining sensitivity of green demand to income as development proceeds. They further show that income growth plays a central role in driving green consumption in poorer economies, whereas targeted green policies become increasingly necessary to sustain further adoption in wealthier countries. Last but not least, these estimates also point to non-homothetic consumption behaviour, whereby income responsiveness differs across green and non-green consumption categories. As a result, income shocks—whether driven by growth, taxation, or transfers—need not scale green and non-green consumption proportionally.

5 Discussion

5.1 Composition effects in the consumption basket

A common assumption in quantitative frameworks used to evaluate redistribution and climate policy is that preferences are homothetic, so that income changes scale consumption proportionally across goods and services. In such settings, redistribution affects the level of consumption but leaves its composition unchanged, implying that income-driven policies have no direct effect on the relative demand for green and non-green consumption. This homothetic framework remains at odds with both empirical evidence on non-linear Engel curves and theoretical contributions emphasizing the role of non-homothetic demand in policy design (Banks et al., 1997; Marceau et al., 2005; Jacobs and van der Ploeg, 2019; Levinson and O'Brien, 2019; Sager, 2019; Shojaeddini et al., 2024). Recent work further shows that heterogeneity in income elasticities across broad consumption categories accounts for a large share of structural change and cross-country variation in emissions, reinforcing the view that the homothetic assumption is not empirically warranted (Chen et al., 2016; Comin et al., 2021; Caron and Fally, 2022). Yet, general equilibrium analyses show that relaxing proportional demand responses can amplify aggregate environmental effects through income-driven rebound mechanisms (Böhringer and Rivers, 2021).

Given that income elasticities differ across the green and non-green components of the consumption basket, income changes under non-homothetic preferences mechanically reallocate consumption within the basket, even in the absence of price or substitution effects. Income growth or redistribution can shift consumption toward green or non-green components, depending on how income elasticities differ between green and non-green consumption, and on where income gains and losses occur along the income distribution. Therefore, the difference between the income elasticities of green and non-green consumption, $(\varepsilon_G - \varepsilon_B)$, captures the direction and magnitude of these income-driven composition effects. A positive difference implies that an income gain increases the relative weight of green consumption in the basket, whereas a negative difference implies a relative shift toward non-green consumption. [9] In this sense, non-homothetic Engel effects operate as a pure income-driven reallocation channel, distinct from substitution effects but potentially capable of generating sizeable aggregate responses.

Figure 3 reports the implied income–elasticity gap between green and non-green consumption. Two results stand out. First, the difference is positive across the entire consumption distribution, indicating that green consumption is systematically more income-elastic than non-green consumption. This directly rejects the homothetic-preferences assumption under which income changes would scale green and non-green consumption proportionally and leave consumption composition unchanged. It is consistent with evidence that expenditure shares on low-carbon and pollution-intensive goods exhibit persistent, income-dependent patterns rather than flattening Engel curves (Levinson and O'Brien, 2019; Caron and Fally, 2022). Second, the magnitude of this difference declines with consumption per capita, implying that income-driven composition effects are strongest in low-income countries and gradually weaken as income rises. In particular, income gains in low-income countries generate larger relative shifts toward green consumption than comparable income changes in high income countries.

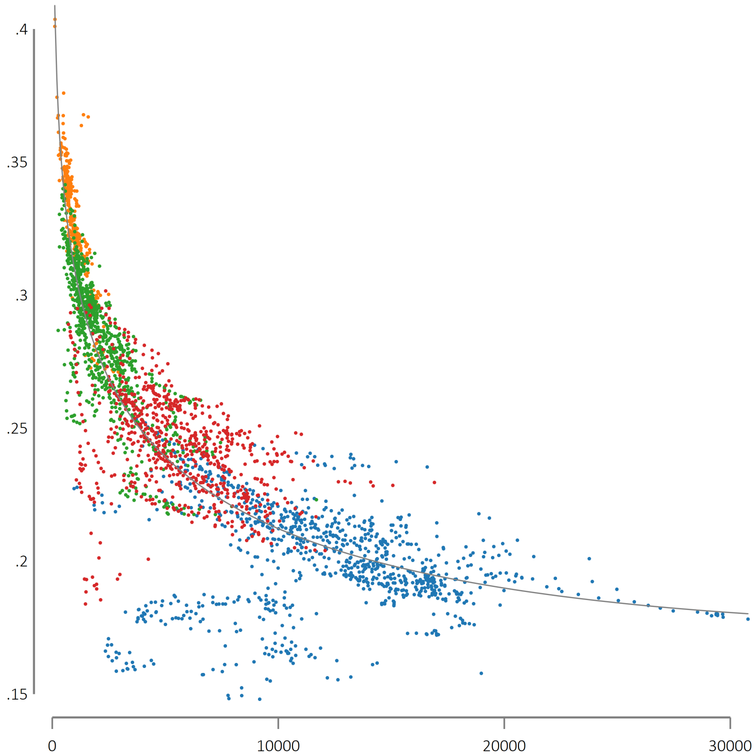
This pattern provides the empirical basis for the comparative-statics exercises below. Because the elasticity gap remains positive over the full distribution, positive income changes tilt consumption toward green relative to non-green goods at all stages of development, although with declining strength as income rises. In a redistributive setting, however, aggregate outcomes also depend on the location of income gains and losses across countries and on initial consumption shares. As a result, a positive elasticity gap at the country level does not mechanically imply a global shift toward green consumption under redistribution. Income-driven composition effects therefore persist even at high income levels, but their aggregate implications depend on how income changes translate into green and non-green consumption across countries.

5.2 Income elasticities and global redistributive climate policy

Given non-homothetic preferences, we show how accounting for empirically estimated income elasticities changes the predicted outcome of redistribution policies designed to foster green consump-

[9] See Appendix D for a formal derivation showing that differences in income elasticities can be interpreted as composition effects.

Figure 3: The income elasticity gap ($\hat{\varepsilon}_{G,i} - \hat{\varepsilon}_{B,i}$) as a function of consumption per capita



Notes: The figure plots the differences in income elasticities between green and non-green consumption as a function of total consumption per capita. Each dot corresponds to a country–year observation over 1995–2015. Observations are grouped by income category: high-income (blue), upper-middle-income (red), lower-middle-income (green), and low-income economies (orange). The fitted line corresponds to a flexible local polynomial regression capturing the average trend across the consumption distribution.

tion. Under unit income elasticities, redistribution scales green and non-green components of consumption proportionally within each country, mechanically ruling out Engel-type composition effects in the consumption basket. This proportional-scaling benchmark underlies many analyses of environmental tax reforms and green fiscal policies in which household demand is modelled with homothetic or quasi-homothetic preferences and distributional effects are assessed under fixed budget shares or consumption composition (Klenert and Mattauch, 2016; Jacobs and van der Ploeg, 2019; Jia et al., 2025). Nevertheless, once heterogeneous income elasticities are allowed for, this proportionality no longer holds. Redistribution activates Engel-type composition effects, and aggregate outcomes may differ from those obtained under unit elasticity assumptions that imply proportional scaling.

Context. We illustrate this mechanism with a stylized Climate Fund that mobilizes annual transfers of 300 US$ billion from high-income to low- and middle-income countries in support of the low-carbon transition. In our framework, the Climate Fund is modelled as a redistribution of disposable income across countries, holding prices fixed and abstracting from substitution effects. [10] Given the OECD–APEC definitions and classifications of Environmental Goods and Services,

[10]Because no optimal consumption choice is modelled, this exercise should not be interpreted as a policy simulation. Rather, it captures the mechanical consequences of accounting for differences in income elasticities across green and non-green components of the consumption basket.

we assume that, in our framework, a redistribution is environmentally more favourable when it shifts consumption toward green relative to non-green goods and services.

Our exercise therefore evaluates redistribution through changes in the composition of demand toward explicitly classified environmental goods and services, rather than through a direct measure of net lifecycle environmental impacts. This setup isolates the role of income elasticities in shaping consumption responses and allows us to assess how redistribution affects the global composition of the consumption basket. Institutional details, country classification as contributors or recipients, and allocation rules are described in Appendix E.

Table 3 reports the comparative-statics outcomes of the stylized Climate Fund for green and non-green consumption under two alternative demand assumptions, the homothetic scenario with unit income elasticities, $\varepsilon_G = \varepsilon_B = 1$, and the non-homothetic scenario based on the estimated elasticities, $\varepsilon_G \neq \varepsilon_B \neq 1$, taken from Section 4.1. We first document the direction and magnitude of consumption adjustments under each scenario. The table then reports the bias of the homothetic benchmark, computed as the difference between the outcomes obtained under unit elasticities and those obtained under estimated elasticities. [11] The comparison therefore isolates how different elasticity assumptions shape the aggregate consumption response to the same policy intervention.

Outcomes of the stylized Climate Fund. First, under unit income elasticities, $\varepsilon_G = \varepsilon_B = 1$, redistribution reduces green consumption in contributor countries and increases it in recipient countries, but the global effect remains negative, with $\Delta G_{\text{World}} = -4.622$ billion US\$. In the same scenario, non-green consumption declines in contributor countries and increases in recipient countries, yielding a net global increase of $\Delta B_{\text{World}} = +75.991$ billion US\$. Under proportional scaling, the redistribution therefore reallocates income toward recipient economies without generating a global expansion of green consumption, while still increasing non-green consumption at the world level. This outcome is mechanical. Because demand scales proportionally with income, the redistribution does not activate Engel-type composition effects within countries; any aggregate change therefore reflects only the reallocation of income across countries with different initial expenditure levels and shares.

Second, when empirically estimated elasticities are used, $\varepsilon_G \neq \varepsilon_B \neq 1$, the pattern for green consumption changes. Green consumption still declines in contributor countries and increases in recipient countries, but the contraction among contributors is smaller and the increase among recipients is slightly larger. As a result, the global effect on green consumption becomes approximately neutral, with $\Delta G_{\text{World}} = +0.058$ billion US\$. For non-green consumption, contributor countries still experience a decrease and recipient countries an increase, but the global rise becomes much larger, reaching $\Delta B_{\text{World}} = +117.622$ billion US\$.

General biases. The comparison reveals a homotheticity bias in the predicted composition of global consumption. In our framework, redistribution outcomes are assessed through the composition of demand between expenditure directed toward goods and services explicitly classified as environmental and expenditure directed toward non-green consumption. Relative to the outcomes obtained under estimated elasticities, the homothetic benchmark predicts a lower global response for both components: the bias amounts to −4.680 billion US\$ for green consumption and −41.631 billion US\$ for non-green consumption. The main distortion therefore does not come from green

[11] Robustness checks and variant schemes reported in Appendix E.4 confirm that these conclusions do not hinge on calibration choices or scale effects.

