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CO_2 EMISSIONS AND ITS EFFECT ON ECONOMIC GROWTH

Master Thesis

by
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MSc in Finance
Supervised by Tong Zhang

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ABSTRACT

This thesis examines the economic impact of fossil fuel dependency, measured by CO_2 emissions per capita, and analyzes it during different periods ranging from 1800 to 2018. We begin with a univariate model and add time lags to the model to create autoregressive models to investigate the impact over time. We use a Vector Autoregressive (VAR) model to analyze the relationship between CO_2 emissions per capita and GDP per capita over time and include contemporary terms for further analysis. Our main goal is to determine whether CO_2 emissions per capita drive GDP per capita or if the relationship is the opposite. Our analysis reveals a conditional cointegration between these two variables. We also investigate this relationship in the context of countries that participated in the Industrial Revolution and explore how it evolved after the implementation of climate change policies in 1970. Our findings indicate a robust association between CO_2 emissions per capita and GDP per capita, with CO_2 emissions per capita significantly Granger causing GDP per capita in consecutive years conditionally. To ensure the reliability of our results, we conduct additional robustness tests. Overall, this study sheds light on the intricate relationship between CO_2 emissions per capita and economic growth per capita, providing insights into the potential consequences of fossil fuel dependency on national economies.

Acknowledgements

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We extend our heartfelt appreciation to our supervisor, Tong Zhang, whose guidance, expertise, and continuous support have been invaluable throughout this thesis.

Contents

List of Abbreviations

UN	United Nations
GDP	Gross Domestic Product
CO2	Carbon Dioxide
HDI	Human Development Index
OWID	Our World in Data
OLS	Ordinary Least Squares
VAR	Vector Auto-Regressive
ADF	Augmented Dickey-Fuller
KPSS	Kwiatkowski-Phillips-Schmidt-Shin
GDPpcap	GDP per Capita
CO2pcap	CO2 per Capita
Pcap	Per capita
Log	Logarithm
OPEC	Organization of the Petroleum Exporting Countries
CO2 -> GDP (or) C -> G	Changes in Carbon Dioxide emissions per capita granger causing changes in Gross Domestic Product per capita
GDP -> CO2 (or) G -> C	Changes in Gross Domestic Product per capita granger causing changes in Carbon Dioxide emissions per capita
Forward Relation	Changes in CO2 emissions per capita granger-causing changes in GDP per capita
Inverse (or) Reverse Relation	Changes in GDP per capita granger-causing changes in CO2 emissions per capita

List of Figures

List of Tables

List of Symbols

β	*Parameter of intercept and/or coefficient in a regression*
γ	*Parameter of coefficient in a regression*
δ	*Parameter of coefficient in a regression*
Δ	*Difference operator to show change in variable across time*
u	*Residuals or Residuals in a regression*
i	*Country "i"*
t	*Year "t"*
D_i	*Dummy variable for country "i"*
B_t	*Dummy variable for time "t"*

1. Introduction and Motivation

1.1. Climate Change Responsibility

Climate change is an urgent and pressing global issue that requires immediate attention and collective action. The scientific consensus is clear: human activities, particularly the burning of fossil fuels and deforestation, are releasing greenhouse gases into the atmosphere, leading to a rise in global temperatures. This increase in temperature has far-reaching consequences, including rising sea levels, extreme weather events, loss of biodiversity, and disruptions to ecosystems and food production. To mitigate the impacts of climate change and ensure a sustainable future for generations to come, it is crucial for individuals, communities, businesses, and governments to take proactive measures. This includes transitioning to renewable energy sources, adopting sustainable practices, promoting green technologies, implementing robust policies, and fostering international cooperation to reduce greenhouse gas emissions and adapt to the changing climate. Time is of the essence, and only through concerted efforts can we hope to mitigate the worst effects of climate change and create a more resilient and sustainable planet for future generations.

The environmental impact of developing countries' growing reliance on fossil fuels has raised concerns among many nations. The US declared to leave the Paris Agreement in June 2017. In the press conference, President Trump explains why, pointing at China and India.[1] However, it is important to acknowledge that developed nations, due to their historical emissions dating back to the industrial revolution, have significantly contributed to net CO2 emissions. These countries had fewer or no regulations on fossil fuel usage during that time, while their current emissions are comparatively lower than

[1] "As someone who cares deeply about the environment, which I do, I cannot in good conscience support a deal that punishes the United States — which is what it does -- the world's leader in environmental protection, while imposing no meaningful obligations on the world's leading polluters. For example, under the agreement, China will be able to increase these emissions by a staggering number of years — 13. They can do whatever they want for 13 years. Not us. India makes its participation contingent on receiving billions and billions and billions of dollars in foreign aid from developed countries. There are many other examples. But the bottom line is that the Paris Accord is very unfair, at the highest level, to the United States." (*Statement by President Trump on the Paris Climate Accord – The White House*, 2017).

those of many developing countries, both in terms of total emissions and per capita.

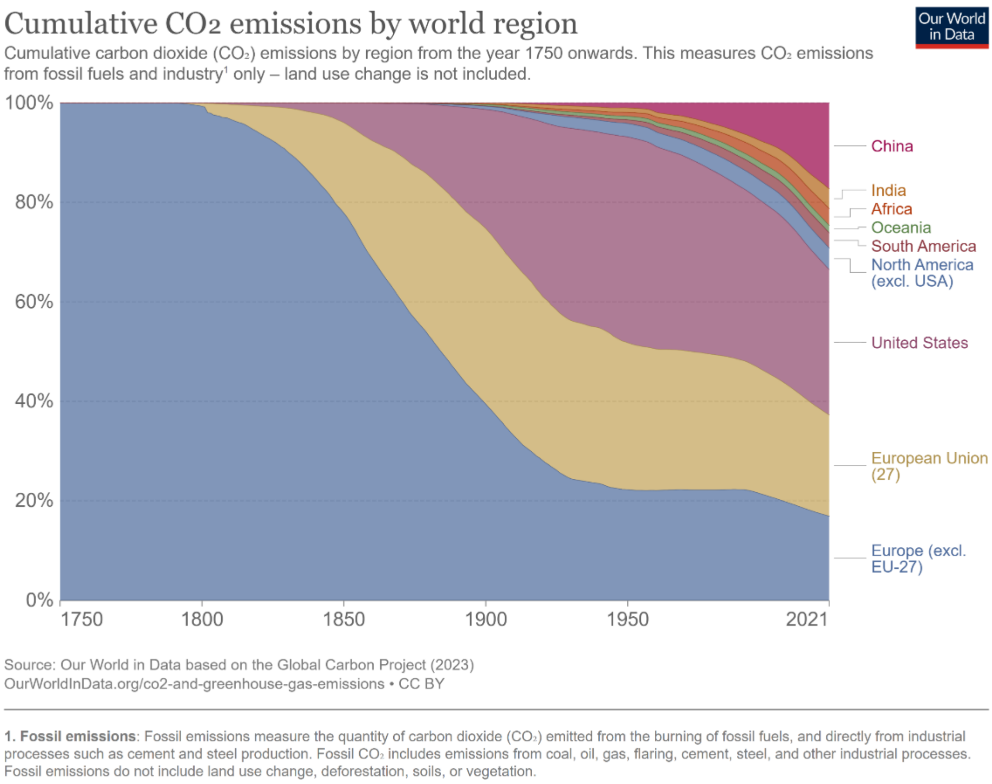

Figure 1-1 Cumulative share of CO2 emission by world region

Source: OWID CO2 data (*ESSD - Global Carbon Budget 2022*, 2022)

Europe was responsible for emitting over half of the historical CO2 emissions until 1950, with the United Kingdom being the primary contributor during that time. Remarkably, the data reveals that prior to 1882, the UK alone accounted for more than half of the world's cumulative emissions. Subsequently, industrialization in the United States propelled its contribution to CO2 emissions over the following century. In the past 50 years, the growth in South America, Asia, and Africa has significantly increased the share of total emissions from these regions.

