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Federica Cappelli

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Federica Cappelli
(University of Ferrara)

Summary

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Keywords: Inequality, Emissions, Income Distribution, Climate Change

JEL classification: D31, D63, Q54, Q57

Corresponding Author:
Federica Cappelli
Assistant Professor
Department of Economics and Management, University of Ferrara
Via Voltapaletto, 11, 44121 Ferrara (Italy)
e-mail: federica.cappelli@unife.it

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Abstract

The question of whether changes in income inequality affect CO_2 emissions remains a topic of debate at both theoretical and empirical levels. The purpose of this paper is to examine the effect of changes in the full spectre of income distribution on consumption-based CO_2 emissions per capita. To do so, we estimate a dynamic difference-GMM model and a dynamic threshold regression model allowing for endogeneity on a panel database covering 107 countries between 1990 and 2019. Our analysis highlights how different income classes contribute very differently to consumption-based CO_2 emissions. In addition, by accounting for between-country inequalities in the average income of each income group, we uncover non-linearities in the impact on carbon emissions. More specifically, the impact of an increase in the income share of the top 10% on per capita consumption-based carbon emissions varies according to their average income level: it is negative at lower income levels and becomes positive as their income rises. The contribution of the middle class is negative at all income levels, while the CO_2 contribution of the poorest segments is negligible.

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1. Introduction

Income inequality has risen in the majority of developed countries since the 1980s (Chancel et al., 2022). The question of whether changes in income distribution affect CO_2 emissions remains a topic of debate at both theoretical and empirical level.

Understanding how different income classes contribute to carbon emissions is crucial for several reasons, first and foremost, but not limited to, equity concerns, which see low-income groups bearing the brunt of climate-related consequences, despite contributing less to greenhouse gas emissions (Diffenbaugh and Burke, 2019; Cappelli et al., 2021; Palagi et al., 2022). In addition, inequalities in carbon emissions along the income distribution may hinder mitigation efforts through the influence exerted on environmental policy directions, as well as the carbon-intensive lifestyle of a small yet significant fraction of the population that risks undermining the benefits obtained from mitigation policies. On the other hand, highlighting such differential contributions may help tailoring mitigation policies, based on different marginal mitigation efforts of each income class (Chancel et al., 2023).

The purpose of the present paper is to examine how changes in the shares of income owned by different income classes affect CO_2 emissions. In doing so, this paper contributes to the literature in several ways: first, to our knowledge, this is the first study to investigate the effect of changes in the full spectre of income distribution on CO_2 emissions. Second, we consider both between- and within-country inequalities, by accounting for non-linearities in the impact of different income classes on carbon emissions contingent upon their average income level. Such heterogeneities have very relevant implications for consumption patterns, especially in terms of their carbon intensity. Third, CO_2 emissions are quantified following a consumption-based accounting to avoid underestimating emissions embedded in international trade (Peters et al., 2011). In this respect, Peters and Hertwich (2008) show that in 2001, 21.5% of global CO_2 emissions were embodied in international trade, with richer countries acting, in most cases, as net importers, and poorer countries as net exporters.

From a methodological perspective, the empirical analysis is based on a panel database covering 107 countries over the period 1990-2019. Following recent literature in this field, we account for endogeneity (e.g., Rojas-Vallejos & Lastuka, 2020; Hailemariam et al., 2020) and check for the possible presence of non-linear impacts on carbon emissions, due to heterogeneities in the average income of each income group across countries.

The main findings of our paper show large differences in how different income classes contribute to carbon emissions. In addition, accounting for between-country inequalities in the disposable income each income class can effectively enjoy is essential to understand the link between consumption patterns and consumption-based CO_2 emissions. In particular, we find that the effect of an increase in the income share of the top 10% on consumption-based carbon emissions per capita varies with their average income: it is negative in those countries where the average income of richer individuals is below €120,598 before taxes and is positive above this threshold. An increase in the income share owned by the middle class has a negative effect on emissions, irrespective of the level of their average income. Finally, the carbon contribution of the poorest shares of the population is negligible: it is negative at lower levels of income and non-significant afterwards.

The rest of the paper is structured as follows: Section 2 reviews key literature on CO_2 emissions and income distribution and presents the main research hypotheses. Section 3 outlines the panel database and the modelling framework. Section 4 presents the main results and checks on models' robustness. Section 5 discusses results. Finally, Section 6 concludes and provides policy implications.

2. Background and research questions

From a theoretical perspective, three main approaches have offered an explanation to the emissions-inequality nexus. The first is the political economy model proposed by Boyce (1994; 2007), who postulates the existence of a "power-weighted decision rule". The power imbalance between rich and poor makes it easier for the rich, who usually own polluting firms and have a more carbon-intensive consumption, to escape environmental regulations and impose environmental costs on the poor. Further, this may lead to unwise policy decisions that over-exploit natural resources. Applying key principles of cost-benefit analysis to the environment-inequality nexus, Boyce (1994) identifies three main ways in which rising income inequality contributes to environmental degradation: first, through an asymmetry in the power-weighted decision rule. Second, through differences in how the poor and the rich value the costs and benefits associated to environmental degradation. Third, through differences in the rate of environmental time preferences applied by the two social groups.

The second approach focuses on the marginal propensity to emit (MPE), which takes inspiration from the marginal propensity to consume (MPC) in the standard Keynesian model. Just as poorer households have a higher MPC than richer households, they also have a higher MPE because they cannot afford low-carbon goods (Ravallion et al., 2000). According to Heerink et al. (2001), the demand for "dirty" goods decreases as income increases, so greater concentration of income and wealth generates less pressure on the environment. Therefore, according to this second approach, reducing income inequality would increase environmental degradation because the poor, to improve their wellbeing, would need to consume more dirty goods and, accordingly, to pollute more.