Table 3: Effect of the stylized Climate Fund on the green *versus* non-green consumption basket

	ΔG	$\Delta G/Y_w$	$\Delta G/C_w$	ΔB	$\Delta B/Y_w$	$\Delta B/C_w$
			$\varepsilon = 1$			
Contributor countries	-11.006	-0.012	-0.026	-130.285	-0.141	-0.311
Recipient countries	+6.384	+0.007	+0.015	+206.276	+0.224	+0.492
Net variations	-4.622	-0.005	-0.011	+75.991	+0.082	+0.181
			$\varepsilon \neq 1$			
Contributor countries	-7.066	-0.008	-0.017	-58.779	-0.064	-0.140
Recipient countries	+7.124	+0.008	+0.017	+176.401	+0.191	+0.421
Net variations	+0.058	+0.000	+0.000	+117.622	+0.128	+0.281
			Bias $(\varepsilon = 1) - (\varepsilon \neq 1)$			
Contributor countries	-3.940	-0.004	-0.009	-71.506	-0.077	-0.171
Recipient countries	-0.740	-0.001	-0.002	+29.875	+0.033	+0.071
Net variations	-4.680	-0.005	-0.011	-41.631	-0.046	-0.100
			Relative bias (in % of $\varepsilon = 1$)			
Contributor countries	-35.8			-54.9		
Recipient countries	-11.6			+14.5		
Net variations	-101.3			-54.8		

Note: Absolute changes in green and non-green consumption are denoted ΔG and ΔB, respectively, and are expressed in constant 2011 US$ billion. The ratios $\Delta G/Y_w$ and $\Delta B/Y_w$ express the changes in green and non-green consumption as percentages of world disposable income, whereas $\Delta G/C_w$ and $\Delta B/C_w$ relate the same changes to total world consumption. Ratios involving C_w and Y_w are expressed in percentage points. The redistribution scheme is progressive and based on disposable income per capita, implying that transfer shares decline with income among recipient countries. See Appendix E.2 for more details. Bias is computed as $(\varepsilon = 1) - (\varepsilon \neq 1)$, so that a negative value indicates that the homothetic benchmark understates the effect relative to the scenario based on estimated elasticities. Relative bias equals this difference divided by the absolute homothetic benchmark prediction, times 100.

consumption, but from the much larger downward bias affecting non-green consumption. Put differently, assuming homothetic demand with unit elasticities mainly understates the increase in non-green consumption generated by cross-country redistribution. In that sense, the bias is directly relevant for the evaluation of redistributive climate policy in our framework because it leads the homothetic benchmark to understate the expansion of consumption directed toward non-green goods and services relative to goods and services whose primary purpose is to prevent, reduce, or mitigate environmental degradation.

This asymmetry is also visible in relative terms. The global relative bias reaches -101.3% for green consumption because the benchmark predicts a negative global change, whereas the specification with estimated elasticities yields a near-zero outcome. However, the more consequential distortion concerns non-green consumption, for which the global relative bias reaches -54.8%.

Origin of the bias. The bias in global green consumption originates primarily in contributor countries. Contributors account for -3.940 billion US$ out of a total global green bias of -4.680 billion US$, whereas recipient countries account for only -0.740 billion US$. In relative terms, the bias reaches -35.8% for contributor countries, compared with -11.6% for recipient countries. This pattern reflects the fact that proportional scaling understates green consumption in high-income contributors by predicting a larger decrease than under estimated elasticities. Under $\varepsilon = 1$, green consumption in contributor countries falls by -11.006 billion US$, compared with -7.066 billion US$ under estimated elasticities. The bias in global green consumption therefore arises mainly from the larger decrease predicted for contributor countries under the homothetic scenario.

Contributor countries are also the main source of the bias in non-green consumption. Under proportional scaling, non-green consumption in contributor countries falls by -130.285 billion US$, whereas under estimated elasticities the decline is much smaller, at -58.779 billion US$. This implies a contributor-country bias of -71.506 billion US$, the largest component of the decomposition. In relative terms, this corresponds to a bias of -54.9%. Recipient countries contribute in the opposite direction. Their increase in non-green consumption is smaller under estimated elasticities than under the homothetic scenario, yielding a bias of $+29.875$ billion US$, or $+14.5\%$ relative to the homothetic scenario. The aggregate bias in non-green consumption nevertheless remains negative, at -41.631 billion US$, because the benchmark predicts a much larger decline in contributor countries, and this effect more than offsets its overstatement of the increase in recipient countries.

This pattern is consistent with the cross-country heterogeneity in income elasticities documented in Figure 3. In contributor economies, proportional scaling implies large expenditure adjustments when income falls. Once estimated elasticities are used, both green and non-green consumption decline by less than under the homothetic scenario, with the largest correction arising for non-green consumption. In recipient countries, income gains still increase both components of consumption, but the correction relative to proportional scaling is smaller and differs in sign between green and non-green consumption. The main source of mismeasurement therefore lies on the contributor side of the redistribution. [12]

Taken together, these results show that the homothetic benchmark does more than alter the magnitude of redistribution effects. It also mischaracterizes their composition by understating the global increase in non-green consumption implied by cross-country transfers.

6 Conclusion

This paper provides cross-country evidence that green consumption follows a non-linear environmental Engel curve. Using a novel, harmonized cross-country measure of households' green consumption based on Environmental Goods and Services for 138 countries over 1995–2015, we show that green consumption behaves as a luxury good at low income levels but gradually becomes a necessity as income rises. Income elasticities decline with development and fall below unity in most high-income economies. We also show that green consumption remains more income-elastic than non-green consumption over the full distribution, implying systematic income-driven composition effects within the consumption basket.

These findings have first-order implications for the evaluation of global redistributive climate policy. In particular, the standard assumption of unit income elasticities, often associated with homothetic preferences, is not neutral. Once heterogeneous elasticities are allowed for, the effects of redistribution on the composition of consumption no longer follow proportional scaling. In our stylized Climate Fund exercise, the global response of green consumption remains limited,

[12] Similar orders of magnitude are obtained under the alternative redistribution schemes reported in Appendix E.6, suggesting that this conclusion is not driven by a particular calibration.

whereas the increase in global non-green consumption becomes substantially larger. The homothetic benchmark does not merely alter the estimated magnitude of redistribution effects. It also understates the extent to which cross-country transfers can increase non-green consumption and, more generally, mismeasures the composition effects generated by redistribution. This homotheticity bias arises because proportional scaling suppresses income-driven composition effects and can mischaracterise both the magnitude and the direction of policy impacts on global consumption patterns.

More broadly, our results underscore a demand-side limitation of global redistributive climate policy. Income transfers alone cannot guarantee a reallocation of consumption toward green goods and services, even when green consumption remains more income-elastic than non-green consumption. Aggregate outcomes depend not only on the gap between green and non-green income elasticities, but also on the cross-country distribution of income gains and losses and on the much larger initial weight of non-green consumption in the basket. As a result, even when income gains tilt consumption toward green goods at the country level, non-green consumption may still generate the larger aggregate response. Global redistributive climate policy is therefore unlikely to be sufficient on its own in the short run and may need to be complemented by policies that directly affect access, prices, and availability of green goods and services, such as targeted subsidies, infrastructure investment, or regulatory constraints, rather than relying solely on income effects.

While our analysis highlights short-run composition effects that are less favourable in our framework, it does not call into question the relevance of global redistributive climate policy. Through diffusion, learning-by-doing, and scale effects, climate finance may gradually compress income elasticities, allowing redistribution to support greener consumption over time. Its effectiveness therefore depends on the speed at which green consumption transitions from luxury to necessity. When elasticities remain high, income-driven composition effects can dampen or even offset shifts in consumption toward green goods and services; as elasticities decline, redistribution becomes increasingly supportive of a reallocation of consumption toward green goods and services.

Our results should also be interpreted in light of the scope of the measure. Green consumption is defined here from the OECD–APEC classification of Environmental Goods and Services and should therefore be understood as expenditure directed toward goods and services whose primary purpose is to prevent, reduce, or mitigate environmental degradation. The paper measures the green component of the consumption basket, not the net lifecycle environmental impacts of consumption. A natural next step is therefore to link this Engel-curve framework to carbon-accounting or lifecycle-based measures in order to assess whether income-driven changes in measured green consumption translate into net environmental gains. More generally, evaluating how growth and redistribution reshape the environmental composition of consumption requires integrating empirically grounded non-homothetic demand into macro-climate frameworks.

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Appendix A. Measurement

A.1 Identities

We observe aggregate household consumption but not its environmental component–green consumption. To recover the environmental component of consumption, we rely on standard apparent-consumption identities based on production and net trade flows, at the product-group level. These identities provide an accounting framework used exclusively to construct environmental goods and environmental services shares, which are then applied to observed household consumption. They do not redefine observed household consumption, which is taken directly from the Penn World Tables.

Let $C_{i,t}$ denote real household consumption in country i and year t, as measured in the Penn World Tables (constant 2011 USD). Green consumption is denoted by $G_{i,t}$ and non-green consumption is defined residually as $B_{i,t} = C_{i,t} - G_{i,t}$. To structure the construction of green consumption, we rely on a standard national-accounting identity that links domestic consumption to production and net trade. At an aggregate level, total consumption in country i and year t can be written as $C_{i,t} = P_{i,t} - X_{i,t} + M_{i,t}$, where $P_{i,t}$ denotes total production, $X_{i,t}$ total exports, and $M_{i,t}$ total imports. This identity clarifies why production, exports, and imports are the relevant aggregates used to recover the environmental component of consumption.

Green consumption is decomposed into environmental goods and environmental services,

$$G_{i,t} = G^{eg}_{i,t} + G^{es}_{i,t},$$

and reconstructed using their shares in total household consumption:

$$G_{i,t} = \omega_{eg,i,t}\, C_{i,t} + \omega_{es,i,t}\, C_{i,t}, \tag{A1}$$

where $\omega_{eg,i,t}$ and $\omega_{es,i,t}$ denote the shares of environmental goods and environmental services in total household consumption, respectively. The aggregate environmental consumption share is $\omega_{egs,i,t} = \omega_{eg,i,t} + \omega_{es,i,t}$, so that $G_{i,t} = \omega_{egs,i,t}\, C_{i,t}$. Accordingly, environmental goods and services are first identified at the product-group level and aggregated into country–year shares. The construction of $\omega_{eg,i,t}$ and $\omega_{es,i,t}$—and their empirical implementation based on production, trade, and final demand data—is described in the following subsections.