While the transition to cleaner alternatives presents many challenges for developing and underdeveloped nations, it is worth noting that developed countries, having already reaped significant benefits from their dependence on fossil fuels, may find the transition to be comparatively less costly. These countries (colonial and post – colonial) have accumulated resources and technological advancements that can facilitate a smoother shift away from fossil fuels. They are the first countries to have made a significant impact on reducing emissions and leading the movement for emission reduction which has now caught traction for the world to adopt these principles. However, it is important to ensure that the burden of transitioning to cleaner alternatives is appropriately distributed among nations, considering their respective levels of development. Placing equal pressure on all countries may exacerbate existing inequalities and impede the progress of developing nations towards sustainable development. Therefore, developed countries should take on a greater share of the burden, while developing countries should bear a moderate burden, and underdeveloped countries should be supported with a lesser burden, to ensure a fair and equitable transition. Fair and equitable support, both in terms of financial resources and technological assistance, should be provided to help these countries overcome the challenges they face in pursuing a sustainable energy transition.

Renewable energy sources, such as solar, wind, hydroelectric, and geothermal power, hold immense potential in driving the transition away from fossil fuels. These clean and sustainable alternatives offer numerous advantages, including reduced greenhouse gas emissions, improved air quality, and decreased dependence on finite resources. Furthermore, renewable energy technologies continue to advance, becoming more efficient and cost-effective over time. Investing in renewable energy not only helps mitigate the environmental impact of energy generation but also presents opportunities for job creation, economic growth, and energy security. By harnessing the power of renewables on a global scale, we can accelerate the shift away from fossil fuels and move towards a more sustainable and resilient energy future. Increased dependence on renewable energy not only allows reducing the emissions but also allows countries to invest in reducing the CO2 accumulated in the atmosphere since the dawn of industrial revolution.

The cumulative emissions of CO2 throughout history reveal a complex relationship between population size, individual contributions, and overall impact. The United States stands out as a significant contributor, accounting for 422 billion metric tons of CO2, roughly a quarter of the world's cumulative emissions. This figure is twice as much as that of China, which holds the title of the world's second-largest national contributor.

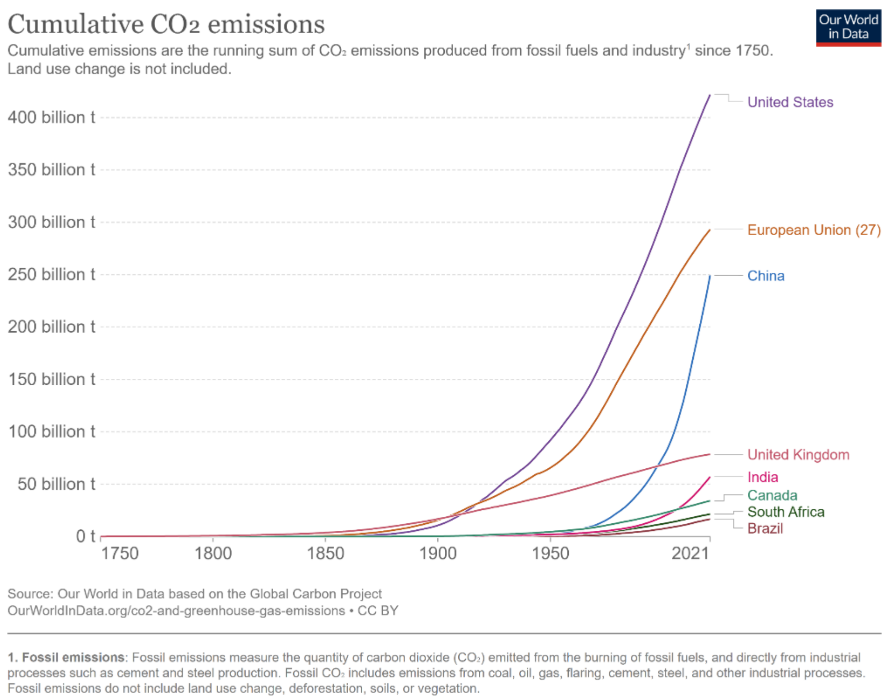

Figure 1-2 Cumulative CO2 emissions by world region

Source: OWID CO2 data (*ESSD - Global Carbon Budget 2022*, 2022)

However, it is important to consider the impact of population size when analyzing these numbers. Notably, countries such as China, India, Brazil, and Indonesia, which are among the top contributors to cumulative emissions, also have large populations. As a result, their per capita emissions are comparatively smaller. Together, these four countries represent 42% of the global population but contribute only 23% of cumulative emissions from 1850 to 2021. In contrast, the remaining countries in the top 10, including the United States, Russia, Germany, the UK, Japan, and Canada, account for only 10% of the world's population but contribute 39% of cumulative emissions. This discrepancy highlights the need to consider both total emissions and per capita emissions when assessing the responsibility and impact of different nations in the context of climate change. It underscores the importance of a comprehensive and equitable approach to addressing emissions, considering factors such as historical contributions, current emissions, population size, and future sustainability goals.

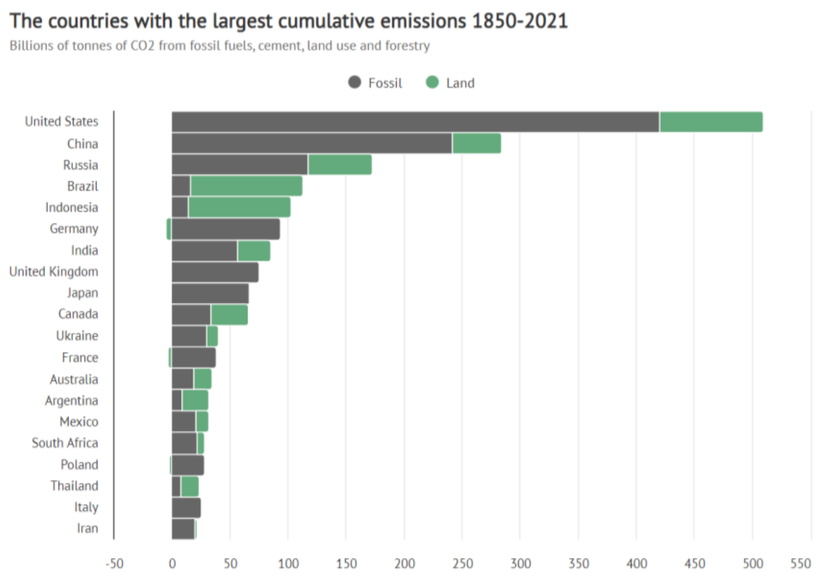

Figure 1-3 Cumulative emissions including change in land usage

The 20 largest contributors to cumulative CO2 emissions 1850-2021, billions of tonnes, broken down into subtotals from fossil fuels and cement (grey) as well as land use and forestry (green). For example, while United States contributes 420 GtCO2 due to fossil fuels and cement, an additional 89.1 GtCO2 originates from deforestation and conversion to agricultural land.

