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Assessing the Impact of Income Inequality and Economic Factors on National Carbon Emissions

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Abstract: In this study, we focused on better understanding and modeling economic factors into a nation's carbon emissions. Our analysis highlights this objective in a two-folded manner, centered on how different economic status groups affect a nation's carbon footprint as well as using key economic and demographic characteristics to categorize nations into high, medium, or low carbon emitters. Utilizing the World Inequality Database (WID), we obtained data on income inequality, national wealth, national income, population, and carbon footprints from ten countries worldwide in a 20-year time frame. We successfully developed two generalized models and concluded that the bottom 50% income bracket accounts for the most carbon emissions within a country. Additionally, by analyzing the values of national income, wealth, and population, we derived a model that predicts and categorizes a country's emission level with 93% accuracy. These conclusions can potentially assist countries in understanding their global standing and facilitates policy-making to control carbon emissions.

Keywords: Carbon Footprint, Income Inequality, Economic Factors, Generalized Mixed Models, Environmental Policy

1 Introduction

When one turns on the news and sees natural disasters caused by weather, the next topic most meteorologists will expose viewers to is climate change. This global phenomenon is defined as the shifts within temperatures and weather patterns caused by human activities, which lead to significant climatic events. With more significant climatic events on the rise, an increasing amount of businesses and countries have changed their perspective and level of effort to combat this in the near future. Similarly, many global countries and leaders have stepped forth to show the importance of this matter through initiatives/agreements such as the Paris Agreement/Paris Accords and establishing other global and national environmental targets.

In conjunction with this shift in climate, there is also a pronounced change within the distribution of wealth within countries across the globe. As the world has adopted technological advancements, the number of billionaires within the world have also increased dramatically. In 2021 alone, the world saw 153 new billionaires – an astounding 3 new billionaires per week (1). The creation of this new wealth has only led to an increase in economic disparity within the world. The International Monetary Fund (IMF) discovered that "the current disparities are extreme". The poorest half of the global population owns just €2,900 (in purchasing power parity) per adult, while the top 10 percent owns roughly 190 times as much. Additionally, the IMF concluded that 48 percent of global carbon emissions are caused by the top 10 percent (2).

This study aims to uncover the true relationship between different economic status groups and their respective effects on a nation's carbon footprint. Building on previous research and additional publications highlighting that the wealthiest bracket emits notably more carbon compared to the bottom bracket (3), we examined how income brackets (top 10%, middle 40%, bottom 50%) affect a nation's carbon footprint. Our goal was to provide a more nuanced understanding of these relationships. Furthermore, by analyzing a nation's economic and demographic statistics, we are aimed at developing a model to predict and categorize countries into their appropriate levels of carbon emissions, which in turn forecasts the carbon emission category for other countries based on unseen data.

2 Literature review

Many studies have explored the relationship between economic factors and carbon emissions (4)(5). Mato et al.(6) employed a flexible econometric model using data from 132 countries from 1971 to 2009, finding a non-linear relationship between CO_2 emissions and per capita GDP. Their study, along with the findings of Shuai et al. (7), indicates that income level is a key factor influencing carbon emissions globally. Shuai et al. specifically found that at the global level, income is the most crucial factor affecting carbon emissions, followed by

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technology and population. Moreover, Silva et al. (8) revealed that increasing the share of renewable energy sources in electricity generation would decrease both GDP per capita and CO_2 emissions per capita, highlighting the potential for sustainable economic growth to mitigate emissions. This aligns with findings by Disli et al. (9) and Wang and Li (10), which underscore the significant impact of income on carbon emissions.

Specifically for income inequality, Jorgenson et al. (11) found that higher income shares in the top 10% correlated with increased CO_2 emissions in the United States, attributing this to the political and economic influence of the wealthy. On the contrary, Jiao et al. (12) discovered that rising income inequality in India led to lower carbon emissions, suggesting the need for improved energy supply plans in poorer areas. Wan et al. (13) examined 217 countries, highlighting a complex, non-linear relationship between income inequality and emissions. The disparity in findings is often linked to varying regional and temporal contexts. Additionally, studies like Ghazouani and Beldi (14) used advanced econometric models to demonstrate a non-linear relationship between income inequality and carbon emissions, indicating that the effect may change depending on the level of inequality and other contextual factors.