A.2 Data inputs and concordances

We combine three data sources. First, BACI (HS6) provides bilateral trade flows used to compute country–year export and import shares of environmental goods. Second, Exiobase3rx provides product-group aggregates for production, exports, and imports, as well as households' final demand by product group. Third, the Penn World Tables provide real household consumption $C_{i,t}$ (constant 2011 USD) and population. Environmental goods are identified using the OECD–APEC Combined List of Environmental Goods at the HS6 level, and environmental services using the OECD–APEC CPC-based classification, mapped to Exiobase3rx service categories using standard concordances (CPC–ISIC–CPA–Exiobase3rx).

A.3 Environmental goods

Environmental goods are identified at the HS6 level using the OECD–APEC Combined List of Environmental Goods as defined in Section 3.2. Their contribution to green consumption is recovered using a trade-based weighting strategy that introduces country–year variation in the environmental composition of tradable goods, combining data from BACI and Exiobase3rx.

BACI. Using BACI, we compute the country–year export and import shares of environmental goods:

$$\omega_{egx,i,t} = \frac{\sum_{h\in EG} X^{BACI}_{i,t,h}}{\sum_h X^{BACI}_{i,t,h}}, \qquad \omega_{egm,i,t} = \frac{\sum_{h\in EG} M^{BACI}_{i,t,h}}{\sum_h M^{BACI}_{i,t,h}}, \tag{A2}$$

where h indexes HS6 products, EG denotes the set of environmental goods HS6 codes, and X^{BACI} and M^{BACI} denote total exports and imports in BACI. These shares measure the environmental goods intensity of each country's export and import baskets.

Because Exiobase3rx product categories aggregate multiple HS6 codes, relying solely on concordance tables would impose a fixed environmental goods structure across countries and over time. To avoid mechanically attributing all cross-country variation in green consumption to differences in expenditure levels, we use BACI-based shares to refine the environmental goods content of production and trade aggregates.

Exiobase3rx. Specifically, we apply the BACI-based environmental goods to weight production and trade flows from Exiobase3rx. By transposing the observed environmental goods trade structure from BACI to Exiobase3rx aggregates, this procedure introduces country–year variation in the environmental goods content of tradable products that is otherwise unobservable in aggregated input–output product categories.

Let $P_{i,t}$, $X_{i,t}$, and $M_{i,t}$ denote Exiobase3rx aggregates for total production, exports, and imports. We construct environmental goods components as:

$$P^{eg}_{i,t} = P_{i,t}\,\omega_{egx,i,t}, \qquad X^{eg}_{i,t} = X_{i,t}\,\omega_{egx,i,t}, \qquad M^{eg}_{i,t} = M_{i,t}\,\omega_{egm,i,t}. \tag{A3}$$

Production and exports are weighted using export-based environmental goods shares, while imports are weighted using import-based shares. This asymmetric weighting reflects the fact that exports provide an observable signal of the environmental goods intensity of tradable domestic production, whereas imports capture the environmental content of goods consumed from abroad.

EG consumption. Environmental goods consumption is then recovered as:

$$G^{eg}_{i,t} = P^{eg}_{i,t} - X^{eg}_{i,t} + M^{eg}_{i,t}, \tag{A4}$$

which corresponds to the environmental goods component of domestic consumption inferred from production and net trade flows. This constitutes an accounting-based measure of the environmental goods content embedded in household consumption, derived from national accounts identities.

The environmental goods consumption share is:

$$\omega_{eg,i,t} = \frac{G^{eg}_{i,t}}{C_{EXIO,i,t}}. \tag{A5}$$

By construction, $\omega_{eg,i,t}$ measures the contribution of environmental goods to total household consumption as captured in the underlying input–output data and enters directly the construction of green consumption in Section 3.2.

A.4 Environmental services

Environmental services cannot be identified using international trade data, as services are not covered by BACI. Accordingly, unlike environmental goods, environmental services consumption is constructed directly from the demand side using household final consumption data from Exiobase3rx. We restrict attention to the household consumption category "services", denoted ϕ, to avoid overstating green consumption. Environmental services are identified using the OECD–APEC CPC-based classification and mapped to Exiobase3rx service categories through standard CPC–ISIC–CPA concordances, as described in Section 3.2. Because services trade is not consistently observable at the required level of disaggregation, this construction relies exclusively on household final demand data.

For each service, $j \in \phi$, we compute the environmental services share $\omega_{es,j,i,t}$ and weight household final demand accordingly:

$$G^{es}_{j,i,t} = \omega_{es,j,i,t} C_{EXIO,j,i,t}, \tag{A6}$$

where $C_{EXIO,j,i,t}$ denotes household final demand for service category j in Exiobase3rx. This procedure isolates the environmental services component embedded in aggregate service consumption at the country–year level. Aggregating across service categories yields:

$$G^{es}_{i,t} = \sum_{j \in \phi} G^{es}_{j,i,t}, \tag{A7}$$

and the environmental services consumption share is:

$$\omega_{es,i,t} = \frac{G^{es}_{i,t}}{C_{EXIO,i,t}} \tag{A8}$$

By construction, $\omega_{es,i,t}$ measures the contribution of environmental services to total household consumption in the underlying input–output data and enters directly the construction of green consumption in Section 3.2.

A.5 From shares to real green consumption

We define the overall environmental consumption share as $\omega_{egs,i,t} = \omega_{eg,i,t} + \omega_{es,i,t}$. This share encompasses the contribution of environmental goods and services to total household consumption in country i and year t. Green consumption is then obtained by scaling these shares by real household consumption from the Penn World Tables:

$$G_{i,t} = \omega_{eg,i,t}\, C_{i,t} + \omega_{es,i,t}\, C_{i,t} = \omega_{egs,i,t}\, C_{i,t}. \tag{A9}$$

By construction, cross-country and time variation in $G_{i,t}$ arises from variation in the environmental consumption shares $\omega_{eg,i,t}$ and $\omega_{es,i,t}$, and from observed household consumption levels. Finally, green consumption per capita is defined as $G_{pc_{i,t}} = G_{i,t}/POP_{i,t}$, where $POP_{i,t}$ denotes total population. This variable constitutes the main dependent variable used in the empirical analysis.

A.6 Assumptions, limitations, and robustness

Our measurement strategy relies on combining trade-based information for environmental goods with final-demand data for environmental services. This approach is necessary given data constraints and entails assumptions that are standard in cross-country measurement exercises based on aggregated input–output tables. Two measurement challenges arise.

A first measurement challenge arises from the level of product aggregation in multi-regional input–output tables. Each Exiobase3rx product category aggregates several HS6 products through standard concordances. Relying exclusively on these concordances would impose a fixed environmental goods structure across countries and over time, such that all cross-country variation in green consumption would reflect differences in expenditure levels rather than differences in consumption composition. To address this issue, our baseline construction relies on BACI-based export and import shares to refine the environmental goods intensity of Exiobase3rx aggregates and introduce empirically observed country–year variation in the composition of tradable goods.

In the absence of harmonized product-level production data consistently classified as environmental across countries and time, we use export-based environmental goods shares to weight production and exports, and import-based shares to weight imports. At the macroeconomic level, the export basket provides a harmonized observable and comparable signal of a country's specialization in tradable goods. Under standard assumptions of joint production and common technology within broad product groups, the environmental goods intensity embodied in exports is informative about the environmental goods intensity of tradable domestic production. This choice introduces empirically observed heterogeneity rather than imposing a uniform EGS structure through concordances.

This approximation may introduce measurement error whose direction depends on country characteristics. For instance, export-based shares may overstate the environmental goods content of production in countries exporting a narrow set of environmental goods while producing mainly non-environmental goods for domestic markets, and may understate green production where environmental goods are largely produced and consumed domestically with limited exports.

The second source of measurement error relates to services and classification. Because BACI does not cover services trade, environmental services are identified from household final demand using CPC–ISIC–Exiobase3rx concordances, which may omit some activities or introduce classification noise. Moreover, the OECD–APEC EGS lists were not designed to measure household pro-environmental behaviour *per se*, so our measure captures the presence of classified environmental goods and services within aggregate consumption rather than the net environmental footprint of consumption.

These limitations, however, do not mechanically generate our main results. First, most sources of potential measurement error affect the level of green consumption $G_{i,t}$ rather than imposing a particular non-linearity with respect to income. Second, plausible income-related omissions—such as within-category quality upgrading or the increasing importance of services at higher income levels—would tend to bias against finding that green consumption becomes a necessity at higher income levels, by understating green consumption in richer economies.

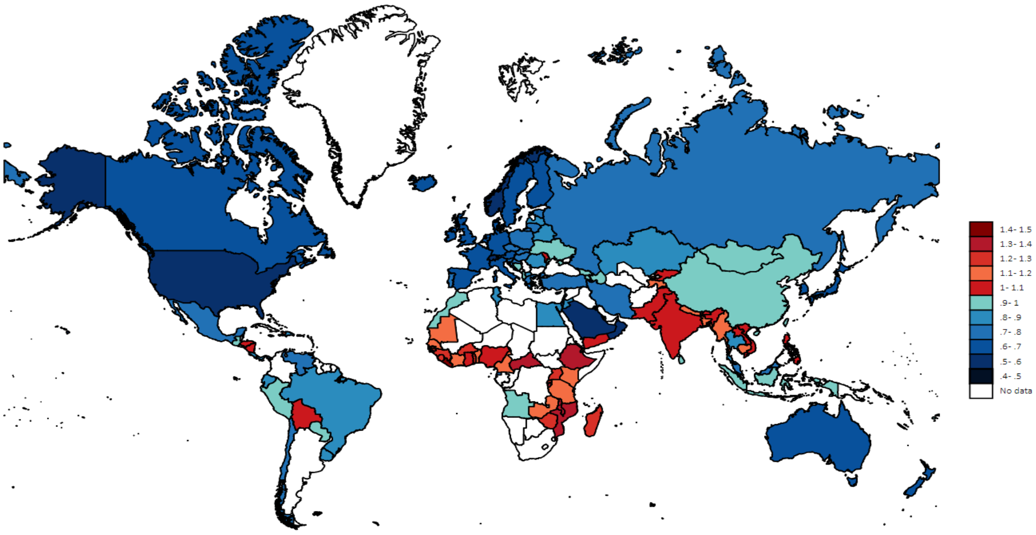
We assess the sensitivity of our results to alternative measurement choices in Section C. In particular, we construct an alternative measure of green consumption, denoted $G_{M_{pc}}$, which assumes that household consumption of environmental goods is proportional to environmental goods imports. We compute the country–year import share of environmental goods using BACI and apply this share to real household consumption while maintaining the same environmental services component. This measure abstracts from production-based weighting and relies exclusively on observed import patterns. Re-estimating our main specifications using$G_{M_{pc}}$ yields qualitatively similar results, as reported in the robustness analysis (Section C). The persistence of the luxury-to-necessity transition across these alternative measures indicates that our findings are not an artefact of a specific measurement strategy.

