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The champagne curve of climate and development inequalities

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ABSTRACT

The article examines the correlation between per capita consumption-based CO2 emissions and the Human Development Index (HDI). The relationship follows a ‘Champagne Curve’ resembling champagne spraying from a freshly sabred bottle: initially, HDI rises with emissions but levels off beyond a certain threshold. Countries with low HDIs (below 0.6) exhibit relatively uniform per capita CO2 emissions, whereas those with higher HDIs (above 0.8) show much greater variation. Our findings indicate that beyond a certain HDI level, additional carbon consumption no longer contributes to well-being. This suggests that once a country reaches a high level of development, energy-saving and efficiency measures can be implemented without reducing individual well-being. Moreover, our results highlight the need for a differentiated approach to climate policy by categorizing countries into three groups: advanced, moderate, and limited transformation capacity. This classification could facilitate a more equitable implementation of climate policies, such as carbon pricing, helping to combat global warming while easing international negotiations.

KEYWORDS

Climate; HDI; energy; CO_2

JEL CLASSIFICATION

O10; Q40; Q50

I. Introduction

The interplay between economic development and pollution has been a central focus in environmental economics (Meadows et al. 1972). The Environmental Kuznets Curve (Grossman and Krueger 1993) posits that pollution increases with income in the early stages of development but eventually declines as countries become wealthier. However, this relationship is not uniform across all nations and various factors, such as income levels, policies, and technology, play a critical role in shaping emissions outcomes. Despite significant research on economic growth and pollution, the link between CO2 emissions and broader measures of human development, such as the Human Development Index (HDI), remains under-explored.

This paper investigates the nuanced relationship between HDI and consumption-based CO2 emissions per capita, using data that account for international trade. By focusing on a more comprehensive measure of human development, our study investigates whether pollution initially positively correlates with development but later becomes a barrier to further improvements in well-being. Our findings reveal a ‘Champagne Curve’, where HDI increases rapidly with emissions per capita but eventually plateaus or declines at higher levels. This suggests that once an HDI of 0.8 is reached, further well-being improvements are no longer tied to rising emissions, challenging the assumption that economic growth inherently compromises environmental goals.

To advance climate policy discussions, we propose a new classification of countries based on their transformation capacity: advanced, moderate, and limited. This classification helps differentiate nations’ potential to transition to low-carbon economics without sacrificing development. By offering a framework for fair and differentiated climate commitments, our approach aligns with the Paris Agreement’s objectives and emphasizes the need for equitable climate action, in line with SDG 13.

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This study addresses crucial gaps in the literature by connecting HDI and emissions patterns while contributing new insights into burden-sharing mechanisms that support sustainable, global climate policies.

II. Literature review

The link between economic development and pollution is central to economics. The Environmental Kuznets Curve (EKC) (Grossman and Krueger 1993) suggests an inverted U-shaped relationship between income and environmental degradation: pollution rises during early growth due to limited eco-friendly technology, then declines as income increases, driven by better awareness, technology, regulations, and a shift to service sectors.

Research on the EKC identifies factors like rising demand for a cleaner environment in wealthier countries (Beckerman 1995) and a shift from industry to services as pollution-reducing elements. International trade, while potentially increasing pollution, can spread cleaner technologies and influence environmental standards. This ties into the 'pollution haven' hypothesis, where polluting industries relocate to countries with weaker regulations (Dinda 2004; D. I. Stern, Common, and Barbier 1996).

However, the relationship between income and emissions is debated. Some suggest a 'race to the bottom', with firms moving to less regulated countries, nullifying global gains Dasgupta (2002). Evidence shows that in some cases, pollution remains steady regardless of income Copeland (2004).

Pollution's economic costs are a growing concern. It is a major negative externality that affects health and welfare (Coase 1960). For example, pollution-related health risks lead to millions of premature deaths and impose high economic costs (Landrigan et al. 2018). Climate change could also cut global GDP by up to 20% (N. H. Stern 2007).

Some studies suggest that resource depletion may hinder economic growth (Arrow et al. 1995), but as economies advance, pollution control technology can surpass emission growth (Brock and Taylor 2010).