In addition to economic factors, demographic characteristics play a critical role in carbon emissions. Research has shown that population size, growth, urbanization, aging, and family size significantly affect CO_2 emission levels. Dating back to 1997, Thomas and Eugene (15) assessed the impacts of population, affluence, and technology on national CO_2 emissions. They concluded that the expected population and economic growth in the following decade would likely intensify greenhouse gas emissions. Mutiple research (16)(17) has supported this conclusion, which underscores the importance of considering both economic and demographic factors in strategies aimed at mitigating carbon emissions.

3 Data and methods

3.1 Variable selection

To conduct our study, our dataset was selected from the World Inequality Database (WID), which is one of the most extensive databases on the evolution of world distribution of income and wealth within and between countries. The database is open-access and has compiled valid data from national databases, surveys, fiscal data, and wealth rankings. With its vast array of features, there are many key economic and social inequality questions that could be answered with access to this data. We has decided to focus our statistical analysis on the impact of certain economical features on a nation's carbon footprint.

While the dataset is vast, we narrowed down our analysis to the following key variables that will help us effectively analyze and assess the impact of economic and demographic statistics on carbon emissions for a subset of ten selected countries: the United States, China, India, Germany, the United Kingdom, Canada, Australia, Brazil, Nigeria, and South Africa. These variables include national income, Gross Domestic Product (GDP), national wealth, income inequality, population, and data from the years 2000 to 2020. These countries were selected due to their diverse demographic, geographic, and economic characteristics, which make our analysis more generalizable and representative of common patterns. It is important to note that to help standardize the findings for all countries, the US dollar was the currency selected for the appropriate variables. The income inequality within a nation (as determined by the following income brackets: Top 10% share, Middle 40% share, and Bottom 50% share) measures the national and personal income/savings between different ranges and can be customized based on the percent range.

The detailed descriptions of selected variables and their descriptive analysis are shown in Table 1. There is notable standard deviation for each variable, the range between the maximum and minimum values varies significantly, due to the distinct characteristics of the countries selected. We will address the issue in the following modeling section.

Table 1 Variable descriptive statistics.

Variable	Description	No. of Obs.	Mean	Std. Dev.	Min	Max
National income (USD)	Average National Income per Adult. It measures the total income available to the residents of a given country. It is equivalent to the gross domestic product (GDP), minus fixed capital used in production processes, plus net foreign income earned by residents in the rest of the world. This measure, defined by the United Nations System of National Accounts (SNA 2008), encompasses all domestic sectors, including the private sector, corporate sector, and government sector.	210	35009	21641	4552	76075
GDP (USD)	Average Gross Domestic Product (GDP) per adult. It represents the total value of goods and services produced by the national economy. It includes all domestic sectors, encompassing entities that are residents of a given country, including the private sector, corporate sector, and government sector.	210	40880	25465	5052	89639
National wealth (USD)	Average market-value national wealth for average adults. It includes the total value of assets such as cash, housing, bonds, and equities owned by the national economy, minus its debts. The national economy, in this context, includes all domestic sectors, encompassing all entities that are residents of a given country, whether they belong to the private sector, the corporate sector, or the government sector.	210	176149	123596	18121	438983
Population	It is comprised of the population including individuals of all ages.	210	348433824	477012659	19028802	1406351872
National CO_2 $footprint$ (MtCO_2e)	This measure accounts for the total carbon dioxide emissions produced by a nation, including emissions from various sources such as industry, transportation, and energy production.	210	1761	2420	47	9229
Top 10% share	Refers to the share of national income held by the top 10 percentile group, specifically for adults considered as tax units. Pre-tax national income is the sum of all pre-tax personal income flows accruing to the owners of production factors, such as labor and capital, before accounting for the tax/transfer system but after considering the pension system.	210	0.4544	0.1007	0.3161	0.6654
Middle 40% share	The share of national income held by the middle 50 to 90 percentile group.	210	0.3793	0.0664	0.2588	0.5044
Bottom 50% share	The share of national income held by the bottom 50 percentile group.	210	0.1471	0.0362	0.0527	0.2154

3.2 Data exploration

To begin our analysis, we explored each country's carbon emission as well as the relationship between that response and the other key economic indicators mentioned above. Figure 1 shows the carbon emissions from 2000 to 2020 for every selected country. In the graph to the left, we included all ten countries and realized a disparity in trends between China and USA versus the other eight. Thus, we classify USA and China as high emitters. The graph on the right zooms in on the remaining eight countries, which are classified as medium/low emitters. There is a linear trend for all countries, which allows us to assume linearity for the models we will fit.