Appendix B. Estimated income elasticities

B.1 Worldwide distribution of elasticities

Figure B1 displays country-level income elasticities of green consumption averaged over the period 1995–2015. For each country, the reported value corresponds to the time average of the estimated income–green consumption elasticities obtained from the baseline specification (Table 2, column 4). The figure shows substantial cross-country heterogeneity in average income elasticities. This cross-sectional dispersion persists even though income elasticities decline over time, as documented in Figure 2. For a subset of countries, the period-average income elasticity remains above unity, indicating that over 1995–2015 green consumption increased more than proportionally with income and behaved as a luxury good on average over this period. These cases are concentrated among lower-income economies, where income growth remains closely associated with the expansion of green consumption. By contrast, countries with period-average elasticities below one exhibit lower income elasticities over the period, implying a less than proportional response of green consumption to income growth. Taken together, Figure B1 shows that the downward convergence of income elasticities documented in the time dimension does not eliminate persistent cross-country differences in period-average income elasticities, reflecting heterogeneity in countries' positions along the transition toward lower income sensitivity of green consumption.

Figure B1: Income–green consumption elasticities



Note: The figure reports country-level income elasticities of green consumption. Values correspond to country averages computed over the period 1995–2015. Elasticities are estimated using the baseline LSDV specification (Table 2, column 4).

B.2 Dynamics of income elasticities by country

Tables B1–B4 present the estimated income elasticities of green and non-green consumption, ε_G and ε_B, at the country level and by income group. Elasticities are reported for the years 1995, 2005, and 2015 and are taken from the baseline specification used in the main analysis (Table 2, column 4). For each income group and year, we report the unweighted mean of country-level elasticities within the group (Mean elasticity $\bar{\varepsilon}$).

Table B1: High income ($N = 46$)

	ε_G			ε_B		
Country	1995	2005	2015	1995	2005	2015
Antigua and Barbuda	0.778	0.740	0.743	0.555	0.525	0.528
Australia	0.663	0.621	0.594	0.465	0.432	0.410
Austria	0.663	0.626	0.616	0.464	0.435	0.428
Bahrain	0.603	0.597	0.593	0.417	0.413	0.410
Barbados	0.876	0.847	0.840	0.633	0.610	0.604
Brunei Darussalam	0.480	0.523	0.496	0.321	0.355	0.333
Canada	0.669	0.624	0.613	0.470	0.434	0.426
Chile	0.831	0.778	0.727	0.597	0.555	0.515
Croatia	0.833	0.749	0.738	0.599	0.532	0.524
Cyprus	0.735	0.682	0.702	0.521	0.480	0.496
Czech Republic	0.766	0.711	0.676	0.546	0.502	0.475
Denmark	0.677	0.644	0.637	0.476	0.450	0.444
Estonia	0.875	0.734	0.700	0.631	0.521	0.494
Finland	0.710	0.643	0.642	0.502	0.449	0.448
France	0.666	0.639	0.633	0.467	0.446	0.441
Germany	0.650	0.624	0.601	0.454	0.434	0.416
Greece	0.750	0.693	0.734	0.534	0.489	0.520
Hungary	0.812	0.739	0.714	0.582	0.525	0.505
Iceland	0.700	0.641	0.625	0.494	0.448	0.435
Ireland	0.691	0.580	0.522	0.487	0.400	0.354
Israel	0.733	0.705	0.665	0.520	0.497	0.466
Italy	0.665	0.640	0.653	0.466	0.446	0.457
Japan	0.656	0.635	0.626	0.459	0.443	0.435
Kuwait	0.465	0.434	0.496	0.309	0.285	0.333
Latvia	0.922	0.780	0.728	0.669	0.557	0.516
Lithuania	0.908	0.781	0.702	0.658	0.557	0.495
Malta	0.789	0.738	0.684	0.564	0.524	0.481
Netherlands	0.650	0.607	0.595	0.455	0.420	0.411
New Zealand	0.739	0.698	0.663	0.525	0.493	0.465
Norway	0.536	0.508	0.491	0.365	0.343	0.330
Oman	0.611	0.586	0.595	0.424	0.404	0.411
Poland	0.863	0.775	0.702	0.622	0.553	0.495
Portugal	0.743	0.704	0.710	0.528	0.497	0.502
Saudi Arabia	0.571	0.564	0.544	0.392	0.387	0.371
Seychelles	0.802	0.778	0.701	0.574	0.555	0.494
Singapore	0.624	0.572	0.511	0.434	0.393	0.345
Slovakia	0.850	0.762	0.697	0.612	0.543	0.492
Slovenia	0.774	0.705	0.689	0.552	0.498	0.485
South Korea	0.774	0.695	0.637	0.552	0.490	0.444
Spain	0.711	0.663	0.662	0.503	0.464	0.464
St. Kitts and Nevis	0.796	0.746	0.727	0.570	0.530	0.515
Sweden	0.690	0.637	0.610	0.486	0.444	0.423
Switzerland	0.578	0.554	0.542	0.398	0.379	0.369
United Kingdom	0.692	0.645	0.635	0.488	0.451	0.443
United States	0.626	0.582	0.569	0.436	0.401	0.391
Uruguay	0.841	0.829	0.750	0.605	0.596	0.533
Mean elasticity $\bar{\varepsilon}$	0.718	0.669	0.646	0.508	0.469	0.452

Table B2: Upper Middle income ($N = 35$)

Country	ε_G 1995	ε_G 2005	ε_G 2015	ε_B 1995	ε_B 2005	ε_B 2015
Albania	1.029	0.933	0.857	0.753	0.677	0.618
Armenia	1.118	0.938	0.867	0.823	0.681	0.625
Azerbaijan	1.073	0.908	0.768	0.788	0.658	0.547
Belarus	0.982	0.840	0.757	0.716	0.604	0.539
Bosnia and Herzegovina	1.149	0.907	0.860	0.847	0.657	0.620
Brazil	0.851	0.837	0.803	0.613	0.601	0.575
China	1.090	0.969	0.829	0.801	0.706	0.596
Costa Rica	0.898	0.861	0.807	0.650	0.620	0.578
Dominica	0.966	0.928	0.900	0.703	0.673	0.652
Dominican Republic	0.952	0.887	0.809	0.692	0.641	0.580
Ecuador	0.913	0.894	0.857	0.662	0.647	0.617
Equatorial Guinea	1.041	0.639	0.675	0.762	0.446	0.474
Fiji	0.973	0.939	0.914	0.709	0.682	0.662
Georgia	1.105	0.967	0.859	0.813	0.704	0.619
Grenada	0.950	0.849	0.837	0.690	0.611	0.601
Guatemala	0.981	0.962	0.934	0.715	0.700	0.678
Jamaica	0.947	0.949	0.955	0.688	0.690	0.694
Jordan	0.917	0.870	0.879	0.665	0.628	0.635
Kazakhstan	0.911	0.796	0.725	0.660	0.570	0.514
Lebanon	0.811	0.818	0.806	0.581	0.587	0.578
Macedonia	0.930	0.886	0.829	0.675	0.640	0.595
Malaysia	0.823	0.779	0.721	0.591	0.556	0.511
Maldives	0.874	0.841	0.773	0.631	0.605	0.551
Mauritius	0.883	0.816	0.742	0.638	0.585	0.527
Mexico	0.823	0.790	0.781	0.591	0.564	0.558
Moldova	1.110	1.053	0.982	0.817	0.772	0.716
Panama	0.886	0.837	0.733	0.640	0.602	0.520
Paraguay	0.975	0.963	0.898	0.711	0.701	0.650
Peru	0.965	0.931	0.850	0.703	0.676	0.612
Romania	0.883	0.806	0.742	0.638	0.577	0.527
Russia	0.815	0.748	0.695	0.584	0.532	0.490
St. Lucia	0.895	0.874	0.843	0.647	0.631	0.607
St. Vincent and the Grenadines	0.983	0.912	0.891	0.717	0.661	0.644
Thailand	0.890	0.853	0.799	0.644	0.614	0.572
Turkey	0.829	0.776	0.707	0.596	0.553	0.499
Mean elasticity $\bar{\varepsilon}$	0.949	0.873	0.820	0.690	0.630	0.588

Table B3: Lower Middle income ($N = 41$)

	ε_G			ε_B		
Country	1995	2005	2015	1995	2005	2015
Angola	1.080	0.969	0.919	0.793	0.706	0.667
Bangladesh	1.227	1.164	1.075	0.908	0.860	0.789
Benin	1.220	1.193	1.160	0.903	0.882	0.856
Bhutan	1.092	1.005	0.909	0.803	0.734	0.658
Bolivia	1.049	1.041	0.981	0.769	0.762	0.715
Cabo Verde	1.096	1.009	0.971	0.806	0.737	0.707
Cambodia	1.293	1.185	1.092	0.961	0.876	0.802
Cameroon	1.152	1.122	1.096	0.850	0.826	0.805
Cote d'Ivoire	1.115	1.128	1.105	0.821	0.831	0.812
Djibouti	1.189	1.197	1.103	0.878	0.885	0.811
Egypt	0.951	0.904	0.859	0.692	0.654	0.619
El Salvador	1.002	0.967	0.947	0.732	0.704	0.688
Ghana	1.118	1.079	1.007	0.823	0.793	0.736
Haiti	1.192	1.207	1.198	0.881	0.893	0.886
Honduras	1.084	1.060	1.034	0.796	0.778	0.757
India	1.151	1.072	0.975	0.849	0.787	0.710
Indonesia	0.974	0.949	0.865	0.709	0.690	0.624
Iran	0.836	0.785	0.774	0.601	0.561	0.552
Kenya	1.159	1.155	1.113	0.855	0.852	0.819
Kyrgyz Republic	1.142	1.073	1.017	0.842	0.787	0.743
Laos	1.153	1.070	0.956	0.851	0.785	0.695
Mauritania	1.130	1.116	1.087	0.832	0.822	0.798
Mongolia	1.025	0.954	0.833	0.750	0.694	0.599
Morocco	1.047	0.993	0.923	0.767	0.725	0.670
Myanmar	1.317	1.149	1.000	0.980	0.847	0.730
Nepal	1.234	1.191	1.135	0.915	0.881	0.836
Nicaragua	1.101	1.059	1.011	0.809	0.776	0.739
Nigeria	1.109	1.043	0.973	0.816	0.764	0.709
Pakistan	1.069	1.035	1.009	0.784	0.758	0.737
Philippines	1.046	1.011	0.943	0.766	0.738	0.685
Sao Tome and Principe	1.123	1.110	1.067	0.827	0.817	0.783
Senegal	1.158	1.121	1.106	0.854	0.825	0.814
Sri Lanka	1.016	0.944	0.840	0.742	0.686	0.604
Tajikistan	1.190	1.130	1.060	0.879	0.832	0.777
Tanzania	1.242	1.190	1.134	0.921	0.879	0.835
Tunisia	0.962	0.894	0.863	0.700	0.647	0.622
Ukraine	0.974	0.902	0.908	0.710	0.653	0.658
Venezuela	0.785	0.790	0.780	0.561	0.564	0.557
Vietnam	1.176	1.075	0.976	0.869	0.789	0.711
Zambia	1.188	1.151	1.073	0.878	0.849	0.788
Zimbabwe	1.256	1.313	1.187	0.932	0.977	0.878
Mean elasticity $\bar{\varepsilon}$	1.108	1.061	1.002	0.815	0.778	0.731