Understanding the relationship between development and pollution is key in suggesting a pathway to burden-sharing approaches to climate change. Chancel and Piketty (2015) propose three alternative strategies. The first targets individuals emitting above the global average (6.2 tCO2-eq/year), paying in proportion to their excess: North Americans would cover 36%, Europeans 21%, China %, and other nations 20%. The second focuses on the top 10% of emitters (above 2.3 times the average): North Americans 46%, Europeans 16%, and China 12%. The final strategy targets the top 1% of emitters (above 9.1 times the average), with North Americans paying 57%, Europeans 15%, and China 6%.

Our study addresses two gaps: first, it uses consumption-based emissions data, which account for international trade, and investigates whether pollution initially aids development but later hinders it – a crucial issue for countries weighing the impact of stricter environmental policies; second, it discusses differentiated burden-sharing approaches.

III. Database and methodology

We merged two datasets: the United Nations Development Programme (UNDP)'s HDI dataset[1] and data on CO2 and Greenhouse Gas Emissions collected by Our World in Data (OWiD)[2] The HDI, computed by the United Nations Development Programme, is our proxy for economic development (see Appendix). The proxy for pollution is consumption-based emissions per capita, which are national emissions adjusted for trade (see Appendix).

We use fixed-effects (FE) models to analyse the relationship between the independent variable $X_{\mathrm{Cons\,CO_2}}$ (consumption-based emissions) and the dependent variable HDI (see equation (3.1)) for the years 2000–2022.

$$\widehat{\mathrm{HDI}}_{iy}(\beta, X_{\mathrm{ConsCO_2}}) = \beta_0 + \beta_1 \cdot X_{\mathrm{Cons\,CO_2},iy} + \sum_{j=1}^{T-1} \gamma_j \cdot D_{yj} + \sum_{k=1}^{N-1} \delta_k \cdot C_{ik} + \varepsilon_{iy} \tag{3.1}$$

[1]https://hdr.undp.org/data-center/documentation-and-downloads
[2]https://github.com/owid/co2-data.

where $X_{\text{Cons CO}_2}$ is consumption-based emissions per capita in country i and year $y \in \{2000, \cdots, 2022\}$, $\widehat{\text{HDI}}_{iy}$ the predicted HDI value for country i in year y, D_{yj}: dummy variables for each year y_j, and C_{ik}: dummy variables for each country i_k. Additionally, we apply a LOWESS regression for 2019 to illustrate cross-country comparisons. Additional models are tested and reported in Appendix.

IV. Results and discussion

The relationship between human development and consumption-based CO2 emissions per capita exhibits a 'Champagne Curve', as illustrated in Figure 1 for 2019 and a 22-year span (2000 to 2022). This metaphor compares the release of carbon dioxide into the atmosphere to the effervescence of a sabred champagne bottle, highlighting that while higher HDI levels are frequently associated with higher emissions, the relationship is non-linear and varies significantly among countries. A regional split of 119 countries (Figure 2) confirms our results.

In low-HDI countries (below 0.6, dark red in Figure 1), emissions are relatively uniform. For countries with HDIs between 0.6 and 0.8 (light red in Figure 1), emissions show greater variability, strongly influenced by policies on energy, transport, and imports. In higher-HDI countries (above 0.8 blue in Figure 1), emissions exhibit even greater variability. Crucially, we find that once an HDI of 0.8 is reached, increases in well-being are no longer tied to carbon emissions, suggesting that emissions reductions can be made without compromising human development. This suggests that at higher levels of development, countries often reach a saturation point where further improvements in well-being are less dependent on emissions but rather lie on efficient climate policies (Dhakal and Minx 2022; Stechemesser et al. 2024), paving the way for new commitments based on these differentiated groups.