Source: Carbon Brief analysis of figures from the Global Carbon Project, CDIAC, Our World in Data, Carbon Monitor, Houghton and Nassikas (2017) and Hansis et al (2015). Chart by Carbon Brief.

Another recurring point in climate justice discussions revolves around the notion that certain countries have managed to lower their domestic territorial emissions while still heavily depending on high-carbon goods imported from abroad. This perspective emphasizes the importance of considering consumption-based emissions, which attribute full responsibility to the countries utilizing products and services that rely on fossil fuels. This approach tends to reduce the emissions burden for major exporters like China.

However, implementing consumption-based emissions accounting faces practical challenges, primarily due to the need for detailed trade data. Consequently, such accounts are only available for the years since 1990, despite international trade in carbon-intensive goods being a part of modern history. Gathering accurate and comprehensive information on the carbon footprint associated with global trade remains a complex task, hindering a complete understanding of the true emissions impact resulting from consumption patterns. However, from offsetting exports and imports data for each country, there is evidence that trade emissions account for negligible percentage points against native CO2 emissions.

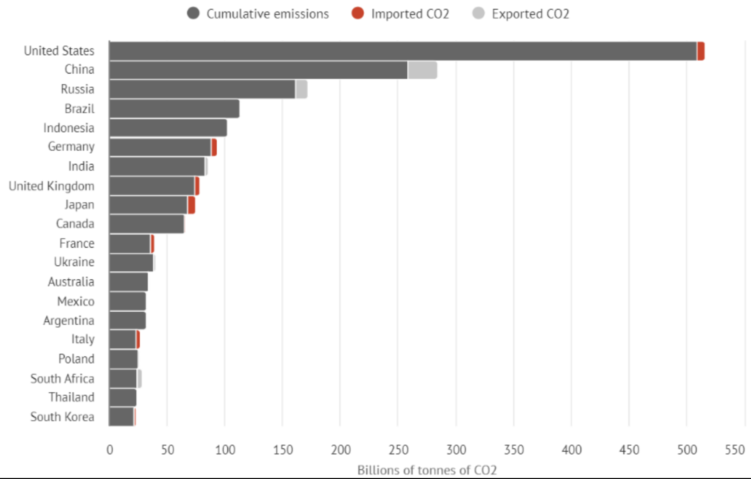

Figure 1-4 Cumulative emissions including traded CO2

The 20 largest contributors to cumulative consumption-based CO2 emissions 1850-2021, billions of tonnes. Grey bars show emissions on a territorial basis with exported CO2 shown in light grey and imports shown in red.

For example, United States' cumulative consumption emissions (grey) stand at 509 GtCO2 while the net imports (red) stand at 7.4 GtCO2. This increase changes the share of United States by +0.3 percentage points.
China's cumulative consumption emissions stand at 258.1 GtCO2 while the net exports stand at 26.3 GtCO2. This reduces China's share by 1.1 percentage points.

Source: Carbon Brief analysis of figures from the Global Carbon Project, CDIAC, Our World in Data, Carbon Monitor, Houghton and Nassikas (2017) and Hansis et al (2015). Chart by Carbon Brief.

The current focus on present-day environmental issues often overlooks the historical context of emissions.[2] The current policies and regulations aimed at addressing climate change have not made significant progress, which is concerning considering the serious and urgent threat it poses to all life on Earth. The distribution of environmental burdens among nations is currently far from optimal or efficient. Developed countries argue that they bear a disproportionate share of the responsibility for reducing CO2 emissions, while developing countries emphasize the significant disparity in historical

[2] "When aggregated in terms of income, we see in the visualization that the richest half (high and upper-middle income countries) emit 86 percent of global CO2 emissions. The bottom half (low and lower-middle income) only 14%." (Ritchie et al., 2020)

emissions. This disparity often leads to debates and challenges in finding common ground.[3] Additionally, similar trend in observed in underdeveloped and a few developing countries during the period 1970-2018. Ranking by CO2 emissions per capita can be found in Appendix D.

When examining the responsibility for climate change in terms of contributing to the mean surface temperature increase, it becomes apparent that a small number of top contributors have played a significant role.[4] In our analysis, we find that developed countries have benefitted from high dependence on fossil fuels (as a proxy using CO2 emissions per capita) for higher economic growth during the period 1800-1970. With the global mean surface temperature rise at 1.61°C, the top six contributors alone account for nearly 1°C of this increase. This observation highlights the disproportionate impact that a few countries or entities have had on driving the rise in global temperatures.

These findings underscore the importance of addressing the contributions of major emitters in mitigating climate change. While collective efforts are required to combat global warming, it is crucial to recognize the responsibility of these top contributors and encourage their active participation in reducing greenhouse gas emissions.

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[3] "But although all countries agree on this goal in principle, they do not agree who is responsible and who should bear the heaviest load. Almost all countries agree on this principle can be seen when looking at the Paris Climate Agreement. By now, all countries besides the US have signed it so far". (Kurzgesagt – In a Nutshell, 2020)

[4] "Exceeding the 1.5°C global warming target would lead to the poorest experiencing the greatest local climate changes." (King & Harrington, 2018).

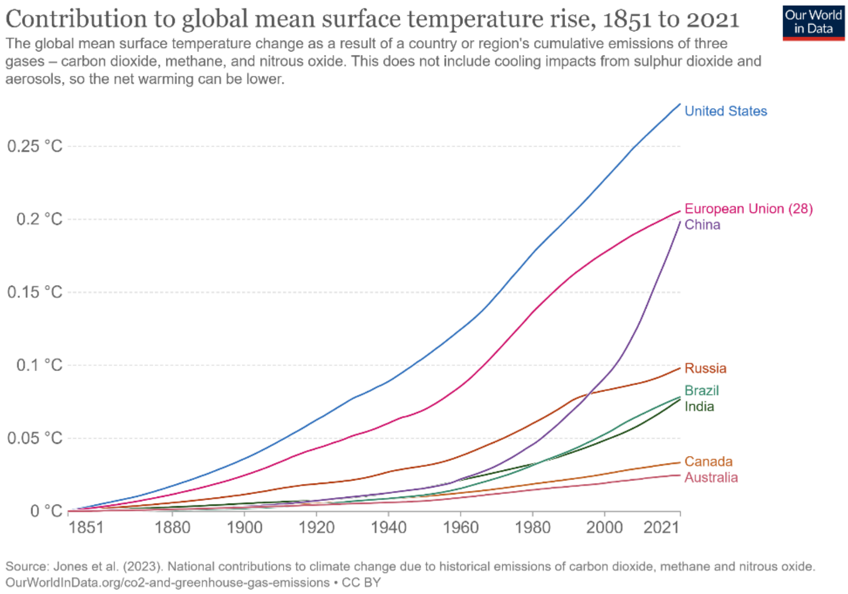

Figure 1-5 This figure shows the share of responsibility in the surface temperature rise