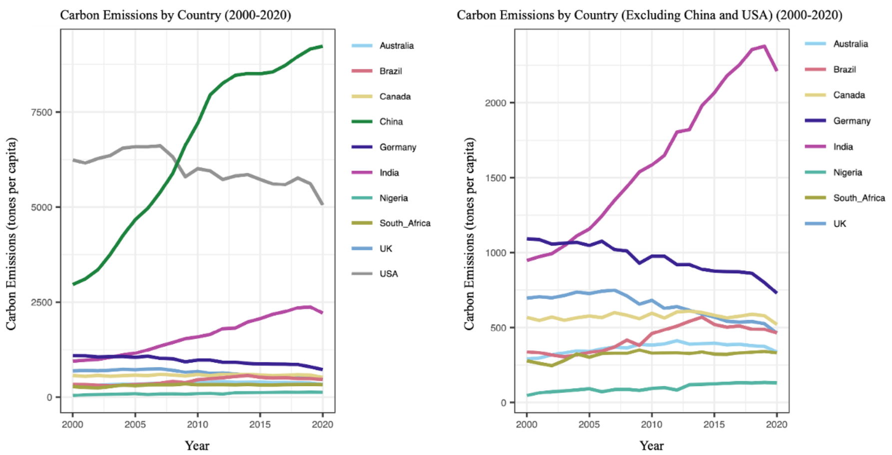

Fig. 1 Trend of national carbon footprint for 10 countries from 2000 to 2020

Upon recognizing the initial linear relationship, we analyzed the distribution and impact of income brackets by fitting a line to the three income brackets against carbon emissions. We observed a clear distinction between the high and medium/low emitters (2. The high emitters, China and USA, rise high above the fit line and the rest either sit on the line or below. This is consistent across the three graphs. According to Xia et al.(18), we classified national carbon footprints greater than 2000 tons as high emitters, between 500 and 2000 tons as medium emitters, and less than 500 tons as low emitters. To correct for the disparity between the high and medium/low emitters, we considered applying a linear transformation on carbon emissions to create a best fit model. Upon examining the medium/low emitters, there is no common direction between carbon emission and income inequality, which led us to account for country-specific factors as a random effect in building a generalized model.

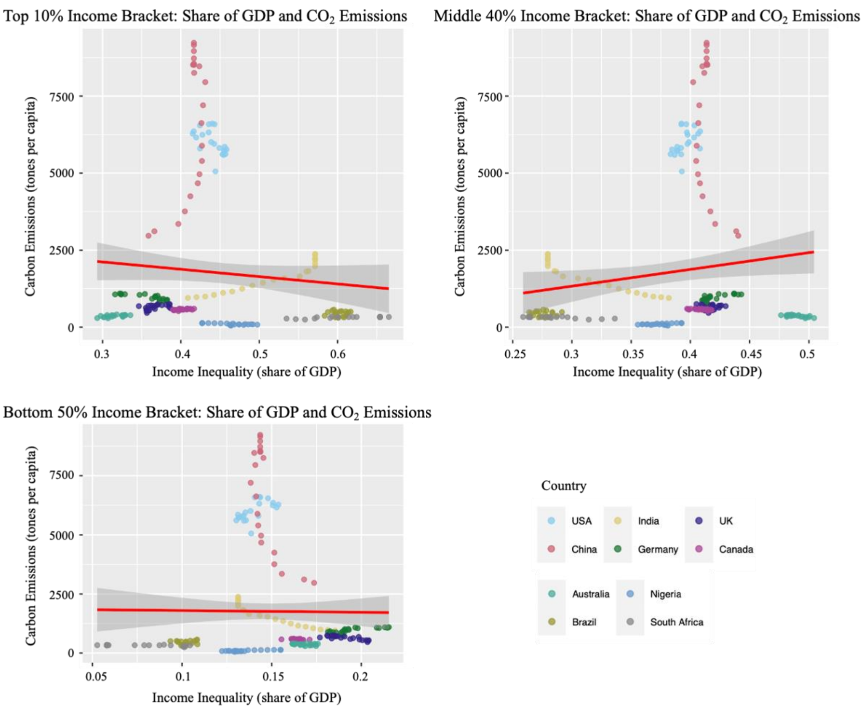

Fig. 2 Impact of Income Inequality on Carbon Emissions Across Various Countries

3.3 Model Assessment

To account for the differences between countries, the best fit models for research is mixed models. Similar to linear regression models, mixed models will enable us to better analyze the carbon emission while estimating the random effect/impact of each country. In addition to taking the impact of country into account, a mixed model will also take into account any correlation that exists within our data. The generalized linear mixed model can be represented through the following framework/model formula:

$$Y = X_i\beta + Z_j u + \epsilon \quad (1)$$

3.3.1 Linear Mixed Model

To understand the relationship between income inequality and national carbon footprint, we opted to use a linear mixed model as compared to a simple linear model. We included country as a random effect to make our model more generalizable since we found each country followed slightly different trends. Additionally, we decided to log transform our outcome variable, carbon emissions, to account for the high variance between high and medium/low emitters, based on insights from the above data exploratory analysis.

In the generalized linear mixed model, the indices i and j represent the number of income brackets (3) and the number of countries (10), respectively. This equates to the following model:

$$Log(CO_2) = \beta_1 Top10\% + \beta_2 Middle40\% + \beta_3 Bottom50\% + (1 \mid Country) \quad (2)$$

For this generalized model, we initially assumed that the similarity amongst the predictors would lead to multicollinearity, since the shares for all three income brackets sum to 1. To resolve this potential multicollinearity issue, we included a negative intercept term, which will offset the intercept brought forth by these income predictors totaling 1 and accounts for the random intercepts of different countries. We confirmed that this approach effectively resolved the multicollinearity issue from the ariance inflation factors (VIFs) being below 5 in Table 2.

Table 2 VIF multicollinearity check for linear mixed model

Top10% share	Middle40% share	Bottom50% share
1.68	3.76	4.88

3.3.2 Cumulative Link Mixed Model

Our objective is to predict national carbon emission levels using various demographic and economic variables. To begin, we plotted the distributions of national income, national wealth, and population across three carbon emission levels: Low, Medium, and High. In each plot, we observed major differences in range and mean among all the three carbon emitter levels. The High carbon emission level consistently shows the largest spread. However, in the graph between carbon emissions level and national population, there is a major difference between low/medium emitters compared to high emitters, which is logical since with more people a country requires more resources and energy to accommodate. Based on this finding, we applied a log transformation to all predictor variables (population, national income, and wealth) to normalize the differences amongst the countries.

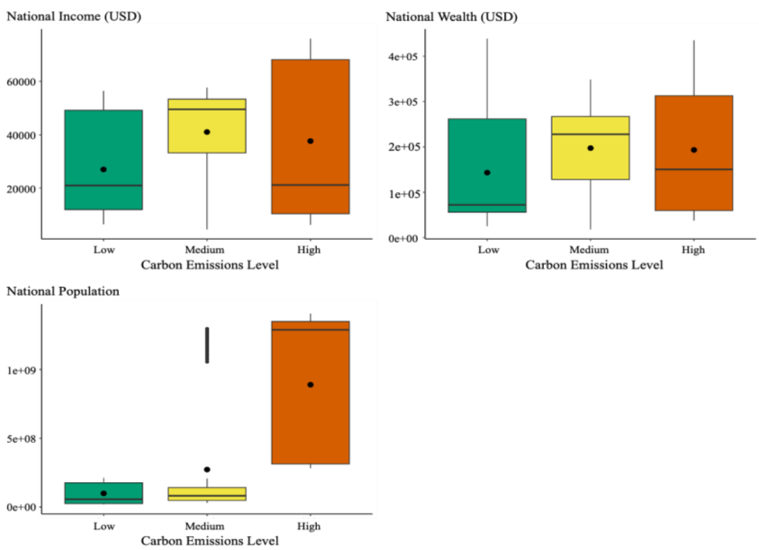

Fig. 3 Comparison of National Income, Wealth, and Population Across Different Carbon Emission Levels