Table B4: Low income ($N = 16$)

	ε_G			ε_B		
Country	1995	2005	2015	1995	2005	2015
Burkina Faso	1.343	1.278	1.236	1.000	0.949	0.916
Burundi	1.335	1.368	1.353	0.994	1.020	1.008
Central African Republic	1.317	1.341	1.391	0.979	0.999	1.038
Ethiopia	1.410	1.365	1.219	1.053	1.018	0.902
Gambia	1.147	1.136	1.134	0.846	0.837	0.835
Guinea	1.235	1.205	1.175	0.915	0.892	0.868
Guinea-Bissau	1.231	1.248	1.236	0.912	0.925	0.916
Liberia	1.628	1.456	1.329	1.225	1.089	0.989
Madagascar	1.219	1.222	1.225	0.903	0.905	0.907
Malawi	1.338	1.341	1.298	0.996	0.999	0.965
Mozambique	1.498	1.369	1.303	1.122	1.020	0.969
Rwanda	1.378	1.292	1.201	1.028	0.960	0.889
Sierra Leone	1.233	1.277	1.240	0.914	0.948	0.919
Togo	1.250	1.273	1.237	0.927	0.945	0.916
Uganda	1.301	1.237	1.185	0.967	0.917	0.876
Yemen	1.086	1.013	1.143	0.797	0.740	0.842
Mean elasticity $\bar{\varepsilon}$	1.309	1.276	1.244	0.974	0.948	0.922

Appendix C. Robustness checks

C.1 Identification strategy

This appendix details the construction and identifying assumptions of the instrumental-variables strategy used to address the potential endogeneity of disposable income in the estimation of the income–green consumption relationship.

Endogeneity concerns and identification strategy. Although country and year fixed effects absorb time-invariant heterogeneity and common shocks, disposable income per capita may still be endogenous to green consumption. Unobserved demand-side factors such as institutional reforms, technological diffusion, or changes in consumption norms may jointly affect income and the diffusion of environmental goods and services. Reverse causality is also plausible if green consumption affects disposable income through tax incentives, energy-cost savings, or labour-market adjustments in environmental sectors. In addition, income taxation may partly reflect policy choices related to environmental objectives, potentially biasing ordinary least squares estimates.

To isolate variation in disposable income that is orthogonal to incentives supporting green consumption or production, we rely on an instrumental-variables strategy inspired by a Bartik (shift–share) design, as described below in detail. The instrument combines predetermined tax structures fixed in an early reference year 1992 with time-varying measures of economic similarity across countries.

Construction of the Bartik-type instrument. The logic of our instrument is to isolate variation in disposable income that is orthogonal to incentives supporting green consumption or production. To this end, we exploit tax structures fixed at an early and pre-sample reference date, 1992, prior to the large-scale emergence of green goods, services, and climate-oriented tax policy. Fixing tax rates at this date ensures that instrumented income variation cannot reflect contemporaneous or anticipated environmental policy. At the same time, we allow countries to evolve economically over time by constructing country-specific exposure as a time-varying weighted average of other countries' tax structures. The weights capture evolving economic similarity across countries, computed from sectoral composition and trade patterns, and are normalized to sum to one. As countries develop and their economic structures change, their similarity to other countries evolves, and so does their exposure to foreign tax structures fixed in 1992.

By construction, the instrument combines predetermined tax structures (the shift component) with time-varying similarity weights (the share component), generating income variation that is plausibly unrelated to contemporaneous domestic policies supporting green consumption. This variant of the conventional Bartik structure is suited to our setting. In a standard shift–share design, exposure shares are fixed and shocks vary over time, so that identification relies on changes in shocks interacting with predetermined exposure. Here, by contrast, foreign tax structures are fixed at a pre-sample date, so that identifying variation comes from changes in countries' exposure to predetermined foreign tax structures rather than from subsequent changes in foreign tax shocks. This implies that the identifying variation remains predetermined with respect to the later expansion of green goods, services, and climate-related policy, while allowing similarity weights to evolve over time to reflect changes in countries' sectoral composition and trade patterns.

Formally, for each country i and year t, we construct a predicted tax shock defined as:

$$\bar{\tau}_{it} = \sum_{j \neq i} \omega_{ij,t}\, \tau_{j,t_0}, \tag{C1}$$

where τ_{j,t_0} denotes country j's tax share in GDP in the reference year $t_0 = 1992$ and corresponds to the tax shifter, while $\omega_{ij,t}$ denotes the normalized time-varying weight assigned to country j in country i's predicted tax shock, based on a cosine measure of economic similarity between countries i and j.

Tax shifter τ_{j,t_0}. The tax shifter τ_{j,t_0} is defined as country j's tax share in GDP at the reference year $t_0 = 1992$. Because it is measured prior to the large-scale emergence of green goods, services, and climate-oriented tax policy, and held fixed over time, τ_{j,t_0} is predetermined with respect to subsequent income and consumption dynamics.

Similarity weights $\omega_{ij,t}$. Let $s_{ij,t}$ denote the raw cosine similarity between countries i and j at time t. The normalized weights are defined as:

$$\omega_{ij,t} = \frac{s_{ij,t}}{\sum_{k \neq i} s_{ik,t}}, \tag{C2}$$

which implies that $\sum_{j \neq i} \omega_{ij,t} = 1$ for each country i and year t. This normalization ensures that the predicted tax shock is a convex combination of foreign tax structures. By construction, $\omega_{ij,t}$ varies over time as countries' economic structures evolve and excludes own-country exposure ($j \neq i$).

First-stage specification. Let $\tilde{\tau}_{it} = 1 - \bar{\tau}_{it}$ denote the non-taxed share of income. We instrument disposable income per capita y_{it} and its square y_{it}^2 using $\tilde{\tau}_{it}$, $\tilde{\tau}_{it}^2$, as well as their lagged values $\tilde{\tau}_{it-1}$ and $\tilde{\tau}_{it-1}^2$. The first-stage equations are given by

$$y_{it} = \delta_{1,1}\tilde{\tau}_{it} + \delta_{1,2}\tilde{\tau}_{it}^2 + \delta_{1,3}\tilde{\tau}_{it-1} + \delta_{1,4}\tilde{\tau}_{it-1}^2 + \Delta_1 \mathbf{C}_{it} + \alpha_{1,i} + \lambda_{1,t} + \epsilon_{1,it} \tag{C3}$$

$$y_{it}^2 = \delta_{2,1}\tilde{\tau}_{it} + \delta_{2,2}\tilde{\tau}_{it}^2 + \delta_{2,3}\tilde{\tau}_{it-1} + \delta_{2,4}\tilde{\tau}_{it-1}^2 + \Delta_2 \mathbf{C}_{it} + \alpha_{2,i} + \lambda_{2,t} + \epsilon_{2,it} \tag{C4}$$

Country and year fixed effects control for time-invariant heterogeneity and common shocks, while $\mathbf{C}_{it}$ denotes the vector of control variables.

Exclusion restriction. Identification relies on the exclusion restriction that tax-induced income variation affects green consumption only through disposable income. In our setting, this assumption is plausible for two reasons.

First, the shift component of the instrument is built from foreign tax parameters that are determined independently of domestic household consumption choices. Specifically, the shift component is constructed from foreign tax shares in GDP measured in 1992 and then held fixed over time. These tax shifters are therefore predetermined with respect to the subsequent evolution of domestic green consumption over 1995–2015 and cannot reflect contemporaneous or anticipated domestic environmental policy.

Second, income taxation does not directly target environmental goods and services, and there is no institutional channel through which foreign income tax structures would directly affect domestic green consumption demand. In our setting, the instrument affects domestic disposable income through time-varying exposure to pre-determined foreign tax structures, where exposure is captured by similarity weights based on evolving sectoral composition and trade patterns. Any remaining correlation between the instrument and green consumption would therefore require foreign tax structures, measured at a pre-sample date, to influence domestic household demand directly rather than through disposable income. Conditional on country and year fixed effects and observed controls, this is unlikely in the context of nationally determined income tax systems.

First-stage diagnostics indicate strong instrument relevance, and Sargan–Hansen tests fail to reject instrument validity. Moreover, IV estimates remain close to fixed-effects estimates, supporting a causal Engel-type interpretation of the income–green consumption relationship.

Sensitivity. As an additional validation, we assess the sensitivity of the results to alternative constructions of green consumption. In particular, we implement an alternative measure of green consumption, denoted $G_{M_{pc}}$, which approximates the environmental goods component using import-based trade shares from BACI while maintaining the same environmental services component as in the baseline measure. Re-estimating the main specifications using $G_{M_{pc}}$ yields results that are qualitatively similar to the baseline IV estimates, as reported in Section C. The persistence of the luxury-to-necessity transition across these alternative measures indicates that the findings are not an artefact of a specific income-instrument or measurement strategy for green consumption.

C.2 Results from robustness checks

Column (1) of Table C1 reports the 2SLS estimates obtained using the Bartik instrument described above (Appendix C.1). Three results stand out. First, the core non-linear income pattern is preserved once disposable income is instrumented: the first-order income term remains positive and highly significant, while the squared term is negative and significant at the 1% level, confirming a concave income–green consumption relationship. This finding indicates that the declining income elasticity documented in Section 4 is not driven by reverse causality or omitted-variable bias. Second, the magnitude of the implied elasticities is remarkably close to the baseline fixed-effects estimates. The mean estimated income elasticity under 2SLS is 0.897, compared to 0.909 in the preferred LSDV specification, and the share of observations with elasticities above unity (33.47%) is virtually unchanged. This stability indicates that endogeneity of disposable income, while conceptually relevant, does not materially bias the baseline estimates. Third, diagnostic tests support the validity of the instrumental-variables strategy. The Cragg–Donald Wald statistic indicates strong instrument relevance, ruling out weak-instrument concerns, while the Sargan–Hansen test fails to reject the over-identifying restrictions.