The total temperature change as of 2021 for the world is 1.61°C. The share of the top contributors is below:

Country	Share of temperature rise
United States	0.28 °C
European Union (28)	0.21°C
China	0.20 °C
Russia	0.10 °C
Brazil	0.08 °C
India	0.08 °C

In our thesis, we find evidence that changes in economic growth (proxied by GDP per capita) have strong correlation with changes in fossil fuel dependency (as proxied by CO2 emissions pe capita) and the lagged fossil fuel dependency for developed countries through 1800-1970 (historic period). This correlation does not hold in the period 1970-2018 which can be interpreted as these countries moving away from fossil fuel dependency (changes in GDP per capita are no longer explained by changes in CO2 emissions). In addition to this, we find a strong correlation between economic growth and fossil fuel dependence (along with its lagged variables) for low and lower-middle income countries in the period 1970-2018. We interpret this as underdeveloped countries benefitting from fossil fuel dependency in the newer period. However, in the robustness tests that we employ, we find that this relation does not hold for any country in any period beyond one lag for first differences analysis in the variables (ΔX, $\Delta \log X$; for variable X)

We emphasize that the low and lower-middle income countries must be allowed to depend on fossil fuels to transition toward cleaner fuels once sufficient economic development is experienced for these countries. The findings of our study bring attention to the pressing issue of poorer countries shouldering the burden of climate change. Not only do they bear the costs resulting from climate change itself, but they also face additional financial burdens due to higher carbon taxation. Our research adds to this perspective that it is crucial to not penalize developing and underdeveloped nations for their current emissions, as they often require support and assistance to overcome economic challenges and promote sustainable development. The complete results for the above analyses can be viewed in Appendix C.

From our complete analysis which includes the above three tables as well as further granger-causality tests and robustness tests, we find evidence that an increase in CO2 emissions per capita might granger-cause increase in GDP per capita. This relation is more prominent in the developmental stages of countries.

2. Review of Literature

During the past two decades, there has been an increasing interest in analyzing growth policies in relation to climate change, global warming, and the greenhouse effect. The economic literature on the relationship between CO2 emissions and economic growth has grown substantially. However, the number of studies specifically examining this relationship in a two period time series, Pre-Climate Change Action Era and Post-Climate Change Action Era, is relatively limited. Despite extensive research on climate change and global warming, only a few studies have focused on investigating the difference between developing and developed countries regarding the relation of economic growth and CO2 emissions.

The energy growth paradox is often studied in terms of its impact on the environment, with some studies suggesting that energy contributes positively to economic growth ((Shahbaz et al., 2013); (Azam et al., 2016); (Baz et al., 2021); (Magazzino et al., 2021); (Zhang et al., 2021)), while others demonstrate a negative impact (Garcia et al., 2020).

In discussions surrounding the pursuit of "sustainable growth" toward reducing CO2 emissions, most papers have focused on analyzing the relationship between economic growth and CO2 emissions. Azam (Azam et al., 2016) examined the relationship between CO2 emissions and economic growth in selected countries with higher CO2 emissions, and found a positive association for China, Japan, and the USA. Other studies have also explored the relationship at the country level, such as Yousefi-Sahzabi (Yousefi-Sahzabi et al., 2011) for Iran, Pablo (Bouznit & Pablo-Romero, 2016) for Algeria, Lešáková (Lešáková, 2018) for the Czech Republic, and Magazzino (Magazzino, 2015) found that real gross domestic product (GDP) influences both energy use and CO2 emissions in Israel.

A review of the literature reveals that few studies have examined the major factors influencing CO2 emissions or analyzed instruments for reducing emissions while promoting economic growth. Recent studies, however, confirm the existence of a global relationship between economic growth and carbon dioxide emissions (Fávero et al., 2022). Martínez (Martínez-Zarzoso & Bengochea-Morancho, 2004) explored the relationship between economic growth and CO2 emissions in ten European Union countries from 1981 to 1995, finding significant differences in emissions control strategies among EU countries. Ozturk (Acaravcı & Ozturk, 2010) employed autoregressive distributed lag (ARDL) bounds testing to examine the causal relationship between CO2 emissions, energy consumption, and economic development in nineteen European countries, identifying a causal relationship in only seven of them. Bilan (Bilan et al., 2019) analyzed the implications of renewable energy sources and CO2 emissions on GDP, confirming a relationship between these variables. Halicioglu (Halicioglu, 2009), also found a close relationship between economic growth, energy consumption, and increased CO2 emissions.

In terms of instruments to reduce greenhouse gas emissions, Seker (Dogan & Seker, 2016) highlights the potential for reducing environmental pollution by increasing the share of renewable energy. (Breed et al., 2021) emphasize the effectiveness of fuel economy regulation in reducing CO2 emissions, particularly in the transportation sector, which accounts for a significant portion of energy-related greenhouse gas emissions. At the global level, Jiang & Guan (Jiang & Guan, 2016) analyzed the determinants of CO2 emission growth and identified coal use and growth in final demands as major contributors to CO2 emissions worldwide.

3. Methodology and Theory

We analyze and understand the causal relationship between CO2 dependence and GDP growth. Our objective is to find evidence suggesting that developing countries may experience positive economic growth as a result of increased reliance on fossil fuels.

3.1. Primary variables for analysis

GDP and CO2 emissions have been recorded since the early 1800s, coinciding with the onset of the Industrial Revolution. Some economic variables even have data dating back to the 1750s. Our objective is to identify trends in various economic variables, such as Energy per GDP, CO2 per GDP, coal and oil usage, renewable energy production and consumption, CO2 trade emissions, and the share of emissions, among other secondary variables. To categorize countries throughout the thesis, we utilize the Human Development Index (HDI), which considers not only GDP but also factors such as corruption, safety and security, and access to electricity. All the data mentioned above is sourced from OWID, which provides a comprehensive structure for existing economic and functional data. As we conduct tests, we seek to understand the results and determine whether it is prudent to draw conclusions from them.

We are mainly interested in two time periods divided by the year 1970: 1800 to 1970 and 1970 to 2018. The year 1970 plays an important role in our analysis for the reason:

a) CO2 emissions per capita peak occurs in the period 1960 – 1980 for developed countries.

b) CO2 emission of oil per capita peak occurs in the period 1960 – 1980 for developed countries.

c) Energy per GDP peak occurs in 1960 – 1980 for developed countries.

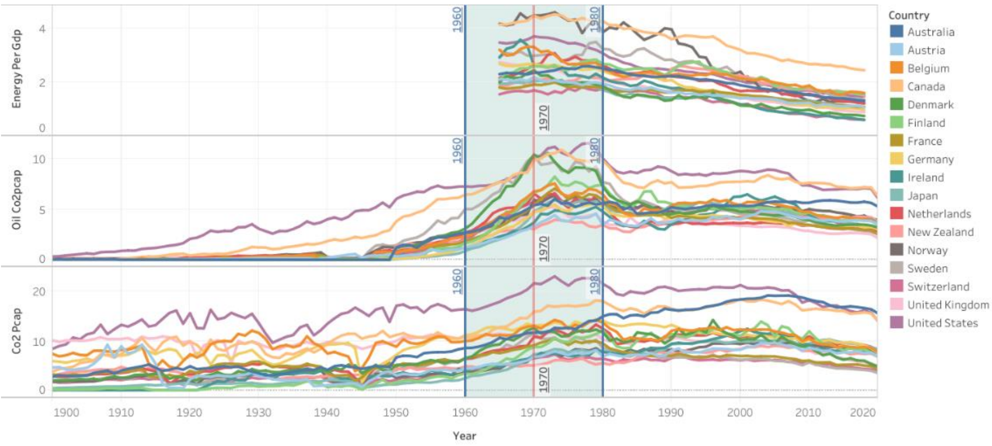

Figure 3-1 Selection of year for sub-sample analysis
This figure depicts the time frame where the following peaks occur:

a) CO2 emissions per capita peak for developed countries.
b) CO2 emission of oil per capita peak for developed countries.
c) Energy per GDP peak for developed countries.