Finally, in the third approach the emphasis is on individual behaviour, which has become increasingly consumerist and individualistic towards the environment as a result of growing inequality (Wilkinson and Pickett, 2010). In this vein, the heightened competition in consumption, driven by income inequality, undermines social cohesion and contributes to the escalation of emissions (Wilkinson and Pickett, 2010). The notion of conspicuous consumption, as theorized by Veblen (1934), suggests that the affluent intentionally consume luxury goods and excessive quantities of items, driven by the need to maintain a favourable reputation (Veblen, 1934). This also leads to increased energy and resource use, resulting in increased carbon emissions. (Jorgenson et al., 2017).

Empirically, the coexistence of these alternative theoretical explanations is reflected in a multitude of papers offering mixed results: some authors find no significant relationship between rising inequality and CO_2 emissions (e.g., Mader, 2018); others find a negative relationship (e.g., Ravallion et al., 2000; Heerink et al., 2001), while in other cases a positive relationship is found (e.g., Qu and Zhang, 2011; Baek and Gweisah, 2013; Knight et al., 2017). Therefore, empirical evidence in search of an unambiguous relationship between CO_2 emissions and income inequality is currently inconclusive. Grunewald et al. (2017) and Rojas-Vallejos and Lastuka (2020) find that income inequality reduces carbon emissions up to a certain level of income, but the effect turns positive afterwards.

Jorgenson et al. (2017) argue that different indicators of income inequality capture different mechanisms and are, therefore, representative of different theoretical arguments. The authors contend that income inequality as measured by the Gini index is more appropriate to describe the MPE approach, inasmuch as it highlights disparities between low- and middle-income households. In this framework, the reduced demand of carbon-intensive goods by low-income households, due to a contraction in disposable income, outweighs the increased demand from high-income households. However, their empirical analysis finds no significant impact of an increase in the Gini index on CO_2 emissions. On the other hand, an increase in the income share owned by the top 10% is positively associated with CO_2 and allows to describe political economy mechanisms and individual behaviours aimed at showing off (Jorgenson et al., 2017). The latter result also finds empirical corroboration at the micro level (Adua, 2022). Similar conclusions are reached by Hailemariam et al. (2020), who find that reducing income inequality measured by the Gini index increases CO_2 emissions, while a reduction in the income share owned by the richest 10% helps reducing carbon emissions.

According to Hübler (2017), the sensitivity of results depends on the sample analysed, the time horizon considered, and the econometric techniques used. In this respect, Grunewald et al. (2017) estimate the relationship on a panel of 158 countries and find that the sign and significance depend on the level of income: in low-income countries higher inequality (measured by the Gini index) reduces CO_2 emissions, while in high-income countries income inequality is a driver of carbon emissions. Looking at methodological aspects, Borghesi (2006) observes that the majority of the models finding a negative relationship between income inequality (mainly represented by the Gini index) and CO_2 emissions were based on a pooled OLS specification, while the relationship turns non-significant with the inclusion of fixed effects. Similar conclusions are reached by Hübler (2017), who finds that with a pooled regression higher inequality helps reducing CO_2 emissions, while the inclusion of fixed effects challenges this result.

Another source of sensitivity is given by the way CO_2 emissions are measured. The ongoing process of globalization has witnessed a continued increase in both international trade and specialization of economic activities. Consequently, the benefits derived from trade exhibit noticeable differences between importing and exporting countries. Within this dynamic, production predominantly takes place in areas characterized by inadequate environmental regulation, while consumption is concentrated in regions where environmental legislation is stringent. As a result, the amount of carbon indirectly embedded in a product within the realm of international trade corresponds to the disparity between carbon emissions generated during the production phase and those arising from consumption (Peters et al., 2009; Peters et al., 2011). In this respect, while most of the studies in this strand of research has measured CO_2 emissions as generated on the national territory (i.e., a production-based perspective), only a few scholars have focused on consumption-based CO_2 emissions (e.g., Baležentis et al., 2020; Liobikienė and Rimkuvienė, 2020). Other authors consider territorial emissions but include trade dependency among key determinants (e.g., Kang, 2022).

As noted above, most of the studies in this strand of literature focus on the Gini index or, in in a smaller number of cases, on the income share of the top 10% of the income distribution. Very recently, Bruckner et al. (2022) and Wollburg et al. (2023) estimate the projected impact of eradicating global poverty on CO_2 emissions. In particular, findings by Wollburg et al. (2023) reveal that, even in the more pessimistic scenario, additional economic growth needed to eradicate global poverty would result in a limited increase in emissions by 2050, without compromising global efforts on climate change mitigation. Nonetheless, to our knowledge, our study so far is the first to explore the effects that changes in the full spectre of income distribution have on CO_2 emission. Building on this literature, we formulate our first research question as follows:

RQ1. How do changes in the full spectre of income distribution affect consumption-based CO_2 emissions?

However, accounting for income shares alone risks hiding large heterogeneities in average income earned by individuals belonging to the same percentile in different countries. Chancel et al. (2023) highlight the presence of large carbon inequalities across income groups within all world regions, but also between them. Accordingly, as energy-intensive luxury goods have the highest income elasticity (Oswald et al., 2020), expenditure and consumption patterns of individuals in the same income class in different countries may differ significantly depending on their income level. Therefore, the sole focus on income shares risks to neglect potential non-linearities in the impact of different income classes on carbon emissions, resulting from (between-country) inequalities in the disposable income individuals in different income classes can effectively enjoy. Accordingly, we formulate the second research question:

RQ2. Are there non-linearities in the impact of income shares on CO_2 emissions, contingent upon the distribution of the average income specific to each class?