Taken together, these results show that instrumenting income reinforces, rather than overturns, the baseline findings and supports a causal Engel-type interpretation of the income–green consumption relationship. For the remainder of the robustness checks reported in Table C1, we present results obtained using both the least square dummy variable and the two-stage least square estimators. This allows us to assess the sensitivity of the findings to alternative specifications while maintaining a consistent comparison between fixed-effects and instrumental-variables approaches.

Alternative measures of green consumption. We next consider an alternative measure of green consumption based solely on imports of environmental goods, denoted $G_{M_{pc}}$. This alternative measure follows the accounting framework introduced in Section 3 but restricts attention to the import component. The intuition is that, particularly in countries with limited domestic production of environmental goods, imports provide a meaningful indicator of households' access to green products. For each country and year, we compute the share of environmental goods in total imports using BACI trade data and OECD–APEC classifications, and apply this share to aggregate household real consumption from the Penn World Tables. While this measure abstracts from domestic production and exports, it offers a transparent robustness check against alternative measurement choices.

Column (2) of Table C1 reports robustness analyses based on alternative import-based measure of green consumption. Column (2) replaces the baseline measure with the import-based measure $G_{M_{pc}}$. The estimated income–green consumption relationship remains strongly non-linear, but the implied elasticities are higher: the mean income elasticity rises to 1.058, and the share of elasticities above unity increases to 58.5%. This upward shift in elasticities indicates that, when green consumption is proxied solely by imports, environmental goods behave more like luxury goods. This pattern is intuitive, as reliance on imports as the main source of environmental goods likely raises their effective cost and restricts access, making adoption more sensitive to income.

Non-green consumption. Columns (4) and (5) of Table C1 examine non-green consumption, B_{pc}, offering a useful benchmark against which to assess the results for green consumption. The estimated income–consumption relationship remains strongly bell-shaped, confirming that the non-linear specification is not specific to green consumption but reflects a general feature of household consumption behaviour. However, the nature of the implied elasticities differs from the green case. As expected, income elasticities for non-green consumption overwhelmingly correspond to necessity goods: the mean elasticity lies well below unity, and only a very small fraction of observations exhibits elasticities above one, concentrated among the poorest countries.

This pattern is consistent with standard consumption theory, as non-green consumption largely satisfies basic needs and becomes progressively less income-responsive as income rises. The fact that the bell-shaped specification yields necessity-type elasticities in this case reinforces the credibility of the empirical framework. Moreover, the sharp contrast with the results for green goods, where consumption behaves as a luxury at low income levels before gradually shifting toward a necessity,

Table C1: Robustness checks using specification (4) of Table 2

	g	$g = G_{M_{pc}}$		B_{pc}		$Y = GDP_{pc}$		Ex. CHN & USA	
	(1) 2SLS	(2) LSDV	(3) 2SLS	(4) LSDV	(5) 2SLS	(6) LSDV	(7) 2SLS	(8) LSDV	(9) 2SLS
y	2.628***	2.417***	2.312***	2.004***	1.941***	2.533***	2.545***	2.609***	2.619***
	(0.483)	(0.528)	(0.313)	(0.490)	(0.241)	(0.741)	(0.442)	(0.769)	(0.449)
y^2	-0.097***	-0.076**	-0.070***	-0.075**	-0.074***	-0.091**	-0.093***	-0.096**	-0.097***
	(0.027)	(0.034)	(0.019)	(0.029)	(0.014)	(0.041)	(0.024)	(0.042)	(0.026)
GPI	-0.019	0.008	0.008	0.005	0.005	-0.019	-0.019	-0.019*	-0.019
	(0.015)	(0.011)	(0.012)	(0.007)	(0.007)	(0.012)	(0.014)	(0.011)	(0.015)
$IRATE$	-0.269***	-0.297***	-0.298***	-0.158*	-0.162***	-0.286*	-0.286***	-0.271*	-0.272***
	(0.093)	(0.113)	(0.078)	(0.095)	(0.047)	(0.145)	(0.101)	(0.149)	(0.102)
Observations	2,898	2,898	2,898	2,898	2,898	2,898	2,898	2,856	2,856
Adj. R-squared	0.310	0.415	0.386	0.577	0.556	0.342	0.309	0.338	0.304
Log likelihood	-1,672.438	-276.731	-276.833	1,064.886	1,064.367	-1,674.370	-1,674.373	-1,667.083	-1,667.091
CDW Statistic	10,048.767	–	10,048.767	–	10,048.767	–	1,427,475.789	–	9,659.126
Sargan-Hansen	0.578	–	3.775	–	0.580	–	0.617	–	0.564
Sargan-Hansen p-value	0.749	–	0.151	–	0.748	–	0.735	–	0.754
Univariate F-test y	3,897.918	–	3,897.918	–	3,897.918	–	327,549.721	–	3,650.317
Univariate F-test y^2	4,202.695	–	4,202.695	–	4,202.695	–	315,225.235	–	3,944.526
Mean elasticity $\bar{\hat{\varepsilon}}$	0.897	1.058	1.050	0.658	0.613	0.881	0.874	0.895	0.881
Share $\hat{\varepsilon} > 1$	33.47%	58.49%	57.56%	2.76%	0.55%	31.12%	30.47%	33.23%	31.62%
$ITP_{\text{lux/nec}}$ (in constant 2011$)	4,599.677	11,474.573	11,159.171	804.394	575.162	4,351.533	4,217.271	4,487.423	4,192.887
$ITP_{\text{nec/inf}}$ (in constant 2011$, thousands)	818.163	8,420.865	13,541.465	629.415	491.392	1,028.550	935.030	833.801	724.180

Note: Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Control variables are included in all models. Country and year-fixed effects are included in all models. Robust standard errors are in parentheses for LSDV models. Bootstrapped standard errors for the 2SLS models. In 2SLS models, instrumented variables are y and y^2, while instrumental variables are $\tilde{\tau}_{it}$, $\tilde{\tau}^2_{it}$ $\tilde{\tau}_{it-1}$, $\tilde{\tau}^2_{it-1}$. Cragg-Donald Wald F-statistic is reported as CDW Statistic. In B_{pc}, we report results where the dependent variable is the non-green consumption per capita, B_{pc}, which is defined as total consumption minus green consumption per capita. In $G_{M_{pc}}$, the dependent variable is an import-based alternative measure of green consumption per capita, built upon imports of environmental goods plus environmental services. In GDP_{pc}, we use GDP per capita as an income measure. The last two columns exclude the USA and China from the sample.

strengthens our interpretation that the observed non-linearities in green consumption reflect a specific adoption process for greener goods and services, rather than a standard income–consumption relationship.

GDP per capita as a measure of income. Columns (6–7) of Table C1 replace disposable income per capita with GDP per capita, GDP_{pc}, as the income measure. The concave income–green consumption relationship persists, with a positive first-order income effect and a negative second-order term. The estimated elasticities are slightly lower, with a mean elasticity of 0.881, indicating that GDP per capita attenuates the income–green consumption link relative to disposable income. Both the implied income threshold point and the distribution of income elasticities are nearly unchanged relative to the baseline, and the share of observations with elasticities greater than one remains very similar. Overall, these results confirm that the core non-linear pattern is robust, while highlighting that measurement choices affect the level of the estimated income elasticities, but leave unchanged their distribution across the income range, including the implied income threshold and the share of observations with elasticities above one.

This stability indicates that the main results are not sensitive to the specific income concept used. In particular, using GDP per capita instead of disposable income does not alter the qualitative or quantitative conclusions regarding the luxury-to-necessity transition of green consumption. This further supports the robustness of our findings and suggests that the estimated non-linear income pattern reflects a structural relationship rather than a measurement artefact.

Sample exclusion. Last, we perform the estimation on alternative sub-samples to account for the potential influence of large and specific economies. In particular, we examine the role of the United States and China, which may act as outliers due to their economic size, structural characteristics, and distinctive positions in global green markets. The United States combines very high disposable income levels with a mature green market characterized by widespread access to environmental goods and services. China, despite lower average income and consumption levels, is undergoing rapid structural transformation supported by large-scale environmental and industrial policies aimed at fostering green markets. These features are not necessarily representative of global consumption patterns and may disproportionately affect the estimated income–green consumption relationship. To assess the sensitivity of our results to the presence of these large economies, we re-estimate the model excluding the United States and China, individually and jointly (Columns 8 and 9). The results remain virtually unchanged. The estimated non-linear income pattern persists, with very similar income threshold points and distributions of income elasticities, as well as comparable shares of observations with elasticities above unity. This stability confirms that our main findings are not driven by the inclusion of these large economies and reflect a general relationship between income and green consumption rather than country-specific dynamics.

Appendix D. Heterogeneity in composition effects

Let $G_{pc_{it}}$ denote green consumption and $B_{pc_{it}}$ non-green consumption, with $C_{pc_{it}} = G_{pc_{it}} + B_{pc_{it}}$. Following our baseline specification, we define the log-variables $g_{it} \equiv \ln G_{pc_{it}}$, $b_{it} \equiv \ln B_{pc_{it}}$, and $y_{it} \equiv \ln Y_{it}$. By assuming that green and non-green consumption follow quadratic environmental Engel curves in income, we estimate the following two specifications:

$$g_{it} = \beta_{1G} y_{it} + \beta_{2G} y_{it}^2 + \Theta_G \mathbf{C}_{it} + \mu_{G,i} + \lambda_{G,t} + \epsilon_{G,it}, \tag{D1}$$

$$b_{it} = \beta_{1B} y_{it} + \beta_{2B} y_{it}^2 + \Theta_B \mathbf{C}_{it} + \mu_{B,i} + \lambda_{B,t} + \epsilon_{B,it}. \tag{D2}$$

with income elasticities reading:

$$\varepsilon_{G,Y,it} \equiv \frac{\partial \ln G_{pc_{it}}}{\partial \ln Y_{pc_{it}}} = \frac{\partial g_{it}}{\partial y_{it}} = \beta_{1G} + 2\beta_{2G} y_{it}, \tag{D3}$$

$$\varepsilon_{B,Y,it} \equiv \frac{\partial \ln B_{pc_{it}}}{\partial \ln Y_{pc_{it}}} = \frac{\partial b_{it}}{\partial y_{it}} = \beta_{1B} + 2\beta_{2B} y_{it}. \tag{D4}$$

To characterize demand-side composition effects, we focus on the relative consumption of green versus non-green goods. The log ratio of green to non-green consumption can be written as $\ln\left(\frac{G_{it}}{B_{it}}\right) = \ln G_{pc_{it}} - \ln B_{pc_{it}} = g_{it} - b_{it}$. Using (D1)–(D2), this implies:

$$\ln\left(\frac{G_{pc_{it}}}{B_{pc_{it}}}\right) = \beta_{GB} y_{it} + \beta_{2GB} y_{it}^2 + \Theta_{GB} \mathbf{C}_{it} + \mu_{GB,i} + \lambda_{GB,t} + \epsilon_{GB,it} \tag{D5}$$

where $\beta_{GB} = \beta_{1G} - \beta_{1B}$, $\beta_{2GB} = \beta_{2G} - \beta_{2B}$, $\Theta_{GB} = \Theta_G - \Theta_B$, $\mu_{GB,i} = \mu_{G,i} - \mu_{B,i}$, $\lambda_{GB,t} = \lambda_{G,t} - \lambda_{B,t}$, and $\epsilon_{GB,it} = \epsilon_{it}^G - \epsilon_{it}^B$.