Data source: OWID CO2 emissions dataset. Created using Tableau public.

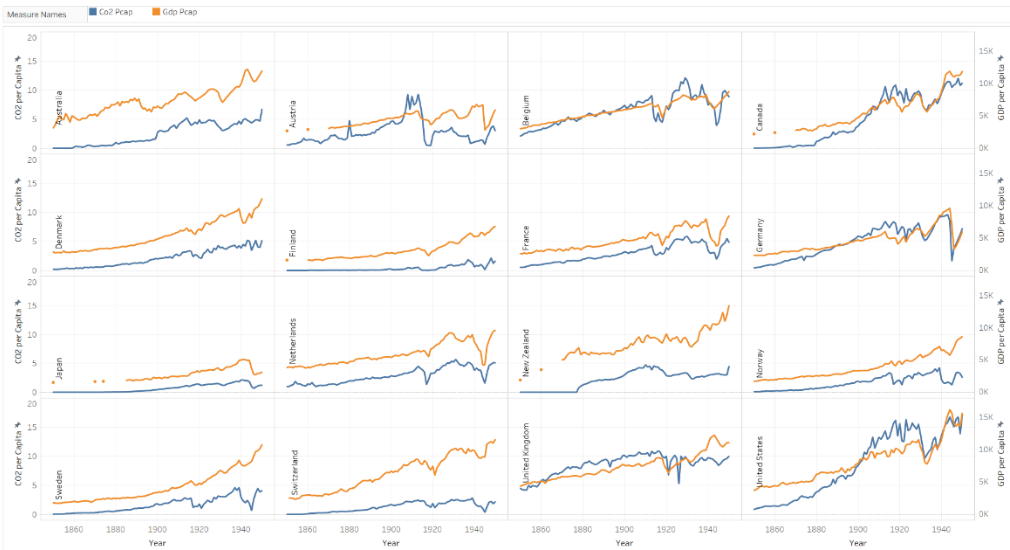

Figure 3-2 CO2 per capita and GDP per capita trends in developed countries

This figure depicts the GDP per capita (Orange) and CO2 per capita (Blue) of 12 developed countries in the period 1850 to 1950.

Data source: OWID CO2 emissions dataset. Created using Tableau public.

3.2. Previous studies and basis for further analysis

Numerous studies attempt to explain GDP using various economic variables, including inflation, industry growth (manufacturing, services, etc.), firm profitability, stock market performance, and currency performance (Samiyu, 2021) and (Chaudhary & Mishra, 2021). However, our focus lies in investigating whether CO2 emissions adequately account for GDP variations.

3.3. Panel Regressions

We conduct panel regression for over 100 countries, with GDP as the dependent variable and CO2 as the independent variable for each country and year. Subsequently, we test the residuals for any discernible trends and diagnose the regression for endogeneity. Additional tests encompass time trend analysis using ADF and KPSS tests, assessing the normality of residuals, examining autocorrelation in both dependent and independent variables, and conducting cointegration tests.

We estimate using the following panel regression:

$$GDP_{i,t} = \beta_0 + \beta_1 CO2_{i,t} + CountryFixedEffects + TimeFixedEffects + u_{i,t} \qquad \textit{Eq. 3.3-1}$$

Alternatively represented in econometric and statistical terms:

$$GDP_{i,t} = \beta_0 + \beta_1 CO2_{i,t} + \gamma_2 D2_i + \cdots + \gamma_n DT_i + \gamma_2 B2_t + \cdots + \delta_T BT_t + u_{i,t} \qquad \textit{Eq. 3.3-2}$$

Where:

GDP is the Gross Domestic Product of country *"i"* and year *"t"* in USD.

CO2 is the Carbon dioxide emission of country *"i"* and year *"t"* in million tons.

DT_i is the dummy variable capturing country fixed effects for country *"i"*.

BT_t is the dummy variable capturing time fixed effects for year *"t"*.

$u_{i,t}$ is the residual in process of estimation.

i represents each country *"i"*.

t represents each year *"t"*.

Considering that GDP and CO2 exhibit exponential growth and that population increase often leads to an increase in both variables, we scale the GDP and CO2 figures to make them more interpretable. Consequently, we refer to them as GDP per capita (GDPpcap) and CO2 per capita (CO2pcap), respectively. Our panel regression model includes GDPpcap as the dependent variable explained by CO2pcap for each country and year. We also subject the residuals and variables themselves to testing.

In panel regressions, our objective is to determine the statistical significance of CO2pcap in explaining GDPpcap. Simultaneously, we strive to ensure that the Residuals in the regression models do not exhibit any discernible trends. By assessing the statistical significance of CO2pcap, we can evaluate its impact on GDPpcap and draw conclusions about their relationship.

We modify Eq. 3.3-1 with the above characteristics as follows:

$$GDPpcap_{i,t} = \beta_0 + \beta_1 CO2pcap_{i,t} + CountryFixedEffects + TimeFixedEffects + u_{i,t} \qquad \textit{Eq. 3.3-3}$$

A modified version of *Eq. 3.3-3* as a univariate regression is as follows:

$$GDPpcap_{i,t} = \beta_0 + \beta_1 CO2pcap_{i,t} + u_{i,t} \qquad \textit{Eq. 3.3-4}$$

3.4. Further Scaling

To account for the characteristics of the variable, we have adjusted our variables through appropriate scaling techniques. In this case, we have applied a logarithmic transformation to the GDPpcap variable, creating a new variable called log_GDPpcap. This transformation helps address specific characteristics of the GDPpcap variable and allows for a more suitable representation in our analysis.

We modify Eq. 3.3-3 as follows:

$$\begin{aligned} log\ GDPpcap_{i,t} &= \beta_0 + \beta_1 CO2pcap_{i,t} \\ &+ CountryFixedEffects \\ &+ TimeFixedEffects + u_{i,t} \end{aligned} \qquad \textit{Eq. 3.4-1}$$

However, we utilize this scaling solely for the purpose of conducting additional robustness tests to further explore the obtained results.

3.5. Time-trend and Cointegration

For individual countries, we employ Vector Auto-Regressive (VAR) tests to identify contemporary and lagged dependencies among the variables. We stress test the models using different subsamples and time periods to ensure we select the appropriate number of lags. The selection of lags is primarily guided by the Schwarz-Bayesian information criterion (SBIC), but we also conduct stress tests using all available information criteria. In addition, we conduct stationarity tests (ADF and KPSS) to assess the level of cointegration between variables, including residuals from the analysis, to test stationarity (or the lack of it). We further include two subsample periods, namely, 1800 to 1970 (pre-climate action era) and 1971 to 2018 (climate change action era), to examine any shifts in the significance of independent variables in the model.