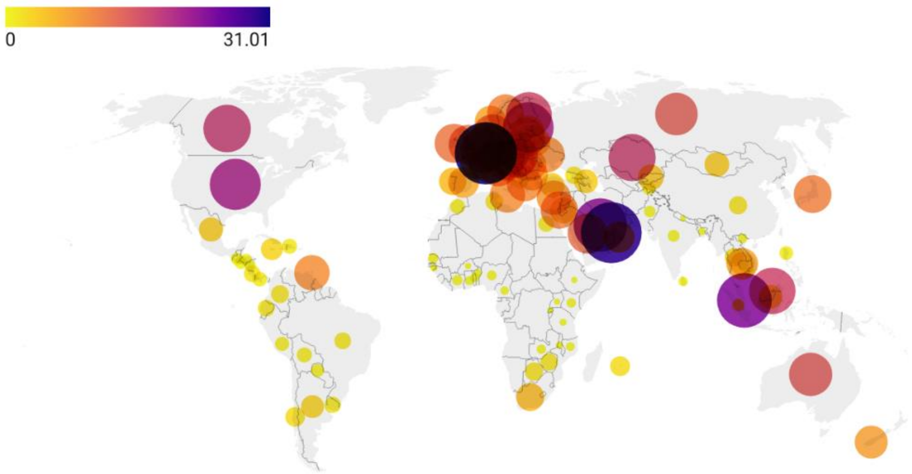
3. Data

The dependent variable

The empirical analysis is based on a panel database composed of 107 countries spanning over the period 1990-2019. The dependent variable represents consumption-based CO_2 emissions per-capita and is gathered from the Global Carbon Project (Peters et al., 2011; Andrew and Peters, 2022; Friedlingstein et al., 2022). Recent research has dedicated great attention to the role of international trade in the quantification of CO_2 emissions. In particular, there has long been a concern that countries might display lower emissions by delocalizing polluting productions to other countries and then re-importing those "dirty" goods produced elsewhere (Steinberger et al., 2012). In so doing, CO_2 emissions are not really reduced, but simply transferred geographically. Accordingly, quantifying carbon emissions according to the location where they are produced risks underestimating the effective CO_2 emissions embedded in final demand, which is only captured by accounting for consumption-based CO_2 emissions.

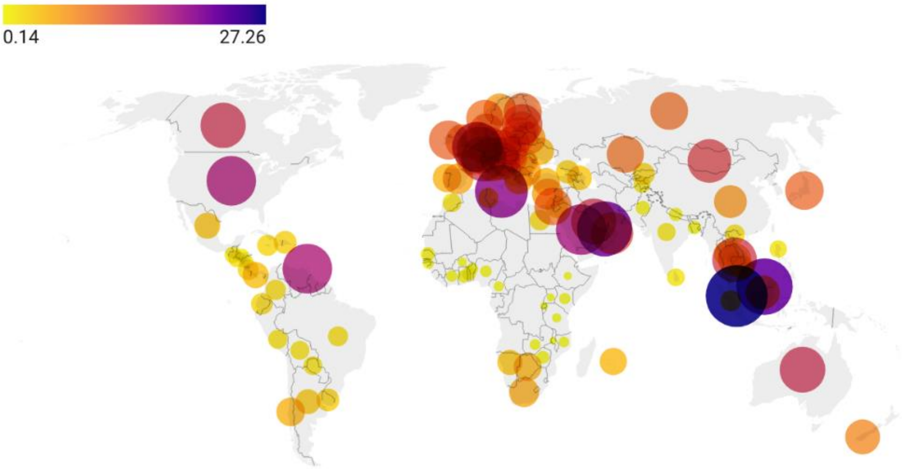
Figures 1 and 2 show the geographical distribution of per capita tons of consumption-based CO_2 emissions in 1990 and 2019, respectively. As it clearly emerges, the average citizen in advanced and industrialised economies and in Gulf countries emits disproportionately more CO_2 compared to the rest of the world in both 1990 and 2019. However, over this period, most countries in the European Union, as well as a few other industrialised economies, have managed to reduce their per capita emissions of CO_2, albeit still standing among the top emitters. On the other hand, citizens in other countries have increased their amount of CO_2 emitted over the period considered. In particular, it appears from the figure that in 2019 the main emitters are now mainly located in Southeast Asia.

Figure 1: Per capita consumption-based tCO_2 emissions in 1990



Source: own elaboration on Global Carbon Project data

Figure 2: Per capita consumption-based tCO_2 emissions in 2019

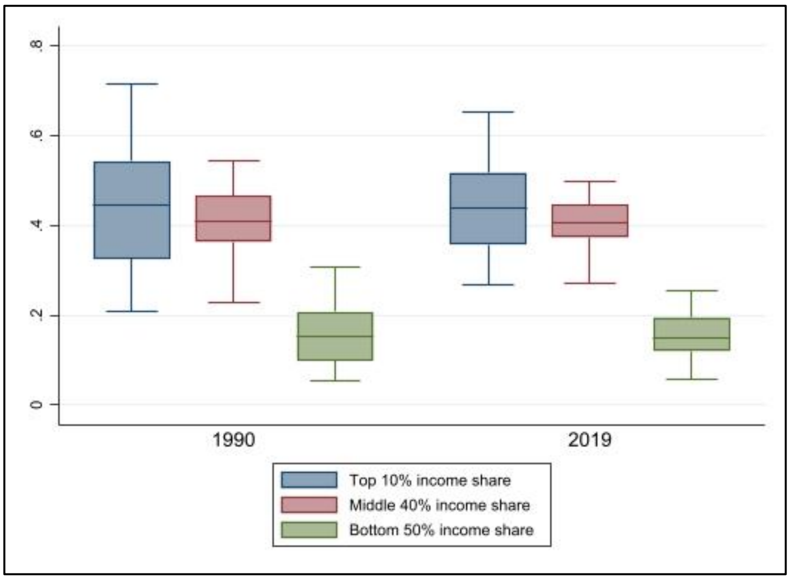


Source: own elaboration on Global Carbon Project data

Key covariates on income distribution

Data on income distribution are provided by the World Inequality Database. For each income class, we collect data on top 10%, middle 40% and bottom 50% income shares, as well as on pre-tax average income (expressed in constant 2022 euros), which we use as a discriminating factor for between-country inequalities. Figure 3 shows how the income shares of the top 10%, middle 40% and bottom 50% have changed between 1990 and 2019. In our sample, the income share owned by the top 10% is the largest in both periods, but its distribution in 2019 is more concentrated than in 1990. To illustrate, the income share owned by the richest 10% ranges between 20.97% (Czech Republic) and 71.55% (Namibia) in 1990, and between 26.78% (Slovak Republic) and 65.41% (South Africa) in 2019. A greater concentration, although less pronounced, is also observed in the income shares held by the middle 40% (that, in 1990, ranges between 22.92% in Namibia and 54.34% in Australia, while in 2019 ranges between 27.07% in Mozambique and 49.91% in Australia) and the bottom 50% (that, in 1990, ranges between 5.53% in Namibia and 30.62% in Hungary, while in 2019 ranges between 5.8% in South Africa and 25.32% in Czech Republic).