In Specification (D5), the sign of each coefficient can be interpreted as the effect of the corresponding explanatory variable on the composition of the consumption basket. A positive coefficient implies that green consumption increases proportionally more than non-green consumption in response to the associated right-hand-side variable, shifting the composition of the consumption basket in favour of environmental goods and services (EGS). Conversely, a negative coefficient indicates that non-green consumption increases proportionally more than green consumption, shifting the composition of the consumption basket in favour of non-environmental goods and services (NEGS).

Differentiating (D5) with respect to income yields:

$$\begin{aligned} \frac{\partial}{\partial y_{it}} \ln\left(\frac{G_{pc_{it}}}{B_{pc_{it}}}\right) &= \frac{\partial g_{it}}{\partial y_{it}} - \frac{\partial b_{it}}{\partial y_{it}} \\ &= \varepsilon_{G,Y,it} - \varepsilon_{B,Y,it}. \end{aligned} \tag{D6}$$

The difference $\varepsilon_{G,Y,it} - \varepsilon_{B,Y,it}$ provides a direct measure of composition effects in consumption as income grows. If $\varepsilon_{G,Y,it} - \varepsilon_{B,Y,it} > 0$, then $\ln(G_{pc_{it}}/B_{pc_{it}})$ increases with income: income growth shifts the consumption basket toward green relative to non-green. Conversely, if $\varepsilon_{G,Y,it} - \varepsilon_{B,Y,it} < 0$, income growth reallocates the consumption basket toward non-green goods and services. Because this difference varies with income through y_{it}, composition effects are heterogeneous across countries and income levels. This heterogeneity, combined with the distribution of income gains and losses across countries, underlies the comparative-statics exercises developed in Section 5.2, which examine how cross-country redistribution affects consumption composition in global redistributive climate policy.

Appendix E. Income elasticities and global redistributive climate policy

This section documents the calibration choices and accounting relationships underlying the comparative-statics exercises presented in Section 5.2. The objective is to characterize short-run consumption responses to cross-country redistribution in global redistributive climate policy under alternative assumptions on income elasticities and allocation rules.

E.1 Analytical framework

We rely on the latest institutional framework of global redistributive climate policy, the Climate Fund. Since the adoption of the United Nations Framework Convention on Climate Change (UNFCCC) in 1992, advanced economies have committed to supporting lower- and middle-income countries in bearing the costs of climate adaptation (UN, 1992). The Copenhagen Accord, signed in 2009, further specified the guidelines of global redistributive climate policy by announcing a commitment among developed countries to mobilize 100 US$ billion per year by 2020 to finance adaptation and mitigation in developing countries (UNFCCC, 2009, 2010). More recently, discussions around scaled-up climate finance have reinforced the relevance of large North-South transfers. In 2024, the 29^{th} Conference of the Parties reinforced this principle by setting a target of 300 US$ billion annually from high-income to lower- and middle-income countries. While the contributor–recipient distinction follows established UNFCCC definitions, the concrete rules governing the allocation of contributions and transfers remain underspecified in practice. [E1] Given the objective of this exercise, we identify 35 contributor countries based on the available institutional classification and treat the remaining 103 countries in our sample as recipient countries.

The comparative-statics exercises contrast two demand assumptions: (i) a unit-elasticity benchmark, $\varepsilon_G = \varepsilon_B = 1$, which implies proportional scaling of consumption with income and rules out Engel-curve composition effects; and (ii) heterogeneous income elasticities, $\varepsilon_G = \hat{\varepsilon}_G$ and $\varepsilon_B = \hat{\varepsilon}_B$, estimated in Tables 2. Throughout, elasticities are evaluated at their 2015 values.

In this exercise, the environmental objective is defined in terms of an increase in green consumption, a reduction in non-green consumption, and a shift in the composition of total consumption toward green goods and services at the global level. We report below the redistribution rules used to allocate the fund and the demand-response equations mapping income shocks into changes in G and B.

E.2 Redistributive scheme.

To calibrate contributions and transfers according to relative wealth levels—rather than country size—the redistribution rule is based on disposable income per capita.

Progressive redistribution. The baseline redistribution rule assigns transfer shares across recipient countries (RC) according to the inverse of their disposable-income per capita shares within the recipient group. Let $Y_{pc,i}$ denote disposable income per capita of country i, and define per-capita income shares within each group as:

$$s_{CC,i} = \frac{Y_{pc,i}}{\sum_{j \in CC} Y_{pc,j}}, \qquad s_{RC,i} = \frac{Y_{pc,i}}{\sum_{j \in RC} Y_{pc,j}}. \tag{E1}$$

Within the recipient group (RC), progressive allocation weights are defined as the inverse of

[E1] Contributors are defined as Annex II Parties: OECD members, and other EU member states included in Annex I Parties: Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, and Slovenia; plus Liechtenstein and Monaco.

per-capita income shares, $s^{-1}_{RC,i}$, as:

$$w_{RC,i} = \frac{s^{-1}_{RC,i}}{\sum_{j\in \mathrm{RC}} s^{-1}_{RC,j}}, \qquad i \in \mathrm{RC},$$

so that poorer RC countries, in disposable income per-capita levels, receive a larger fraction of the total transfer. Using per-capita income avoids mechanical scale effects that would arise under aggregate disposable income, where large-population countries would dominate the allocation rule irrespective of their relative wealth levels. At the aggregate level, redistribution-induced variations ΔY_i are:

$$\Delta Y_i = \begin{cases} -T\, s_{CC,i}, & \text{if } i \in \mathrm{CC}, \\ +T\, w_{RC,i}, & \text{if } i \in \mathrm{RC}. \end{cases} \qquad \text{where} \quad T = 300 \text{ US\$ billion, denotes the total Climate Fund.} \tag{E2}$$

While allocation weights are calibrated using per-capita income to reflect relative living standards, income variations ΔY_i are expressed in national aggregates to ensure consistency with the macro-level demand responses of G_i and B_i. By construction, the scheme is globally revenue-neutral, with total contributions from CC exactly matching total transfers to RC, and affects consumption exclusively through income effects. At the same time, we introduce progressive allocation rules on the recipient side whereby, relatively poorer recipient countries receive disproportionately larger transfers.

E.3 Demand response to changes in disposable income ΔY

For this exercise, all variables are expressed in aggregate national levels. The consumption response to income variations induced by redistribution is characterized as follows. Let aggregate consumption be $C = G + B$, where G denotes green consumption and B non-green consumption. Since $C = G + B$, it follows that $\Delta C = \Delta G + \Delta B$. Under Engel-type demand responses, it is straightforward to show that

$$\Delta C = \frac{G}{Y}\hat{\varepsilon}_G \Delta Y + \frac{B}{Y}\hat{\varepsilon}_B \Delta Y = \left(\frac{G}{Y}\hat{\varepsilon}_G + \frac{B}{Y}\hat{\varepsilon}_B\right)\Delta Y. \tag{E3}$$

Here, ΔY denotes the variation in national disposable income induced by redistribution, which is negative for contributor countries (CC) and positive for recipient countries (RC). The ratios G/Y and B/Y represent the shares of green and non-green consumption in national income, respectively. Given this framework, we consider two alternative scenarios. First, under the standard proportional-scaling assumption, income elasticities are set to unity, $\varepsilon_G = \varepsilon_B = 1$. Second, we allow for heterogeneous demand responses using the estimated income elasticities $\hat{\varepsilon}_G$ and $\hat{\varepsilon}_B$ for 2015, as reported in Tables B1–B4.

Equation (E3) illustrates the mechanism underlying the comparative-statics results. Redistribution affects aggregate consumption through income effects, while changes in the composition of consumption between G and B depend on relative income elasticities and baseline budget shares. Given $\hat{\varepsilon_G} \neq \hat{\varepsilon_B}$, income transfers generate composition effects, implying that proportional scaling constitutes a restrictive special case.

E.4 Extensions

Redistributive scheme: proportional. We consider a variant of the baseline redistributive policy that modifies the allocation of transfers across recipient countries (RC), while leaving the contribution rule unchanged. Contributor countries (CC) continue to contribute according to the proportional lump-sum rule defined in equation (E1). Differences arise exclusively from the allocation of funds within the recipient group.

We implement an alternative allocation rule relying on proportional shares, $s_{RC,i}$, following a lump-sum redistribution scheme at the country level. Under the proportional scheme, transfers to RC are allocated proportionally to their per-capita disposable income shares within the RC group. Let $s_{RC,i}$ and $s_{CC,i}$ denote per-capita shares defined as in equation (E1). In contrast to the progressive scheme, richer recipient countries (in per-capita terms) receive a larger fraction of the total transfer, while poorer RC receive relatively less. Contributions from CC remain proportional within their group. Therefore, the aggregate redistribution-induced income variation becomes

$$\Delta Y_i = \begin{cases} -T\, s_{CC,i}, & \text{if } i \in \text{CC}, \\ +T\, s_{RC,i}, & \text{if } i \in \text{RC}, \end{cases} \qquad \text{where} \quad T = 300 \text{ US\$ billion}, \tag{E4}$$

Allocation shares are calibrated using per-capita variables to reflect relative wealth and avoid mechanical size effects, while income changes ΔY_i are expressed in national aggregates to ensure consistency with the demand responses described in Section E.3.