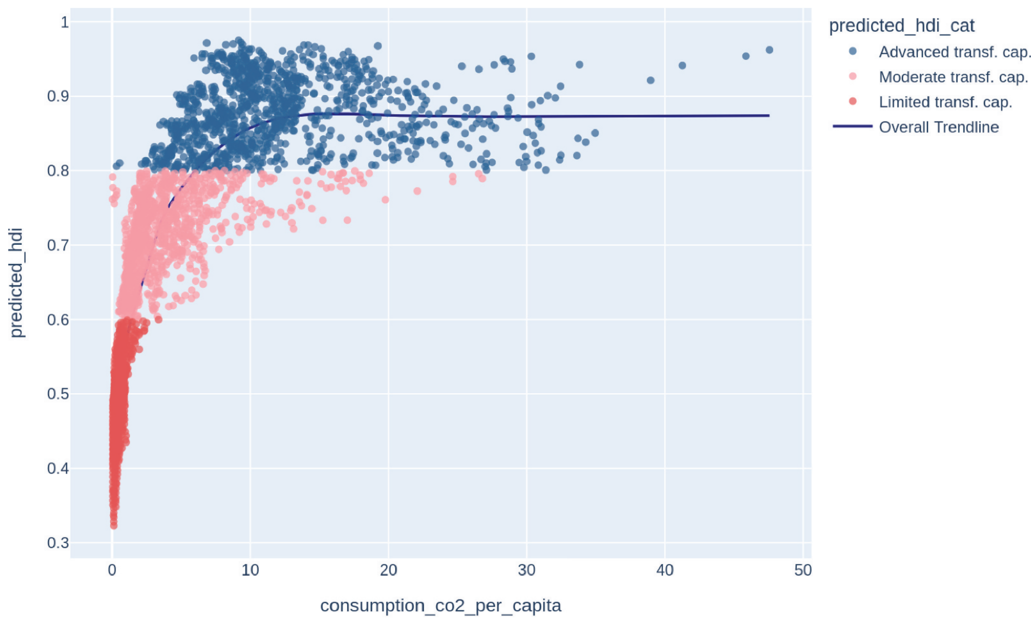
Our findings enable a classification of countries into three categories based on their capacity to reduce emissions, providing a framework for creating binding commitments (see Table A1 in appendix). Advanced transformation capacity countries (high HDI) can decouple emissions from development, improving well-being while reducing emissions. However, even these countries may face 'lock-in' situations (Thaler 2008), where existing infrastructure or vested interests in carbon-intensive industries hinder further progress towards decoupling, despite their high transformation capacity. Moderate transformation capacity countries (medium HDI) face a trade-off between growth and sustainability, requiring investment in green technologies. Limited transformation capacity countries have uniform emissions, with development linked to industrialization, and face challenges in reducing emissions due to limited resources and technology. The Kyoto Protocol exposed difficulties in differentiation based on historical responsibilities, while the Paris Agreement's flexibility balances diverse national contexts but complicates enforcement. Our three-category classification opens avenues for debates on financial mechanisms for equitable climate action, highlighting tensions between fairness, responsibility, and global solidarity.

V. Conclusion

Pollution and economic development are closely related, but fewer studies explore how pollution impacts human development. This paper examines the link between pollution and HDI, showing that carbon emissions do not boost well-being beyond a certain HDI level. Consumption-based emissions per capita remain relatively uniform for countries with an HDI below 0.6 but display notable disparities beyond 0.8. Our results suggest that developed nations could cut emissions without reducing well-being if social inequalities are addressed.

To support global climate goals, we propose classifying countries by transformation capacity: advanced, moderate, and limited. This classification can guide tailored, binding commitments based on emission-reduction potential. It encourages sustainable development aligned with the Paris Agreement while preventing poorer nations from stagnating. Further work could study whether inequalities and cultural differences hinder such commitments.

(a) LOWESS-fit $\widehat{\mathrm{HDI}}_{i\,y}\,(\beta_n, X_{\mathrm{Cons\,CO_2}})$ for 2019



(b) OLS (fixed-effect)-fit $\widehat{\mathrm{HDI}}_{i\,y}\,(\beta_n, X_{\mathrm{Cons\,CO_2}})$ for year $y \in \{2000, \cdots, 2022\}$

Figure 1. HDI versus consumption-based CO2 *per capita* with LOWESS and OLS regressions on fixed-effect model $R^2 = 0.992$; Adj-$R^2 = 0.991$.