Figure 3: Top 10%, middle 40% and bottom 50% income shares in 1990 and 2019



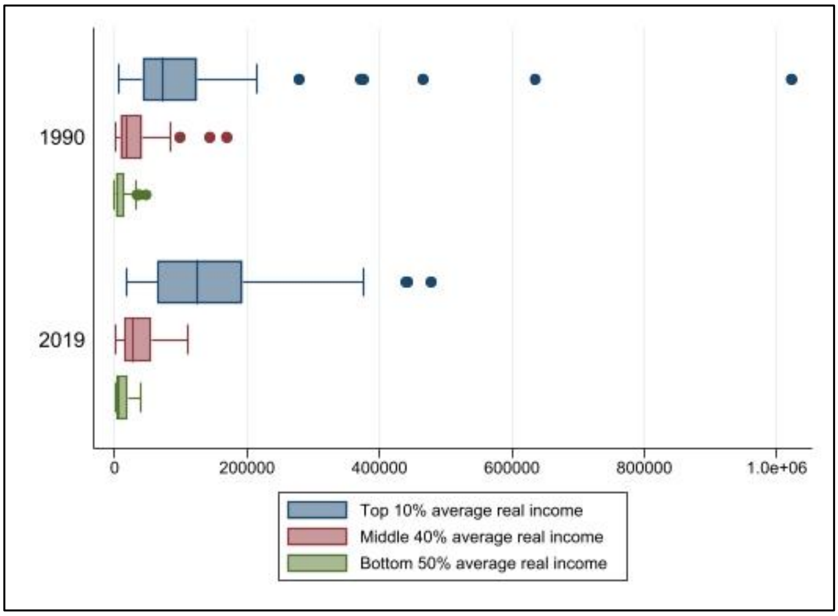
Note: The boxes represent 25th percentiles (left hinge), median and 75th percentiles (right hinge), while the whiskers describe the minimum and the maximum values. Source: own elaboration on WID data

However, a more complete picture can be obtained from Figure 4, which shows the distribution of the average real income of the top 10%, the middle 40% and the bottom 50% in 1990 and 2019. To illustrate, in 1990 the average income of the richest 10% individuals in our sample ranges between pre-tax constant 2022 €7,184.18 in Mozambique and €213,566.5 in the United States[1]. Some countries (i.e., Luxembourg, Oman, Bahrain, Brunei Darussalam, Saudi Arabia, and the United Arab Emirates) show values outside the range, up to €1,021,918.4 in the United Arab Emirates. The gap in adjacent values is larger in 2019: Mozambique remains the country where the rich earn less than their counterparts elsewhere, although their average income has risen to €19,119.12 before taxes, while the upper adjacent value is now €376,332.7 in the United States. The average income of the countries that were outside the range in 1990 has decreased compared to 1990.

Similarly, the average income of the middle 40% and the bottom 50% is very unequal between countries. In particular, the average income of the middle 40% in 1990 ranges between €859.68 in Mozambique and €84,892.14 before taxes in Luxembourg (with maximum outside value represented by the United Arab Emirates, with an average real income of the middle class of €168,976.52). In 2019, the gap ranges from €2,001.78 in Mozambique to €109,775.87 in Luxembourg. Looking at the poorest shares of the population, in our sample the average income earned by the poorest 50% individuals ranges between constant 2022 €193.99 in Mozambique and €32,075.48 in Switzerland before taxes (considering outside values, the maximum income earned by poorest individuals in 1990 is €47,591.03 in Brunei Darussalam). The gap in 2019 is very similar, ranging between €490.94 in Mozambique and €40,203.67 in Norway.

As we can notice from the graph, the average income of the richest in some countries is higher than that of the poorest in others. It is striking to observe that, in 2019, the average income of the poorest individuals in Norway is more than double that of the richest individuals in Mozambique.

Figure 4: Average income of the top 10%, middle 40% and bottom 50% in 1990 and 2019



Notes: Average income is expressed as pre-tax constant €2022.
The boxes represent 25th percentiles (left hinge), median and 75th percentiles (right hinge), while the whiskers describe the minimum and the maximum values, in the absence of outside values (the dots).
Source: own elaboration on WID data

[1] Data are sourced from the World Inequality Lab.

Control variables

Main explanatory variables include standard factors in the IPAT model (Ehrlich and Holdren, 1971), augmented with different income shares representing income distribution and control factors well acknowledged in the literature. Following the STIRPAT model (Dietz and Rosa, 1997; York et al., 2003) – i.e., the stochastic version of the IPAT model -, the Impact variable (in our case, consumption-based CO_2 emissions per capita) is a function of Population, Affluence and Technology: I=PAT. The STIRPAT model is a widely acknowledged formula used to analyse the effect of human and economic activities on the environment (e.g., York et al., 2003; Yang et al., 2021; Schneider, 2022; Liang et al., 2023). To avoid possible collinearity issues, we use population growth as representative of the P factor, and real GDP growth as representative of affluence. We source both data from the World Development Indicators by World Bank. Finally, technology is represented by the carbon intensity of GDP and the share of total final energy consumption met by renewable energy sources to account for the energy mix, as in Kang (2022).

Table 1 presents descriptive statistics and data sources for the variables included in the econometric analysis. Table A1 in the Appendix displays the correlation matrix.