By utilizing VAR tests, our objective is to determine the time lags at which CO2pcap emissions have an impact on GDPpcap and assess whether GDPpcap exhibits auto-regressive characteristics. These tests allow us to examine the time related dynamics between CO2pcap emissions and GDPpcap over time.

We aim to identify the specific VAR models (optimal lags) in which changes in CO2pcap emissions affect GDPpcap (and vice-versa) and whether GDPpcap's or CO2pcap's past values play a role in influencing its current values. Understanding these relationships provides valuable insights into the long-term impact of CO2pcap emissions on GDP and the self-reinforcing nature of GDP fluctuations.

The VAR model takes the following structures:

$$GDPpcap_{i,t} = \beta_{10} + \beta_{11} GDPpcap_{i,t-1} + \cdots + \beta_{1p} GDPpcap_{i,t-p} + \gamma_{11}\, CO2pcap_{i,t-1} + \cdots + \gamma_{1p} CO2pcap_{i,t-1} + u_{1t} \qquad \textit{Eq. 3.5-1}$$

$$\mathrm{CO2}pcap_{i,t} = \beta_{20} + \beta_{21} GDPpcap_{i,t-1} + \cdots + \beta_{2p} GDPpcap_{i,t-p} + \gamma_{21}\, CO2pcap_{i,t-1} + \cdots + \gamma_{21} CO2pcap_{i,t-1} + u_{2t} \qquad \textit{Eq. 3.5-2}$$

These equations with 1 lag (e.g.) take the following structure:

$$GDPpcap_{i,t} = \beta_{10} + \beta_{12} GDPpcap_{i,t-1} + \gamma_{11}\, CO2pcap_{i,t-1} + u_{1i,t} \qquad \textit{Eq. 3.5-3}$$

$$CO2pcap_{i,t} = \beta_{10} + \beta_{11} CO2pcap_{i,t-1} + \gamma_{11} GDPpcap_{i,t-1} + u_{2i,t} \qquad \textit{Eq. 3.5-4}$$

3.6. Granger-Causality tests

To identify any shifts in the significance of independent variables, we conduct Granger causality tests for each country individually and analyze each period separately. This analysis aims to detect any changes in causal relationships. Furthermore, we examine the Residuals for time trends and other deviations from statistical assumptions. By analyzing the Residuals, we can assess whether there are any systematic patterns or trends that violate the underlying assumptions of the regression model. These evaluations help ensure the reliability of our findings. By conducting Granger-causality tests, our aim is to identify any significant changes in the relationship between CO2 per capita and GDP per capita, specifically examining the influence of CO2pcap on GDPpcap and vice versa.

We seek to answer the question:

"Does an increase in CO2 per capita in previous years lead to an increase in GDP per capita in subsequent years?"

Additionally, we perform the reverse test to analyze whether an increase in GDP per capita in previous years leads to a subsequent increase in CO2 per capita.

We are interested in the contemporary terms as well, and so, we create a model. The model which includes 1 lag (e.g.) as well as the contemporary terms takes the following structure:

$$GDPpcap_{i,t} = \beta_{10} + \beta_{11}GDPpcap_{i,t-1} + \gamma_{11}\,CO2pcap_{i,t} + \gamma_{12}\,CO2pcap_{i,t-1} + u_{1i,t} \qquad \textit{Eq. 3.6-1}$$

$$CO2pcap_{i,t} = \beta_{10} + \beta_{11}CO2pcap_{i,t-1} + \gamma_{11}\,GDPpcap_{i,t} + \gamma_{12}GDPpcap_{i,t-1} + u_{2i,t} \qquad \textit{Eq. 3.6-2}$$

3.7. Human Development Index (HDI)

In our data, we use HDI as an additional filter to categorize countries to better understand economic development. The Human Development Index (HDI) was established to emphasize that the assessment of a country's development should focus on the well-being of its people and their capabilities, rather than solely relying on economic growth as a measure of progress.[5] HDI serves as a composite index developed by the United Nations to evaluate the social and economic development of countries worldwide. The HDI considers three key indicators of human development: life expectancy, education, and per capita income. (Roser, 2014)

[5] The HDI is calculated as the geometric mean (equally-weighted) of life expectancy, education, and GNI per capita, as:
HDI = $(I_{\text{HEALTH}} + I_{\text{EDUCATION}} + I_{\text{INCOME}})^{1/3}$. (Roser, 2014)

While analyzing the relationship between CO2 emissions and GDP growth, we consider three categories of countries based on their HDI scores: High HDI, High Variance HDI, and Low HDI. It is important to note that the assessment of development is based on the average HDI scores over a specific period, recognizing that some countries, like Singapore, may have been considered developing for the majority of the past five decades despite being considered developed by today's standards. By incorporating a multidimensional perspective of development, the HDI perspective provides a more comprehensive understanding of a country's progress beyond GDP alone.

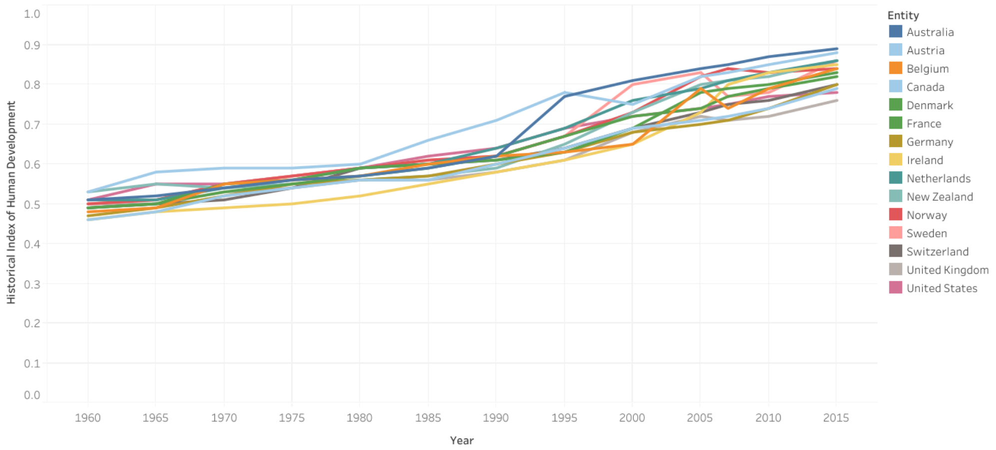

Figure 3-3 High HDI country list (15)

This figure shows the countries with the highest cumulative HDI score. These countries are proxied for developed countries (along with the consus