Allocation criteria: consumption-based emissions. Both redistributive schemes, proportional and progressive, can be implemented using alternative per-capita criteria to compute allocation shares. In addition to disposable income per capita (Y_{pc}), we consider consumption-based emissions per capita (CBE_{pc}), taken from Global Carbon Budget and Our World in Data (2025), as an alternative basis for redistribution. Because CBE_{pc} reflects emissions embodied in domestic consumption rather than territorial production, it provides a consumption-consistent basis for computing contribution and transfer shares. This extension allows us to assess whether our results depend on the underlying allocation base, holding constant the redistributive structure and the estimated income elasticities. Using CBE_{pc} replaces an ability-to-pay criterion based on income with an allocation rule indexed to per-capita consumption-related emissions. Let $\text{CBE}_{pc,i}$ denote per-capita consumption-based emissions of country i, and define group-specific shares as in equation E1:

$$s_{CC,i} = \frac{\text{CBE}_{pc,i}}{\sum_{j \in CC} \text{CBE}_{pc,j}}, \qquad s_{RC,i} = \frac{\text{CBE}_{pc,i}}{\sum_{j \in RC} \text{CBE}_{pc,j}}, \tag{E5}$$

Under the proportional scheme, countries with higher per-capita consumption-based emissions receive (within RC) or contribute (within CC) larger transfers relative to their group. Under the progressive scheme, inverse shares are applied to CBE_{pc}, thereby reallocating transfers toward countries with lower per-capita emissions.

E.5 Additional results

Table E1 reports the implied changes in green and non-green consumption, both in levels (ΔG, ΔB) and normalized by world disposable income and world consumption ($\Delta G/Y_w$, $\Delta B/Y_w$, $\Delta G/C_w$, $\Delta B/C_w$). Across specifications, global effects remain small relative to world aggregates. However, the sign and composition of net variations depend systematically on the redistributive scheme and income elasticities.

Allocation criteria: CBE. Panel (a) reports the outcomes of the progressive redistribution scheme when transfers are allocated according to consumption-based emissions per capita. This specification is included as a robustness exercise and mirrors the structure of the income-based progressive scheme introduced in Section 5. Under unit income elasticities ($\varepsilon = 1$), global green consumption declines by 5.32 billion US\$, while non-green consumption increases by 71.16 billion US\$, corresponding to 0.078% of world disposable income and 0.171% of world consumption. Allowing for heterogeneous income elasticities substantially modifies these outcomes. When $\varepsilon \neq 1$, the global contraction in green consumption is almost offset ($\Delta G \approx -0.15$), while the expansion of non-green consumption becomes larger, reaching 114.64 billion US\$ (0.126% of world income and 0.276% of world consumption). This pattern reflects Engel-type composition effects that amplify non-green demand responses in recipient countries under a progressive allocation rule. Using CBE per capita as the allocation base does not change the pattern of the results obtained under the income-based progressive scheme (Table 3). However, relative to that benchmark, it slightly

Table E1: Effect of the stylized Climate Fund on the green and non-green consumption basket

	ΔG	$\Delta G/Y_w$	$\Delta G/C_w$	ΔB	$\Delta B/Y_w$	$\Delta B/C_w$
	(a) CBE per capita — Progressive scheme					
	$\varepsilon = 1$					
Contributor countries	-11.760	-0.013	-0.028	-133.968	-0.147	-0.323
Recipient countries	6.442	0.007	0.016	205.132	0.225	0.494
Net variations	-5.318	-0.006	-0.013	71.163	0.078	0.171
	$\varepsilon \neq 1$					
Contributor countries	-7.570	-0.008	-0.018	-60.556	-0.066	-0.146
Recipient countries	7.419	0.008	0.018	175.193	0.192	0.422
Net variations	-0.151	-0.000	-0.000	114.637	0.126	0.276
	(b) Disposable income per capita — Proportional scheme					
	$\varepsilon = 1$					
Contributor countries	-11.006	-0.012	-0.026	-130.285	-0.141	-0.311
Recipient countries	5.768	0.006	0.014	130.783	0.142	0.312
Net variations	-5.238	-0.006	-0.012	0.498	0.001	0.001
	$\varepsilon \neq 1$					
Contributor countries	-7.066	-0.008	-0.017	-58.779	-0.064	-0.140
Recipient countries	4.618	0.005	0.011	76.825	0.083	0.183
Net variations	-2.448	-0.003	-0.006	18.046	0.020	0.043
	(c) CBE per capita — Proportional scheme					
	$\varepsilon = 1$					
Contributor countries	-11.760	-0.013	-0.028	-133.968	-0.147	-0.323
Recipient countries	4.659	0.005	0.011	113.351	0.124	0.273
Net variations	-7.101	-0.008	-0.017	-20.617	-0.023	-0.050
	$\varepsilon \neq 1$					
Contributor countries	-7.570	-0.008	-0.018	-60.556	-0.066	-0.146
Recipient countries	3.535	0.004	0.009	62.714	0.069	0.151
Net variations	-4.035	-0.004	-0.010	2.158	0.002	0.005

Note: Absolute changes in green and non-green consumption are denoted ΔG and ΔB, respectively, and are expressed in constant 2011 US$ billion. The ratios $\Delta G/Y_w$ and $\Delta B/Y_w$ express the changes in green and non-green consumption as percentages of world disposable income, whereas $\Delta G/C_w$ and $\Delta B/C_w$ relate the same changes to total world consumption. Ratios involving C_w and Y_w are expressed in percentage points.

attenuates the global contraction in green consumption under both elasticity assumptions, while reinforcing the increase in non-green consumption.

Redistributive scheme: proportional. Panels (b) and (c) report the outcomes obtained under proportional redistribution schemes described in Section E.4, which display weaker compositional effects than the progressive scheme.

With disposable income per capita as the allocation criterion (panel b), the global net effect under unit elasticities is characterized by a contraction in green consumption ($\Delta G = -5.24$) and an almost neutral change in non-green consumption ($\Delta B = +0.50$), corresponding to less than 0.01% of world income or consumption. Relative to the progressive scheme, proportional redistribution implies a similar contraction in green consumption but an almost neutral effect on non-green consumption, indicating that progressivity is the main driver of global compositional effects under unit elasticities. When heterogeneous income elasticities are introduced, the contraction in green consumption is attenuated ($\Delta G = -2.45$), while non-green consumption increases by 18.05 billion US$, corresponding to 0.020% of world income and 0.043% of world consumption. This increase in non-green consumption reflects Engel-type composition effects, but its magnitude remains substantially smaller than under the progressive scheme, indicating that proportional redistribution limits the scope for demand reallocation toward non-green goods and services. Although Engel-type effects become operative under proportional redistribution, their quantitative impact remains limited relative to the progressive schemes.

Panel (c) reports the proportional redistribution scheme based on CBE per capita. Under unit elasticities, both green and non-green consumption decline globally, with $\Delta G = -7.10$ and $\Delta B = -20.62$ billion US$. Allowing for heterogeneous elasticities mitigates the contraction in green consumption ($\Delta G = -4.04$) and reverses the sign of the non-green effect, which becomes slightly positive ($\Delta B = +2.16$). As in panel (b), the rebound in non-green consumption remains modest and smaller than under progressive redistribution, confirming that proportional allocation dampens the amplification of Engel-type effects. These results confirm that, even under proportional redistribution, allowing for non-homothetic preferences modifies the near-mechanical outcomes obtained under unit elasticities. However, the magnitude of the induced composition effects remains limited relative to the progressive schemes.

Taken together, these extension results indicate that the demand-side effects of global redistributive climate policy depend less on the choice of allocation base (income versus CBE per capita) than on the redistributive structure of the policy and its interaction with heterogeneous income elasticities. Proportional schemes generate more limited composition effects, whereas progressive schemes amplify the role of income elasticities and produce substantially larger increases in non-green consumption.

E.6 Homotheticity bias across policy schemes

Table E2 compares the magnitude of the homotheticity bias across alternative redistribution schemes. The table reports both absolute biases (in billion US$) and bias relative to the homothetic benchmark.

First, for green consumption, the aggregate bias remains non-negligible across all designs. Under progressive schemes, the global bias ranges between -4.68 billion US$ (panel a) and -5.17 billion US$ (panel b). Under proportional schemes, its absolute magnitude declines but remains substantial, between -2.79 billion US$ and -3.07 billion US$. In all cases, the bias is driven primarily by contributor countries: the homothetic benchmark predicts larger decreases in green consumption in high-income economies than those obtained under estimated elasticities. Recipient-country contributions are smaller in magnitude and become positive under proportional designs, reflecting the interaction between transfer rules and the income distribution.

Second, for non-green consumption, the aggregate bias remains negative across all designs. Progressive schemes generate biases exceeding -40 billion US$, while proportional schemes reduce the aggregate bias but do not eliminate it. The source of the bias differs from the green case. Under progressive designs, the dominant mechanism is the larger decrease predicted for contributor countries under the homothetic benchmark, partly offset by a smaller increase in recipient countries under estimated elasticities. Under proportional rules, recipient-country responses offset a larger share of the contributor-country bias, but do not reverse the aggregate sign. The relative percentage can become mechanically inflated when the homothetic prediction is close to zero, as in the disposable-income proportional scheme; for this reason, absolute magnitudes provide the more informative indicator.

Taken together, these comparisons indicate that the homotheticity bias is not an artefact of a particular calibration or allocation rule. Its magnitude varies across redistribution designs, but its direction is systematic. Assuming unit income elasticities consistently distort the predicted composition effects by understating the expansion of non-green consumption induced by international transfers.

Table E2: Homotheticity bias across redistribution schemes

	Green consumption (ΔG)			Non-green consumption (ΔB)		
	CC	RC	Net	CC	RC	Net
	(a) Disposable income – Progressive scheme					
Bias	-3.940	-0.740	-4.680	-71.506	29.875	-41.631
Relative bias (%)	-35.8	-11.6	-101.3	-54.9	14.5	-54.8
	(b) CBE per capita – Progressive scheme					
Bias	-4.190	-0.977	-5.167	-73.412	29.939	-43.474
Relative bias (%)	-35.6	-15.2	-97.2	-54.8	14.6	-61.1
	(c) Disposable income – Proportional scheme					
Bias	-3.940	1.150	-2.790	-71.506	53.958	-17.548
Relative bias (%)	-35.8	19.9	-53.3	-54.9	41.3	-3523.3
	(d) CBE per capita – Proportional scheme					
Bias	-4.190	1.124	-3.066	-73.412	50.637	-22.775
Relative bias (%)	-35.6	24.1	-43.2	-54.8	44.7	-110.5

Note: Contributor countries, recipient countries and global net variation are denoted CC, RC and Net, respectively. Bias is computed as $(\varepsilon = 1) - (\varepsilon \neq 1)$, so that a negative value indicates that the homothetic benchmark understates the effect relative to the scenario based on estimated elasticities. Relative bias equals this difference divided by the absolute homothetic benchmark prediction, times 100.

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