Table 1: Data sources and descriptive statistics

Variable	Source	N. obs.	Mean	St. Dev.	Min	Max
Consumption-based CO_2 emissions (tCO_2/person)	Global Carbon Project	3,210	6.35	6.39	-0.58	47.78
Top 10% average income (pre-tax constant €2022)	WID	3,210	118,985.1	108,874.3	6644.78	1,021,918
Middle 40% average income (pre-tax constant €2022)	WID	3,210	31,395.38	29,304.25	795.13	237,628.4
Bottom 50% average income (pre-tax constant €2022)	WID	3,210	10,025.69	10,418.14	179.43	88,479.92
Top 10% income share	WID	3,210	0.45	0.10	0.21	0.72
Middle 40% income share	WID	3,210	0.40	0.05	0.23	0.54
Bottom 50% income share	WID	3,210	0.14	0.05	0.05	0.31
Population growth	World Bank	3,103	0.013	0.014	-0.038	0.199
Real GDP growth	World Bank	3,103	0.035	0.04	-0.449	0.345
CO_2 intensity (tons of CO_2 per capita/mln GDP per capita)	World Bank	3,210	0.64	0.518	-0.065	4.32
Renewable energy consumption (% of total final energy consumption)	World Bank	3,210	28.58	26.92	0	97.51

4. Methodology

To investigate the effect of changes in income distribution on consumption-based CO_2 emissions, we make use of two different econometric techniques. To answer the first research question, we employ a dynamic difference-GMM estimator (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). Then, in order to identify the potential existence of thresholds in the average income of the different income groups, which give rise to non-linearities in the effect of their income shares on carbon emissions, we employ a dynamic panel threshold model that also allows to account for the endogeneity of regressors (Kremer et al., 2013; Diallo, 2020).

4.1 Baseline model with endogenous regressors

Several papers investigating the inequality-emissions nexus have raised endogeneity concerns (Rojas-Vallejos and Lastuka, 2020; Hailemariam et al., 2020; Uddin et al., 2020) that, if neglected, may lead to biased results. Endogeneity may be driven by reverse causality between income shares and CO_2 emissions through mitigation policies. Arguably, with rising carbon emissions, countries are demanded to intensify mitigation efforts. This affects the overall national income level as well as how income is distributed within countries through tax levy. Further, between-country income distribution will be affected as well through Nationally Determined Contributions based on the United Nations' principle of common but differentiated responsibilities. For these reasons, we also consider GDP growth, the carbon intensity of GDP and the share of renewable energy (which is a direct result of mitigation policies) as endogenous covariates. Further sources of endogeneity are conveyed by Drabo (2011), who suggests that income inequality might affect health status through environmental degradation, and Taylor et al. (2016), who point to the intricate nature of this relationship and underscore the likelihood of influential confounding factors being at play.

Taking stock of this, we estimate our baseline model by means of both a Two-Stage Least Squares (2SLS), as well as a dynamic difference-GMM estimator (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998) to give continuity with the second part of our estimation (Section 4.2). Both estimators require the identification condition is satisfied, whereby the number of included endogenous variables must be lower than or equal to the number of excluded exogenous variables:

$$m_i \leq (K - k_i) \qquad (1)$$

Where m_i is the number of endogenous variables, K is the sum of the number of exogenous variables (k_i) and the number of excluded exogenous variables (instruments). A common practice when addressing endogeneity is to include lagged values of endogenous variables as instruments. However, to be sure to eliminate all sources of endogeneity, we include in our model the two-year lags of endogenous variables, as well as two external instruments, namely the adolescent fertility rate and the distance from the Equator. The adolescent fertility rate, gathered from the World Development Indicators by World Bank, is measured as births per thousands of women between 15 and 19 years old and it is a well-established instrument for income inequality (e.g., Hotz et al., 2005; Fletcher and Wolfe, 2009; Aiyar and Ebeke, 2020). The rationale behind is that high adolescent fertility rates are likely to hinder human capital accumulation and adversely affect future labour market prospects, widening the gap in income distribution (Kearney and Levine, 2012).

The distance from the Equator has also been long used as an instrument in the literature for development levels (Kamarck, 1976), GDP (Theil and Finke, 1983), human development (Ram, 1997), as well as social infrastructure (Hall and Jones, 1999). The logic behind is that different levels of development are associated with adverse climatic and geographical conditions affecting tropical countries' economic progress. To compute these distances in kilometres, we compute the great-circle distances from the Equator based on the Haversine formula by taking the latitude and longitude of each country's centroid.

To test empirically our first research question, we estimate the following model:

$$CO_{2i,t} = \beta_0 + \beta_1 CO_{2i,t-1} + \beta_2 I_{i,t} + \beta_3 GDP\_gr_{i,t} + \beta_4 Pop\_gr_{i,t} + \beta_5 CO2\_int_{i,t} + \beta_6 RES_{i,t} + \eta_t + \varepsilon_{i,t} \quad (2)$$

where CO_2 is per capita consumption-based CO_2 emissions, I is the income share owned by the different income groups, *GDP_gr* is the growth rate of real GDP, *Pop_gr* represents population growth, *CO2_int* is the carbon intensity of GDP, *RES* represents the share of renewable energy sources, η controls for common global shocks. Finally, ε are the uncorrelated error terms. Furthermore, in the 2SLS specification, we also include fixed effects that, in a GMM model, are an orthogonal component of the disturbance term (Roodman, 2009).