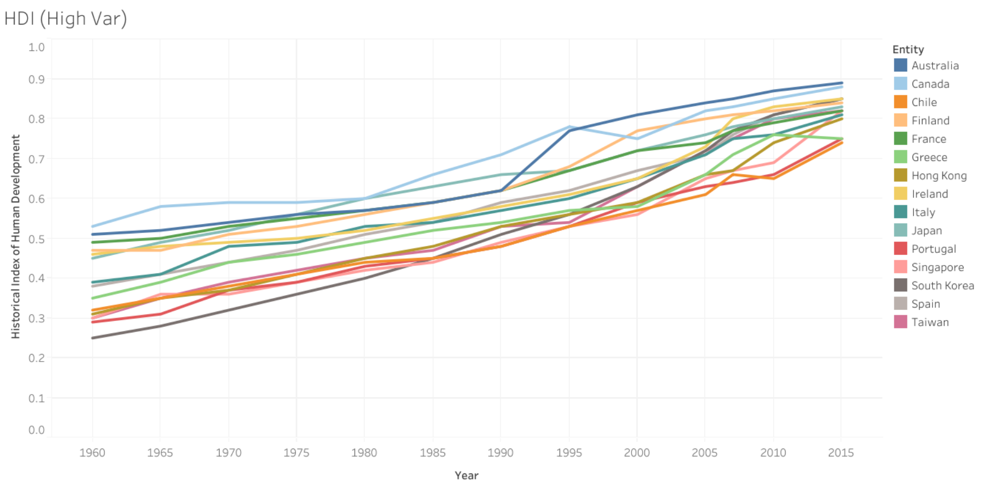

Figure 3-4 High HDI variance country list (15)

This figure shows the countries with the highest variance in HDI score in the full sample time-length. The countries included have the fasted change from low HDI to high HDI. These countries are proxied for developing countries.

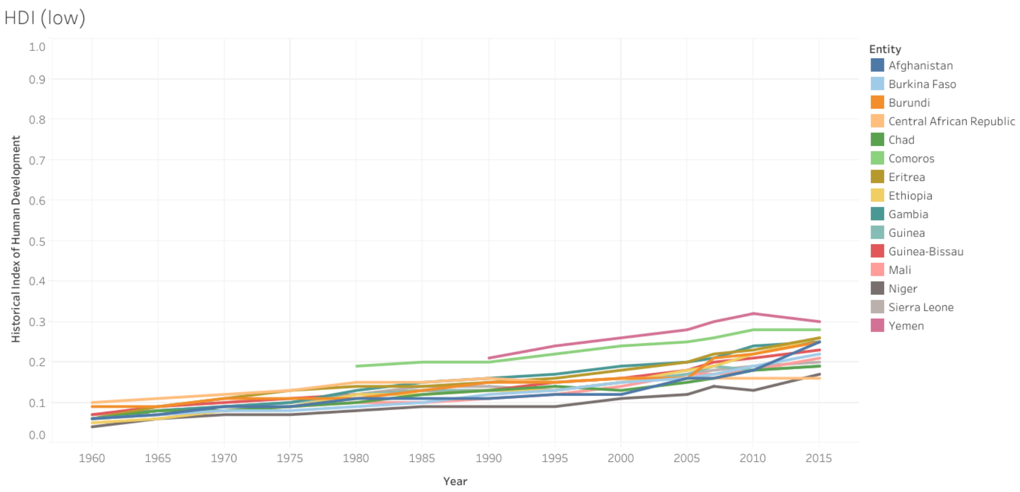

Figure 3-5 Low HDI country list (15)

This figure shows the countries with the low cumulative HDI score. These countries are proxied for underdeveloped countries

3.8. Economic Interpretations

Through this analysis within the periods 1800-1970 and 1971-2018, we aim to gain insights into the following areas:

1) The impact of reliance on coal and oil during the industrial revolution on countries within the 1800-1970 period.
2) Whether developed countries experienced a positive effect during their own stages of development.
3) The potential positive effect experienced by developing countries in their current developmental phase.
4) Any discernable trends within specific subcategories, including:
    a. Organization of the Petroleum Exporting Countries (OPEC+).
    b. Highly developed countries.
    c. Fastest developing countries.
    d. Least developed countries
    e. Island nations

In addition to finding the relation between economic growth and pollution, we would also like to examine whether there are different results based on the country's stage of development. To do so, we use the Human Development Index (HDI) to assess the countries falling into the categories; developed, developing and underdeveloped country along with United Nation's list of categories of countries depending on their income levels.[6]

We aim to uncover significant patterns and understand the causal relationships between CO2 emissions and GDP growth across different periods and categories.

3.9. Additional tests

Throughout this thesis, we systematically employ panel regressions, VAR, and Granger-Causality models to thoroughly examine the impact of all previously defined variables. Our objective is to eliminate potential bias towards any one scaling method and extensively assess the variations in outcomes when utilizing different variables. The primary purpose of these tests is to ascertain robustness and consistency in our analyses, ensuring the reliability of the findings presented in this thesis.

For the final model in Eq. 3.6-1, we employ additional tests to make sure the results can be interpreted without bias. We perform Augmented Dickey-Fuller (ADF) test as described by (Cheung & Lai, 1995) where we test the null hypothesis of an existence of a Unit Root in the variables we use or the residuals in the regression models we employ. We perform Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test as described by (Shin & Schmidt, 1992) where we now test the null hypothesis of an existence of Unit Root in the variables we use or the residuals in the regression models that we may employ. A rejection of the ADF test and a non-rejection of the KPSS test allows us to view the variables or residuals as stationary.

[6] This is based on the model developed and maintained by United Nations. This can be viewed in OWID website as well. (UNDP (United Nations Development Programme), 2022).

4. Data

4.1. OWID Data

We primarily source our data from Our World in Data (OWID) on CO2 emissions, with the Global Carbon Project being its major source. We obtain nearly 30 different variables, including CO2, GDP, Coal CO2, Oil CO2, and many others. Each variable corresponds to a 2-dimensional data with country and year as the dimensions. Initially, we extract the data from Git sources using any programming language (in our case, we used R for data retrieval).

Next, we clean the data using filters, such as a specific set of countries (we used a list of 110 countries) to include only country data, excluding continental, OPEC+, income-categorized, and other additional data that falls outside the scope of our research. The 5 main variables for our analyses are Country, Year, CO2 emissions, GDP, and Population. The remaining variables are used solely to gain additional insights and for running robustness tests, but not in our primary analyses.

We construct additional variables using the 5 main variables as follows:

- GDP per capita (GDPpcap)

$$GDPpcap_{i,t} = \frac{GDP_{i,t}}{population_{i,t}} \qquad \textit{Eq. 4.1-1}$$

where GDP is the Gross Domestic Product calculated in USD. GDP per capita is measured in USD per capita.

- CO2 per capita (CO2pcap)

$$CO2pcap_{i,t} = \frac{CO2_{i,t}}{population_{i,t}} \qquad \textit{Eq. 4.1-2}$$

where CO2 represents the total Carbon Dioxide in million tons. We multiply by 1M to standardize it to Kg CO2 per person.

- Log GDPpcap

$$\log GDPpcap_{i,t} = \ln[GDPpcap_{i,t}] \qquad \textit{Eq. 4.1-3}$$

- Log CO2pcap

$$\log CO2pcap_{i,t} = \ln[CO2pcap_{i,t}] \qquad \textit{Eq. 4.1-4}$$

The logarithmic variables are only used in robustness tests for our data, considering that GDP per capita and CO2 per capita exhibit exponential behavior in certain time periods.

We define two time periods:

1. The Pre-Climate Change Action Era encompasses the time period from 1800 to 1970. This era predates significant actions taken to address climate change.
2. The Climate Change Action Era spans from 1971 to 2018, during which various efforts were made to combat climate change and its impacts.