To further refine our analysis, we aimed to predict each country's level of carbon emissions for each year. Since the outcome is ranked low, medium, and high, we chose to fit a cumulative link mixed model to predict the ordinal outcome variable. Similar to the generalized linear mixed model, a cumulative link mixed model enables one to analyze ordinal response variables while still maintaining random effects. As we aim to categorize and rank countries based on their respective carbon emission levels, it is more powerful to maintain order as compared to a multinomial model. To maintain and account for this order, the generalized linear mixed model is tweaked to the following model:

$$Y = \alpha_j - X_i\beta + Z_{t[i]}u_t + \epsilon \quad (3)$$

where α is the intercept/threshold coefficient between the different level comparison combination (i.e. Low|Medium and Medium|High), and the i, j and t represent the number of predictors (income, wealth, population), the number of emission levels (low, medium, high), and the number of countries, respectively. This equates to the following model:

$$P(Y \leq j) = \alpha_j + \beta_1 Log((Income) + \beta_2 Log\ (Wealth) + \beta_3 Log\ (Population) + (1 \mid Country). \quad (4)$$

We then validated our ordinal model by checking the proportional odds assumption using the Brant test, a test/function that calculates parallel regression and assesses proportionality amongst predictors, and found that the model does not violate this assumption with the omnibus and the associated predicted having probabilities equal to or close to 1 (see Table 3). We also checked for multicollinearity (Table 4 and found that all VIF values fell under the threshold.

Table 3 Proportional odds assumption check for cumulative link mixed model

Indicator	X_2	df	probability
Omnibus	0.0002	3	1.00
Log(Income)	0.0001	1	0.99
Log(Wealth)	0.0001	1	0.99
Log(Population)	0.0002	1	0.99

Table 4 VIF multicollinearity check for cumulative link mixed model

Log(Income)	Log(Wealth)	Log(Population)
1.00	1.34	1.40

4 Results and discussion

4.1 Impact of Income Inequality on National Carbon Footprint

Output for linear mixed model is shown in Table 5. With country as our random effect, we tested the fixed effects with a Wald test. The Wald test compares the coefficient's estimated value with the estimated standard error for the coefficient. Our null hypothesis states that the variance between coefficients for the random effect is zero. With a 5% significance level, we found all three predictors to be statistically significant. We can also confirm there is no variance between the coefficients of the three income brackets when inferring their relationship with carbon emissions. Therefore, our resulting model to test the equivalence amongst the income bracket is the following:

$$Log(CO_2) = 8.92 Top10\% + 2.89 Middle40\% + 10.74 Bottom50\% + (1 \mid Country) \quad (5)$$

Table 5 Summary results for linear mixed model

Indicator	Coefficient	P-value
Top10%	8.92***	0.00
Middle40%	2.89**	0.04
Bottom50%	10.74***	0.0001

[1] ***$p < .01$; **$p < .05$; *$p < .1$;
[2] R^2=0.97; Log Likelihood=19.88; AIC=-29.75; BIC=-13.02

The coefficients for the Top 10% share, Middle 40% share, and Bottom 50% share are 8.92, 2.89, and 10.74, respectively, all with highly significant p-values ($p < 0.05$). This indicates that while increases in income share within any of these brackets are strongly associated with increases in carbon emissions, bottom 50% share contributes the most to a country's carbon emissions, which is different from the IMF. This can be explained by several factors. Firstly, this group represents a vast number of individuals, so even if their per capita emissions are relatively low, the cumulative effect is substantial. Additionally, lower-income groups often lack access to energy-efficient technologies and appliances with underdeveloped infrastructure, and it is highly possible that they rely on older, less efficient options that result in higher emissions per unit of energy consumed. They may also be more dependent on fossil fuels for heating, cooking, and transportation, as cleaner alternatives are often less accessible due to higher costs.

The R-squared value is 0.97, suggesting 97% of the variability in CO_2 emissions can be explained, highlighting the robustness of our model fit. Additionally, the inclusion of a random effect for the country addresses country-specific variations, enhancing the model's generalizability. These findings emphasize the critical role of income distribution in national carbon emissions, suggesting that policies aimed at income equity could also influence environmental outcomes.