Author contributions

CRediT: **Thomas Porcher:** Conceptualization, Investigation, Methodology, Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing; **Raphaël-Homayoun Boroumand:** Conceptualization, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing; **François Gemenne:** Conceptualization, Investigation, Methodology, Project administration, Supervision, Validation, Writing – original draft, Writing – review & editing; **Antoine Giraldi:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration,

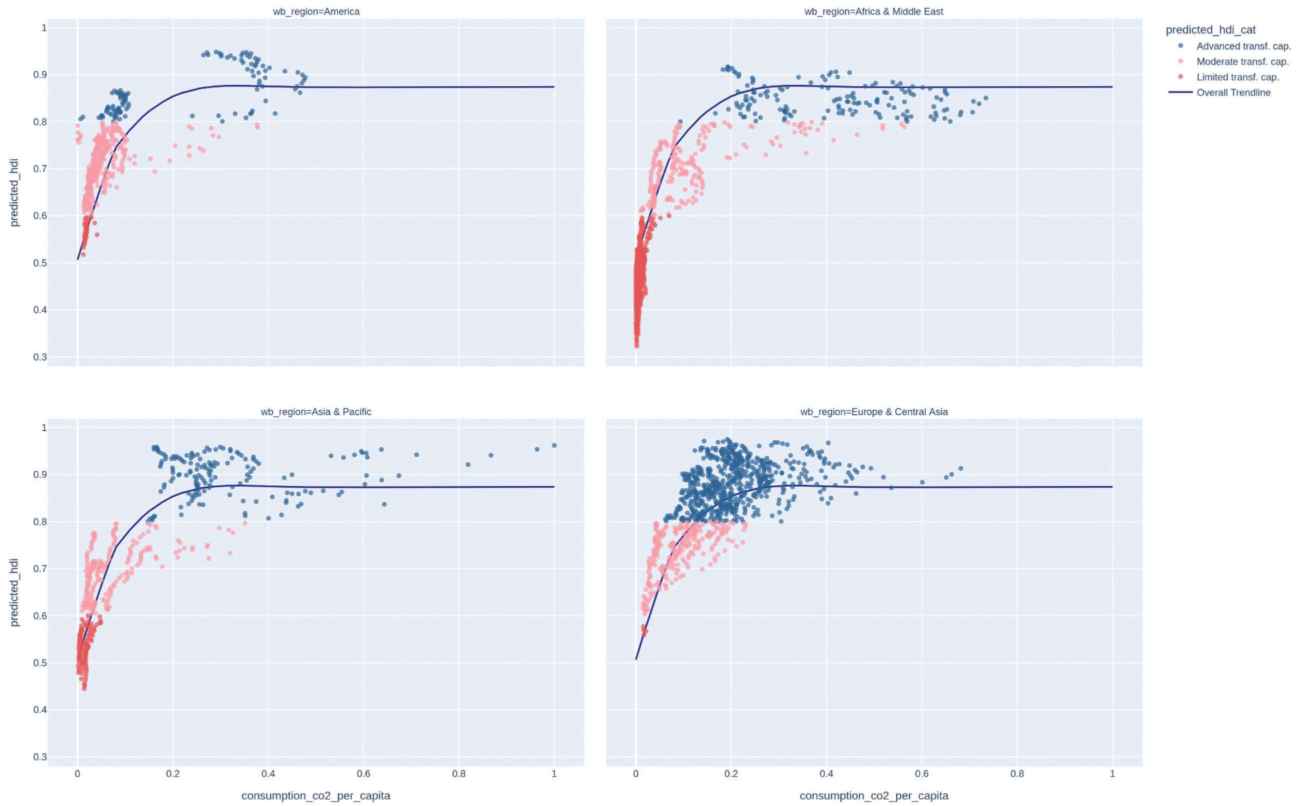


Figure 2. Regional pathway: HDI versus consumption-based CO_2 *per capita* with LOWESS and OLS regressions on fixed-effect model: $R^2 = 0.992$; $Adj - R2 = 0.992$.

Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing; **Simon Porcher:** Conceptualization, Investigation, Methodology, Project administration, Supervision, Validation, Writing – review & editing.

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Appendices

Appendix

As explained in section III, this article merges two datasets: the Human Development Index dataset[3] and Greenhouse Gas Emissions dataset created by Our World in Data[4]

The merged dataset facilitates the study of correlations and developmental links between HDI values and environmental footprints, such as per capita consumption-based CO2 emissions. The latter represents production-based emissions minus emissions embedded in exports, plus emissions embedded in imports. The OWiD dataset serves as a benchmark for the collection of various environmental characteristics, contributing to a comprehensive analysis of global greenhouse gas emissions.

The initial transformation of the HDI dataset involved several key steps to ensure the relevance and usability of the data for subsequent analysis. First, columns related to HDI components - namely, life expectancy at birth, expected years of schooling, average years of schooling, and gross national income per capita - were removed due to their redundancy in this context. The dataset was then filtered to exclude entries corresponding to unidentified countries and non-country entities. The dataset was then transformed from a wide format to a long format through an unpivoting process to allow for more efficient data manipulation and analysis. Finally, a copy of the dataset was created to preserve the original data while allowing for further modification and analysis. This extensive transformation process was essential to prepare the dataset for detailed examination and interpretation.

1. Additional details on the database

The HDI, calculated by the UNDP, compares countries in terms of health, education, and income. The following three indices are used to calculate the HDI: *life expectancy at birth*, which measures the average number of years a newborn can expect to live; *education*, which is measured by the rate of adult literacy rate and the gross enrolment ratio for primary, secondary and tertiary education; *standard of living*, which is measured by gross national income (GNI) per capita, adjusted for purchasing power parity (PPP to compare living standards between countries taking into account differences in the cost of living). The HDI is expressed as a value between 0 and 1, with 0 representing the lowest possible level of human development and 1 representing the highest. It is the geometric mean of three indices: I_{Health}, $I_{\text{Education}}$, and I_{Income}. As explained in the UNDP report[5], HDI classifications are based on fixed HDI cutoff points, which are derived from the quartiles of the distributions of component indicators: the cutoff points are HDI of less than 0.550 for low human development, 0.550–0.699 for medium human development, 0.700–0.799 for high human development, and 0.800 or more for very high human development (see Table A1).

Table A1. New classification with advanced, moderate, and limited transformation capacity.

Classification type	Value
Advanced transformation capacity	$v \geq 0.8$
Moderate transformation capacity	$0.8 > v \geq 0.6$
Limited transformation capacity	$v < 0.6$

The pollution variables are derived from the OWiD dataset, which collects many environmental variables on global greenhouse gas emissions. The following https://github.com/owid/co2-data/tree/master#our-source-data-and-code sources are used to build this database Global Carbon Budget data and emissions embodied in goods and services: Global Carbon Project https://globalcarbonbudget.org/fossil-co2-emissions-at-record-high-in-2023/ – National contributions to climate change https://zenodo.org/records/14054503 (Jones et al. 2024).

The categories allow countries to be classified into three groups, each with a quite different development position within the Champagne curve. This classification depends solely on the HDI, since the consumption-based emissions are different and evolve according to the country and its position on the curve.

The Jupyter notebook and its associated Python code are available upon request.

[3]https://hdr.undp.org/data-center/documentation-and-downloadsUNDP's
[4]https://github.com/owid/co2-dataOWiD.
[5]UNDP report UNDP (2024), HDI classifications are based on fixed HDI

2. Additional details on consumption-based emissions

This metric accounts for the displacement hypothesis, the pollution haven hypothesis, and compositional effects of economic structure. In addition, consumption-based emissions per capita take into account the full life cycle of energy consumption, including emissions from the production and transportation of goods and services.

$$X_{\mathrm{ConsCO_2}} = X_{\mathrm{ProdCO_2}} - X_{\mathrm{ExpoCO_2}} + X_{\mathrm{ImpoCO_2}} \tag{A1}$$

where:

- $X_{\mathrm{Cons\,CO_2}}$: Consumption-based CO_2 emissions per capita.
- $X_{\mathrm{Prod\,CO_2}}$: Production-based CO_2 emissions per capita.
- $X_{\mathrm{Expo\,CO_2}}$: CO_2 emissions embodied in exports per capita.
- $X_{\mathrm{Impo\,CO_2}}$: CO_2 emissions embodied in imports per capita.