4.2 *Dynamic panel threshold model*

Then, our second research question enquires the potential presence of non-linearities in the impact of an increase in the income share owned by each specific income group at different levels of their average income. To answer this question, we are interested in understanding whether there exists a threshold in the level of disposable income each income class in different countries effectively enjoys, which can drive heterogeneities in the impact on carbon emissions. The threshold regression approach proposed by Hansen (1996) allows to determine the existence of such threshold endogenously, estimating the threshold parameter alongside the other parameters of the model. Since Hansen's seminal contributions, the threshold model has been extended to be employed also within a panel setting (Hansen, 1999; Wang, 2015). However, these models relied on the strict assumption of exogeneity of all regressors. More recently, a dynamic version that also allows for the presence of endogeneity has been developed by Kremer et al. (2013) and implemented by Diallo (2020), where the GMM estimator is used to address endogeneity[2]. Accordingly, to test empirically our second research question, we estimate the following model:

$$CO_{2i,t} = \beta_0 + \beta_1 CO_{2i,t-1} + \beta_2 I_{i,t}(q_{i,t} \leq \gamma) + \beta_3 I_{i,t}(q_{i,t} > \gamma) + \beta_4 X_{i,t} + \varepsilon_{i,t} \quad (3)$$

Where q_{it} is the threshold variable, i.e., the average real income specific to each income group. The equation allows different parameter estimates, β_2 and β_3, for the two groups of observations, respectively. The former estimates the effect of an increase in the income share of a given income class for a value of the class-specific average income lower than or equal to the threshold value γ and the latter estimates the effect when the class-specific average income is higher than the threshold value.

4.3 *Robustness checks*

We subject our analysis on some robustness checks, in order to verify the validity of the model. First, we test the effect of the urban share of the population, as well as population number, in place of population growth, and real GDP, expressed in constant 2015 US$ in place of per capita real GDP. Then, from a methodological perspective, we estimate Tables 2 and 3 without addressing endogeneity: for this purpose, the baseline model is estimated via an OLS fixed-effects estimator, while the thresholds are identified by means of a Fixed-effect panel threshold model (Wang, 2015) that does not allow for endogenous regressors. Results are comparable to those of our main model specifications and are provided in Table A2 in the Appendix.

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[2] For a deeper analysis of the estimation procedure, see Kremer et al. (2023).

5. Results

Table 2 reports results for the baseline model estimation by means of a 2SLS (Models 1-4) and a difference-GMM estimator (Models 5-8). In both cases, to test the effect of changes in income distribution on consumption-based emissions, we first estimate a dynamic STIRPAT equation as a baseline model (Models 1 and 5) and results confirm previous evidence in the literature. As expected, the effect of both GDP and population growth is always positive and statistically significant, confirming their importance in the STIRPAT model. Results for technological factors are in line with our expectations, as a higher share of renewable energy sources within the national energy mix contributes to mitigation while a higher CO_2 intensity of GDP drives emissions up. Further, the past dynamics of carbon emissions is a driving factor for additional CO_2 emissions.

Turning to the effects of changes in the distribution of income, we find that the average effect of an increase in the income share of the top 10% does not significantly affect per capita consumption-based carbon emissions (Models 2 and 6). Similar results are found for changes in the income share owned by the bottom 50% (Models 4 and 8). On the other hand, an increase in the share of income owned by the middle class (Models 3 and 7) is found to reduce carbon emissions. The latter effect is stronger in magnitude with a GMM estimator, compared to a 2SLS estimator.

Table 2 – Baseline results

	2SLS				GMM			
	M1	M2	M3	M4	M5	M6	M7	M8
Constant	6.3178***	5.5467***	9.4510***	5.5159***				
	(0.3560)	(0.7705)	(1.0562)	(0.6380)				
Population growth	29.035***	28.677***	28.168***	29.481***	11.070***	10.391***	9.170***	11.440***
	(3.6934)	(3.7057)	(3.6950)	(3.7049)	(3.3409)	(3.2880)	(3.2969)	(3.2580)
Renewables (%)	-0.0501***	-0.0505***	-0.0503***	-0.0490***	-0.0129**	-0.0169**	-0.0289***	-0.0078
	(0.0069)	(0.0069)	(0.0069)	(0.0070)	(0.0066)	(0.0070)	(0.0072)	(0.0067)
GDP growth	4.7722*	4.8436**	5.0062**	4.7167*	1.2318**	1.5591***	1.5521***	1.5483***
	(2.4363)	(2.4382)	(2.4334)	(2.4371)	(0.5407)	(0.5294)	(0.5300)	(0.5294)
CO_2 intensity	1.1474***	1.1662***	1.2283***	1.1463***	1.6380***	1.6699***	1.7481***	1.6311***
	(0.2350)	(0.2359)	(0.2372)	(0.2349)	(0.1268)	(0.1265)	(0.1273)	(0.1255)
Top 10% share		1.7739				2.8240		
		(1.5576)				(1.9346)		
Middle 40% share			-7.782***				-16.271***	
			(2.5058)				(3.3694)	
Bottom 50% share				4.9284				5.1993
				(3.2261)				(3.2104)
$L.CO_2$					0.5031***	0.5070***	0.5021***	0.4994***
					(0.0188)	(0.0184)	(0.0184)	(0.0186)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes				
N. obs.	2,903	2,903	2,903	2,903	3,003	3,003	3,003	3,003
AR(1)					[0.000]	[0.000]	[0.000]	[0.000]
AR(2)					[0.675]	[0.653]	[0.675]	[0.709]

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Instruments include two-year lags of endogenous covariates, the adolescent fertility and the distance from the Equator.

Then, to answer the second research question we test for the potential presence of non-linearities in the impacts of the different income shares, conditional on the level of average income of the same income group. This allows us to account for inequalities both between and within countries. Operatively, we estimate a dynamic panel threshold model that allows for the endogeneity of regressors within a GMM estimation framework. Results are reported in Table 3.

For all income groups, we identify the presence of a significant threshold, suggesting that the effect of an increase in their income share depends on the level of their average income. As for the top 10% of the income distribution, the threshold in their average real income is found at pre-tax constant 2022 €120,598, which corresponds to approximately the 60th percentile. In particular, below this threshold the effect of an increase in their income share on emissions is negative and turns positive afterwards.