4.2 Predictive Classification of National Carbon Emission Levels

The cumulative link mixed model estimates the probability of a country being classified as a low/medium/high carbon emitter using log-transformed values of national income, wealth, and population as predictors. From Table 6, all three predictors being statistically significant (p-value<0.01) underscores the strong relationship between these economic and demographic factors and a country's carbon emission levels. Overall, the model demonstrates a good fit with high R-squared values and low root mean squared error (RMSE). The model's marginal R-squared value of 0.790 indicates that 79% of the variability in carbon emission levels can be explained by the fixed effects, i.e. national income, wealth, and population, indicating that these predictors are highly effective in accounting for the variation in emission levels. The conditional R-squared value of 0.995, which includes both fixed effects and random effects (country-specific variations), captures 99.5% of the variability. These high R-squared values, with a low RMSE of 1.17, confirms that the model not only fits well but also generalizes effectively across different countries, accounting for both common patterns and unique country-specific factors in carbon emissions.

$$P(\text{Low} \leq \text{Medium}/\text{Low} > \text{Medium}) = 601.38 + 6.82 Log(\text{Income}) + 12.15 Log(\text{Wealth}) + 21.25 Log(\text{Population}) + Z_{t[i]}u_t + \epsilon \quad (6)$$

Table 6 Summary results for cumulative link mixed model

Indicator	Coefficient	P-value
Intercept	601.379***	0.001
Log(Income)	6.817***	0.002
Log(Wealth)	12.149***	0.002
Log(Population)	21.252***	0.003

[1] ***$p < .01$; **$p < .05$; *$p < .1$;
[2] N=210; AIC=62.4; BIC=82.5
[3] Marginal R^2=0.79; Conditional R^2 = 0.995, RMSE=1.17

Now that we have fitted the model to predict carbon emission levels, we move forward to test its predictive ability. With our specified standards for high (> 2000 tons), medium (500 – 2000 tons), and low (< 500 tons) emitters, there are only two countries in the world that fit the definition of a high emitter: the USA and China. Since we trained our model with both countries, we do not have other countries to test our model's ability to predict high emitters. In fact, we are more concerned about the precision of our model distinguishing between low and medium emitters given the disparity between high and low/medium emitters is so large. Therefore, we selected countries which are similar to our training set in that they are geographically spread out and fall between these two categories.

Table 7 shows the prediction results of our model. The model successfully predicted the emission levels of the test set countries with 93% accuracy. As is shown in the confusion matrix, there is high sensitivity (94%) with the low emitter class, meaning our model correctly classified most low emitters. In comparison, our model correctly classified 85% of countries as medium class carbon emitters. These results affirm the robustness of our model in practical applications.

Table 7 Confusion matrix for cumulative link mixed model

		Predicted	
		Low emitter	Medium emitter
Actual	Low emitter	94	6
	Medium emitter	3	17

5 Conclusion

In this study, we successfully built two strong statistic models to 1) identify the relationship between income inequality and national carbon footprint, and 2) generally predict a country's carbon emission level using demographic and economic information. Both models demonstrated strong performance, achieving high accuracy and good generalizability across different countries.

From the model results, we were able to ultimately refute the conclusion presented by the IMF as we did

not find the top 10% income bracket contributing the most to the level of carbon emissions within a country, but rather the bottom 50%. This can be due to various factors, such as the sheer number of individuals in the bottom 50%, their reliance on less efficient energy sources, and their limited access to cleaner technologies. The predictive model can successfully forecast a country's carbon emission level, making it a potentially valuable tool for policymakers.
Based on the results, we are confident to present several suggestions to policy makers to address carbon emissions effectively:

- **Improve Access to Clean Energy for Low-Income Populations**: Given the significant impact of the bottom 50% income bracket on carbon emissions, policies should focus on improving access to clean and affordable energy solutions for lowincome households. Subsidies or financial incentives for solar panels, energy-efficient appliances, and cleaner cooking technologies can help reduce emissions from this large population segment.

- **Enhance Public Transportation and Infrastructure**: Since larger populations are associated with higher carbon emissions, investing in public transportation and sustainable infrastructure can mitigate this effect. Developing efficient public transit systems, expanding cycling and pedestrian pathways, and promoting carpooling can reduce the carbon footprint of densely populated areas.