In contrast to production-based emissions, consumption-based emissions attribute emissions to the location where goods and services are consumed, rather than produced. If a country's consumption-related emissions exceed its production-related emissions, it is considered a net importer of CO2. Conversely, if the consumption-related emissions are lower than the production-related emissions, the country is considered a net exporter. The data concerning global emissions has been converted from tonnes of carbon to tonnes of carbon dioxide using a conversion factor of 3.664.[6]

Figure A1 shows that most high-income countries (e.g. the USA, Switzerland, and France) have experienced a decline in their consumption-based CO2, while developing countries (e.g. China, India, Costa Rica, and Nigeria respectively) have shown an opposite trend.

3. Additional details on short-listed models

In this study, we conducted an evaluation of two regression models: Spline Regression (SR) and the FE OLS, using data from 119 countries. Table A2 provides a comparison of these models in terms of their methodology, flexibility, and performance metrics.

SR provides greater flexibility by modelling local polynomial relationships within segments, making it highly effective at capturing complex relationships. The FE OLS model accounts for unobserved heterogeneity and is well suited for panel data with fixed effects, providing a global fit while accounting for year and country fixed effects.

We used a continental categorization approach to maintain the reliability of the results within each area and to preserve the same pattern in the regional breakdown statistics. Each country's graph was carefully checked for uniformity to ensure that no points appeared disproportionately emphasized (Figure A1). The continents are delineated as follows: Europe & Central Asia; Asia & Pacific to integrate nations from the World Bank's "East Asia & Pacific" and "South Asia" regions; the Americas to include nations from the World Bank's "Latin America & Caribbean" and "North America" regions; Africa & Middle East to combine nations from the World Bank's "Sub-Saharan Africa" and "Middle East & North Africa" regions.

This reorganization allows for more in-depth analysis by clustering countries based on comparable economic and geographic characteristics. Within each region, the results are consistent, showing the same patterns and trends across different continents. The combination of a high R^2 and a significant F-statistic indicates that the fixed effect model effectively identifies the relationship between HDI and CO2 emissions based on consumption.

In addition, the presence of a high condition number is expected due to multicollinearity, which is typical in fixed effects models with many dummy variables. To address this issue in the present analysis, we have captured the interaction between consumption-based emissions and HDI categories (Table 1), with a lagged HDI value included to account for temporal dynamics. The results are presented in Figure 1 without any scaling, allowing a direct interpretation of the raw data. Conversely, a MinMaxScaler() is used to normalize the features in the regional continental trend analysis. This scaling helps to mitigate multicollinearity and ensures that the trends are comparable across regions, providing a clearer understanding of the regional variations in the relationship between $\widehat{\mathrm{HDI}}$ and $X_{\mathrm{Cons\,CO_2}}$.

In our analysis, a threshold of $p \leq 0.05$ is often used, which means that the data has less than a 5% chance of occurring under the null hypothesis. If the p value is below the selected alpha level, we conclude that the test result is statistically significant.

[6]https://ourworldindata.org/co2-and-greenhouse-gas-emissions.