On average, the disposable income of countries in the middle-low/low percentiles of the distribution of the average income of the top 10% corresponds to that of countries in the middle-high/high percentiles of the distribution of the average income of the middle 40%. In this sense, the negative coefficient of values below the threshold is in line with results for the middle 40%: in this case, the threshold at pre-tax constant 2022 €21,484.99 does not indicate a change in the sign of the impact, which is always negative and statistically significant, but rather a contraction in its magnitude.

Finally, for the bottom 50% of the population the threshold is found at constant 2022 €6,560.15 before taxes (corresponding, approximately, to the 55th percentile of the distribution of their average real income). Below this value the effect of an increase in the income share of the poorest segments of the population reduces carbon emissions per capita, while the effect turns non-statistically significant above this threshold.

Table 3 – Non-linearities in the impact of different income shares on emissions

	Top 10%	Middle 40%	Bottom 50%
L.CO2	0.7404***	0.7362***	0.7616***
	(0.0085)	(0.0078)	(0.0050)
Population growth	17.1948***	22.8520***	18.1257***
	(1.5170)	(2.0503)	(1.8425)
Renewables (%)	-0.0453***	-0.0437***	-0.0400***
	(0.0018)	(0.0016)	(0.0012)
GDP growth	4.1675***	4.5263***	4.7819***
	(0.0898)	(0.1096)	(0.1165)
CO_2 intensity	0.4274***	0.7871***	0.6948***
	(0.0172)	(0.0220)	(0.0229)
Income share ($q \leq \gamma$)	-0.7858**	-4.7505***	-6.2893***
	(0.3337)	(0.5761)	(0.7610)
Income share ($q > \gamma$)	1.2173***	-1.7836***	-0.0270
	(0.3101)	(0.5708)	(0.6844)
Constant	2.2669***	3.2507***	2.2145***
	(0.1832)	(0.2241)	(0.1145)
Threshold	120,598	21,484.99	6,560.15
N. obs.	3,103	3,103	3,103

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Instruments include two-year lags of endogenous covariates, the adolescent fertility and the distance from the Equator.

6. Discussion

Our work reinforces the exploration of the nuanced relationship between income inequality and carbon emissions, by extending the analysis to the full spectre of income distribution and to between-country inequalities. The empirical findings suggest that different income classes contribute very differently to consumption-based CO_2 emissions. In addition, our results are also very heterogeneous within income classes, highlighting the need to account for inequalities both between and within countries. In this vein, an important result of our study is that extending the analysis to inequalities between countries allows to uncover how, for the top 10%, the composition effect, given by the composition of consumption, outweighs the scale effect, resulting from a mere increase in their income share. The key takeaway from these results is that it is not just about being among the richest in your country, but that income levels make a difference to the consumption and investment patterns of a relatively small segment of the world's population in terms of their impact on carbon emissions.

Framing the results obtained in the light of the theoretical approaches proposed in the literature, our findings are consistent with Boyce's political economy approach, pointing to a link between increased income concentration at the top and higher carbon emissions, particularly in countries where the affluent class enjoys an average income that exceeds 60% of their counterparts in other countries. This connection is reinforced by the conspicuous consumption patterns of the wealthy, who indulge in more opulent and carbon-intensive lifestyles. Wealthier individuals often own large private mansions, drive larger and more fuel-intensive cars, are more frequent flyers (Ivanova et al., 2016), and possess large corporations with substantial carbon footprints (Hinton, 2020). These sumptuous lifestyles not only amplify their personal carbon emissions but also set aspirational benchmarks that may influence societal norms, fostering a culture of excess and high resource consumption. At the same time, they can also better insulate and protect themselves from environmental risks and polluted environments, for example buying real estate in places with better environmental quality and at higher costs (Boyce, 2007).

The middle class, on the other hand, has fewer opportunities than the wealthy to insulate themselves but can adopt conscious consumption choices and demand greater environmental protection where they live. It has been observed, since the origin of the first environmental movements, that individuals from the middle class tend to possess the knowledge, time and sufficient money to allow them to engage in activism (Bagguley, 1992). In a similar vein, our results confirm findings from the sociological study conducted by Rhead et al. (2018), which analyses the UK's 2009 Survey of Public Attitudes and Behaviours towards the Environment and finds that the most environmentally aware respondents are well-educated individuals belonging to the middle class. These people are also actively engaged in shifting to more environmental-friendly consumption choices, such as taking less flights and preferring public over private transport (Rhead et al., 2018). Our results are also consistent with Shao et al. (2018), who confirm the pro-environmental attitude of the middle class, finding that, in China, this is the segment of the income distribution with the highest willingness to pay for environmental protection.

As for the poorest segments of the population, we do not find evidence supporting the MPE approach but, on the other hand, in line with Bruckner et al. (2022) and Wollburg et al. (2023) our results suggest that the marginal contribution of the bottom 50% to consumption-based carbon emissions is negligible. This is also consistent with Chancel et al. (2023), who find that in all world regions except Europe and North America, the carbon footprint of the poorest segments of the population is close to the 1.5°C target.

7. Conclusions

Our analysis provides a first insight into the different contributions to consumption-based CO_2 emissions across different income classes and how they differ among countries. In particular, it highlights the need to account for between-country in addition to within-country inequalities, in order to uncover non-linearities in the impacts and heterogeneities in the relative contribution of different income groups across countries. However, further research is needed to understand the different mechanisms that are specific to each income class. Moreover, the analysis should be integrated with micro-level analysis of households' consumption expenditure, in order to better link consumption patterns of each income class to the carbon content of the goods and services effectively consumed.

Future research may also benefit from recent advancements in emissions calculations, in order to overcome some of the limitations of the consumption-based approach highlighted by Chancel and Rehm (2023). For example, under this approach, consumers are fully responsible for all direct and indirect emissions generated by the production system, regardless of whether they can choose to consume less carbon-intensive goods or not. In this calculation, capital owners, who would have a voice in production decisions, enter the accounting of emissions only as consumers and not likewise as business owners. As a result, this approach to emissions calculation does not allow to account for the role of investment decisions, which play a relevant role in the channel linking environmental degradation to the existence of a "power-weighted decision rule" highlighted by Boyce (1994). In this vein, the newly proposed approach by Chancel and Rehm (2023) offers possibilities for new research avenues, by computing emissions based on capital ownership, as well as a combination of the consumption-based and ownership approaches.