- **Support Sustainable Economic Growth**: As wealthier nations tend to have higher emissions, supporting economic growth that prioritizes sustainability is crucial. This includes investing in green technologies, encouraging businesses to adopt sustainable practices, and creating green jobs. Policies that promote sustainable industries can help decouple economic growth from carbon emissions.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

1. Block, F. (2022, March 17). The world's billionaire population tops 3,381, adding 3 each week last year. Barron's. Retrieved November 26, 2022, from https://www.barrons.com/articles/the-worlds-billionaire-population-tops-3-381adding-3-each-week-last-year-01647548271
2. Ritchie, H., and Roser, M. (2023). Global inequalities in CO2 emissions. Our World in Data. (https://ourworldindata.org/inequality-co2?ref=hackernoon.com)
3. Staley, A. (2022). World Inequality Report. The World Inequality Lab. (https://wir2022.wid.world/)
4. Holtz-Eakin, D., and Selden, T. M. (1995). Stoking the fires? CO2 emissions and economic growth. Journal of public economics, 57(1), 85-101. (https://doi.org/10.1016/0047-2727(94)01449-X)
5. Jaunky, V. C. (2011). The CO2 emissions-income nexus: evidence from rich countries. Energy policy, 39(3), 1228-1240. (https://doi.org/10.1016/j.enpol.2010.11.050)
6. Mao, Y. H., Liao, H., Han, Y., and Cao, J. (2016). Impacts of meteorological parameters and emissions on decadal and interannual variations of black carbon in China for 1980–2010. Journal of Geophysical Research: Atmospheres, 121(4), 1822-1843. (https://doi.org/10.1002/2015JD024019)
7. Shuai, C., Chen, X., Shen, L., Jiao, L., Wu, Y., and Tan, Y. (2017). The turning points of carbon Kuznets curve: evidences from panel and time-series data of 164 countries. Journal of cleaner production, 162, 1031-1047. (https://doi.org/10.1016/j.jclepro.2017.06.049)
8. de Oliveira Silva, R., Barioni, L. G., Hall, J. A., Folegatti Matsuura, M., Zanett Albertini, T., Fernandes, F. A., and Moran, D. (2016). Increasing beef production could lower greenhouse gas emissions in Brazil if decoupled from deforestation. Nature Climate Change, 6(5), 493-497. (https://doi.org/10.1038/NCLIMATE2916)
9. Disli, M., Ng, A., and Askari, H. (2016). Culture, income, and CO2 emission. Renewable and Sustainable Energy Reviews, 62, 418-428. (https://doi.org/10.1016/j.rser.2016.04.053)
10. Li, S., Wang, S., Wu, Q., Zhang, Y., Ouyang, D., Zheng, H., and Hao, J. (2023). Emission trends of air pollutants and CO 2 in China from 2005 to 2021. Earth System Science Data, 15(6), 2279-2294. (https://doi.org/10.5194/essd-15-2279-2023)
11. Jorgenson, A., Schor, J., and Huang, X. (2017). Income inequality and carbon emissions in the United States: a state-level analysis, 1997–2012. Ecological Economics, 134, 40-48.(https://doi.org/10.1016/j.ecolecon.2016.12.016)
12. Jiao, Z., Sharma, R., Kautish, P., and Hussain, H. I. (2021). Unveiling the asymmetric impact of exports, oil prices, technological innovations, and income inequality on carbon emissions in India. Resources Policy, 74, 102408. (https://doi.org/10.1016/j.resourpol.2021.102408)
13. Wan, G., Wang, C., Wang, J., and Zhang, X. (2022). The income inequality-CO2 emissions nexus: Transmission mechanisms. Ecological Economics, 195, 107360. (https://doi.org/10.1016/j.ecolecon.2022.107360)
14. Ghazouani, T., and Beldi, L. (2022). The impact of income inequality on carbon emissions in Asian countries: Non-parametric panel data analysis. Environmental Modeling and Assessment, 27(3), 441-459. (https://doi.org/10.1007/s10666-021-09811-4)
15. Dietz, T., and Rosa, E. A. (1997). Effects of population and affluence on CO2 emissions. Proceedings of the National Academy of Sciences, 94(1), 175-179. (https://doi.org/10.1073/pnas.94.1.175)
16. Cole, M. A., and Neumayer, E. (2004). Examining the impact of demographic factors on air pollution. Population and Environment, 26(1), 5-21. (https://www.jstor.org/stable/27500022)

17. Lonngren, K. E., and Bai, E. W. (2008). On the global warming problem due to carbon dioxide. Energy Policy, 36(4), 1567-1568. (https://doi.org/10.1016/j.enpol.2007.12.019)
18. Xia, Lijuan, Yongli Li, and Xiaochen Ma. Identification of key carbon emitters from the perspective of network analysis. Ecological Indicators 150 (2023): 110284. (https://doi.org/10.1016/j.ecolind.2023.110284)