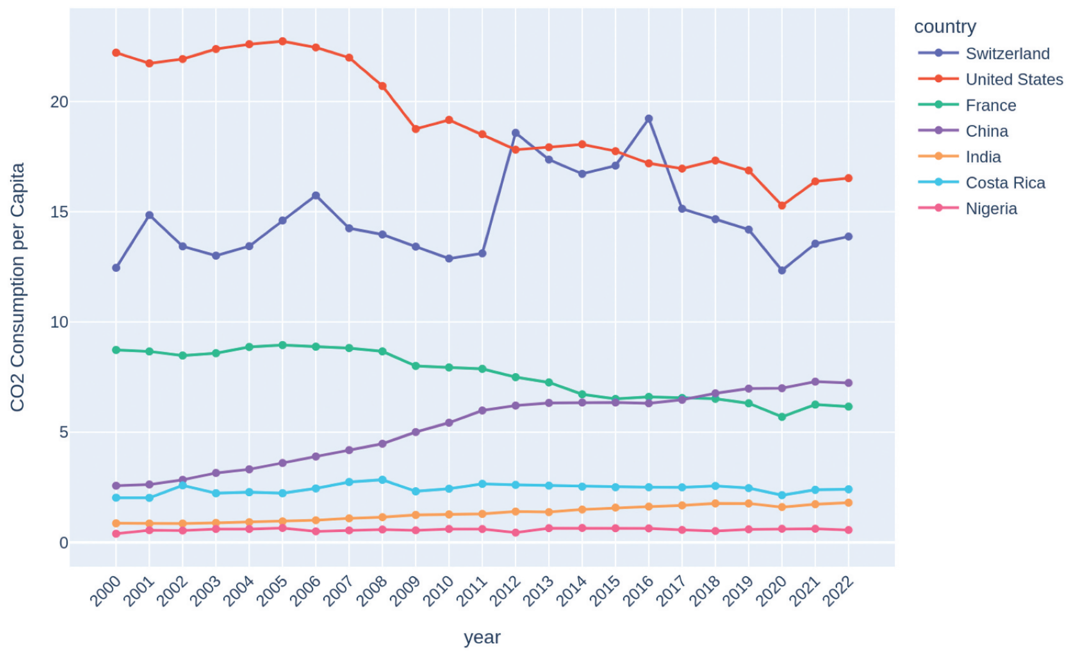

Figure A1. A quick overview at the relevant consumption_co2_per_capita features for 7 countries: Switzerland, United States, France, China, India, Costa Rica, and Nigeria.

Table A2. Comparison of spline regression and fixed-effect models

Spline Regression	Fixed-Effect Model
Methodology Fits piecewise polynomials to different segments of the data.	Incorporates dummy variables to account for fixed effects of years and countries.
Model $\widehat{\mathrm{HDI}}_{iy} = \beta_0 + \sum_{j=1}^{k} \beta_j B_j(X_{\mathrm{Cons\ CO_2},iy}) + \varepsilon_{iy}$	$\widehat{\mathrm{HDI}}_{iy} = \beta_0 + \beta_1 X_{\mathrm{Cons\ CO_2},iy} + \sum_{j=1}^{T-1} \gamma_j D_{yj} + \sum_{k=1}^{N-1} \delta_k C_{ik} + \varepsilon_{iy}$
Parameters $\widehat{\mathrm{HDI}}_{iy}$: The predicted HDI value for country i in year y $X_{\mathrm{Cons\,CO_2}}$ is the independent variable for each country i and year $y \in \{2000, \cdots, 2022\}$ ε_{iy} the error term for country i in year y and β_0 the intercept term:	
• β_j: The coefficients fitted by the Ridge regression. • $B_j(X_{\mathrm{Cons\ CO_2},iy})$ are the basis functions generated by the SplineTransformer used with scikit-learn. For splines, these basis functions are typically piecewise polynomials that are smoothly joined at certain points called knots.	• D_{yj}: dummy variables for each year y_j • C_{ik}: dummy variables for each country i_k • β_1: The coefficient for the independent variable $X_{\mathrm{Cons\ CO_2},iy}$. • γ_j: Coefficients for the year dummy variables. • δ_k: Coefficients for the country dummy variables.
Model performance metrics for 2019 data MSE : 0.00396 RMSE : 0.0629 MAE : 0.0502 R^2 : 0.831	**for 2000, 2022 regional data** p − value : 0.00 R^2 : 0.992 Adj-R^2 : 0.992 F − statistic : 2280