Our analysis calls for a broader understanding of carbon inequalities and the potential implications it has for climate targets and policies. A nuanced understanding of who the major contributors are is needed to tailoring effective environmental policies that, at present, do not contemplate per-capita targets (Chancel, 2022). This knowledge allows policymakers to design targeted measures that address specific challenges faced by different income classes, ensuring a fair and impactful transition to a sustainable future. Indeed, on the one hand, the ecological transition faces potential obstacles from the affluent segment of society, as their conspicuous consumption patterns contribute significantly to environmental degradation. On the other hand, Chancel et al. (2023) also point out that the rich require a significantly lower marginal abatement efforts, as a large part of their emissions are related to the consumption of non-essential goods.

Taking stock of this, policymakers may consider implementing tailored regulations and measures, compelling wealthier individuals to invest more substantially in eco-friendly initiatives. By imposing specific demands on the affluent class to contribute significantly to the ecological transition and by implementing targeted redistributive strategies, governments can foster a more equitable distribution of responsibilities and resources, aligning with the principles of a just transition. Nonetheless, given the complex relationship between economic inequalities and ecological impacts, caution must be paid in interpreting these results in terms of a mere redistribution of income. As found in Millward-Hopkins and Oswald (2021), reducing income inequalities lowers inequalities in energy and carbon footprints, but an absolute reduction in such footprint can only be achieved through a contraction in total household expenditure. In this vein, Kilian et al. (2023) propose a combined approach of redistribution of income and extended access to public goods and services for tailoring climate policies on different income groups: while taxation may be an effective redistributive strategy for affluent households, whose carbon emissions are closely coupled with their income, extended access to a wide range of public services, including safe and high-quality housing, may contribute to emissions reduction in low-income households. This is particularly relevant as the emissions of the latter are already decoupled from their income levels.

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9. Appendix

Table A1: Correlation matrix

	CO_2	Top 10 av. income	Middle 40 av. income	Bottom 50 av. income	Top 10% share	Top1% share	Middle 40% share	Bottom 50% share	Pop growth	Renewables	GDP growth	CO_2 intensity
CO_2	1											
Top 10 av. income	0.77	1										
Middle 40 av. income	0.84	0.88	1									
Bottom 50 av. income	0.79	0.75	0.96	1								
Top 10% share	-0.41	-0.03	-0.41	-0.55	1							
Top1% share	-0.34	-0.01	-0.34	-0.44	0.91	1						
Middle 40% share	0.38	0.03	0.39	0.48	-0.96	-0.92	1					
Bottom 50% share	0.40	0.04	0.40	0.57	-0.95	-0.82	0.83	1				
Pop growth	-0.05	0.19	-0.02	-0.12	0.47	0.40	-0.46	-0.44	1			
Renewables	-0.60	-0.47	-0.50	-0.45	0.33	0.28	-0.33	-0.30	0.28	1		
GDP growth	-0.07	-0.04	-0.10	-0.12	0.13	0.15	-0.13	-0.13	0.13	0.10	1	
CO_2 intensity	-0.01	-0.22	-0.26	-0.25	-0.07	-0.04	0.06	0.08	-0.14	-0.26	-0.04	1

Table A2: Robustness checks with exogenous regressors

	OLS				Threshold		
	M1	M2	M3	M4	Top 10%	Middle 40%	Bottom 50%
Population growth	27.3392***	26.8311***	26.4554***	27.5811***	26.9105***	22.9741***	24.0129***
	(3.5754)	(3.5837)	(3.5742)	(3.5840)	(3.4982)	(3.4761)	(3.4959)
Renewables (%)	-0.0344***	-0.0350***	-0.0349***	-0.0340***	-0.0474***	-0.0394***	-0.0457***
	(0.0052)	(0.0052)	(0.0052)	(0.0052)	(0.0050)	(0.0050)	(0.0050)
GDP growth	0.7570	0.7215	0.7109	0.7788	1.6502**	1.3922**	2.1673***
	(0.7135)	(0.7135)	(0.7119)	(0.7139)	(0.6717)	(0.6679)	(0.6726)
CO_2 intensity	2.2114***	2.2360***	2.2701***	2.2047***	2.0153***	2.2520***	2.2851***
	(0.1285)	(0.1291)	(0.1291)	(0.1287)	(0.1210)	(0.1233)	(0.1258)
Top 10% share		2.1145*					
		(1.1058)					
Middle 40% share			-6.9305***				
			(1.7816)				
Bottom 50% share				2.1467			
				(2.1990)			
Income share ($q \leq \gamma$)					1.0218	-13.8375***	-10.2002***
					(1.0935)	(1.7799)	(2.3373)
Income share ($q > \gamma$)					4.5298***	-9.6481***	1.4881
					(1.0882)	(1.7429)	(2.1538)
Constant	5.0808***	4.1726***	7.9027***	4.7303***	4.9695***	10.2722***	6.3995***
	(0.2666)	(0.5446)	(0.7726)	(0.4472)	(0.5179)	(0.7141)	(0.3823)
Year	Yes	Yes	Yes	Yes			
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Threshold					122,982.85	17,577.15	6,864.62
N. obs.	3,103	3,103	3,103	3,103	3,103	3,103	3,103
R^2	0.1682	0.1692	0.1724	0.1684	0.1698	0.1781	0.1692
R^2 adj.	0.1295	0.1302	0.1336	0.1294	0.1387	0.1473	0.1381

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Fondazione Eni Enrico Mattei

Fondazione Eni Enrico Mattei
Corso Magenta 63, Milano – Italia

Tel. +39 02 403 36934

E-mail: letter@feem.it
www.feem.it

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ENRICO MATTEI