4.2. Human Development Index

We obtain the Human Development Index data from OWID dataset. This data sources back to United Nations Human Development Index calculations which are the basis for our analysis. We have used data visualization software Tableau which allows visualizing HDI index and placing the filter on GDP and CO2 emission measures (among others).

4.3. Additional Filters

For our analysis, we exclude the years 2018 to 2023 due to specific features of the data, including missingness, abrupt changes, and other characteristics that may affect the reliability of the findings. In our robustness analyses, we apply an additional filter to exclude data where CO2 emissions for certain countries are zero. This is necessary because when CO2 per capita emissions are zero, applying a logarithm function is not applicable.

Similarly, when analyzing the use of coal and oil, it is important to note that certain countries, such as Singapore, may not rely solely on coal during certain time periods. Therefore, we take into consideration the specific characteristics of each country and exclude data where the dependency on coal or oil is not significant or where alternative energy sources are dominant. This ensures that our analysis accurately reflects the trends and patterns related to coal and oil usage.

5. Results and analysis

5.1. CO2 and GDP

We analyze the results through the proposed model in Eq. 3.3-1. An excerpt of the result briefly describes the full summary.

	Gdp
Predictors	*Estimates*
(Intercept)	729286.77 ***
co2	2581.02 ***
t cat [1821]	-82727.54
t cat [1822]	-83729.13
…	…
t cat [1899]	-736389.73 ***
t cat [1900]	-723741.47 ***
t cat [1901]	-763069.90 ***
t cat [1902]	-766287.59 ***
…	…
c cat [Israel]	-982.00
c cat [Italy]	216340.68 **
c cat [Jamaica]	-18034.72
c cat [Japan]	271985.10 **
…	…
c cat [Yemen]	8250.02
c cat [Zambia]	-7675.91
Observations	13461
R^2 / R^2 adjusted	0.937 / 0.935
* $p<0.05$ ** $p<0.01$ *** $p<0.001$	

Table 5.1-1 Summary of Basic Regression Results.

This table briefly summarizes the regression result from Eq. 3.3-1 where we follow the general regression model “GDP ~ CO2 + Country fixed effect + Time fixed effects”.

GDP is scaled by a factor of 1,000,000 USD

Based on this regression model, we find that CO2 does not explain GDP. This outcome was rather expected due to the exponential nature exhibited by both GDP and CO2. Furthermore, CO2 trends can be contradictory in different time periods, and the periods of GDP and CO2 growth vary among different country categories. These trends can be viewed in the following panel images.

5.2. CO2 per capita and GDP per capita

We analyze the results through the proposed model in Eq. 3.3-3. An excerpt of the result is as shown:

	gdppcap
Predictors	*Estimates*
(Intercept)	-16753.10 ***
co2pcap	136.69 ***
t cat [1821]	-2926.58
t cat [1822]	-2927.58
…	…
t cat [1957]	13117.17 ***
t cat [1958]	13306.79 ***
t cat [1959]	13566.01 ***
t cat [1960]	13667.07 ***
…	…
c cat [Honduras]	1524.2
c cat [Hong Kong]	20108.79 ***
c cat [Hungary]	10755.56 ***
c cat [Iceland]	22069.97 ***
c cat [India]	6979.14 ***
c cat [Indonesia]	7620.86 ***
…	…
c cat [Yemen]	1641.45
c cat [Zambia]	380.24
c cat [Zimbabwe]	343.21
Observations	13461

R2 / R2 adjusted	0.735 / 0.728
** p<0.05 ** p<0.01 *** p<0.001*	

Table 5.2-1 Summary of Regression Results.
This table briefly summarizes the regression result from *Eq. 3.3-3* where we follow the general regression model "GDPpcap ~ CO2pcap + Country fixed effect + Time fixed effects".

Based on the results of our regression model, we find that CO2 per capita exhibits a high explanatory power when predicting GDP per capita for individual countries. Additionally, we observe that the significance of the year (factor) coefficients is relatively low in the period prior to 1920. However, the country (factor) coefficients tend to be highly significant for most countries. For a detailed view of the complete results, please refer to the provided link.

We further analyze the contemporary relation between CO2 per capita and GDP per capita using the univariate model for each country individually to test the Residuals for time trend.

	1800 - 1970		**Residuals**	**1971 - 2018**		**Residuals**
Country	**ADF**	**KPSS**	**Stationarity**	**ADF**	**KPSS**	**Stationarity**
Algeria	H1	H0	stationary	H0	H1	non-stationary
Angola	H1	H0	stationary	H1	H1	non-stationary
Argentina	H1	H1	non-stationary	H1	H1	non-stationary
Australia	H1	H1	non-stationary	H0	H1	non-stationary
Austria	H0	H1	non-stationary	H0	H1	non-stationary
…	…	…	…	…	…	…
Turkey	H1	H0	stationary	H1	H0	stationary
Ukraine	NA	NA	non-stationary	H0	H1	non-stationary
United Arab Emirates	NA	NA	non-stationary	H0	H1	non-stationary
United Kingdom	H0	H1	non-stationary	H0	H1	non-stationary
United States	H0	H1	non-stationary	H0	H1	non-stationary
Uruguay	H1	H0	stationary	H0	H1	non-stationary
Uzbekistan	NA	NA	non-stationary	H0	H1	non-stationary
Vietnam	H0	H0	non-stationary	H1	H1	non-stationary
Zambia	H1	H1	non-stationary	H0	H1	non-stationary
Zimbabwe	H0	H1	non-stationary	H1	H0	Stationary

Table 5.2-2 ADF and KPSS tests for univariate model for all countries

This table presents the stationarity tests conducted on the residuals of the univariate model structured in *Eq. 3.3-4*. The ADF test is used to assess the null hypothesis that there is a unit root, while the alternate hypothesis suggests the absence of a unit root. On the other hand, the KPSS test examines the null hypothesis of no unit root, with the alternate hypothesis indicating the presence of a unit root. Here we represent "Reject H0" or rejection of null hypothesis as H1 and "Do not reject H0" or non-rejection of null hypothesis as H0.

We find tchat the residuals exhibit a time-trend in the univariate model with contemporary terms. For this reason, we cannot interpret the coefficients in the model.

5.3. Addition of lagged GDP per capita and CO2 per capita

We analyze the explanatory power of the model with modification which allows usage of lagged terms up to a maximum of 5 lags as entailed by Eq. 3.6-1 and Eq. 3.6-2. An excerpt of the result is given below:

	1800 - 1970			**1971 - 2018**		
All Countries	**CO2 -> GDP**	**GDP -> CO2**	**Lags**	**CO2 -> GDP**	**GDP -> CO2**	**Lags**
Algeria	0.7639	0.0095	5	0.7266	0.0204	2
Angola	0.1339	0.0056	5	0.2163	0.0058	2
Argentina	0.4716	0.0022	1	0.5756	0.1441	1
Australia	0.0366	0.0837	1	0.0105	0.0871	1
Austria	0.8336	0.2552	1	0.0539	0.5852	1
Azerbaijan	NA	NA	NA	0.0908	0.1654	2
Bahrain	0.2257	0.0772	5	0.7021	0.9731	2
Bangladesh	0.4530	0.0748	1	0.0004	0.5382	1
Belarus	NA	NA	NA	0.0140	0.3324	2
Belgium	0.0068	0.0013	1	0.7845	0.0623	1
Benin	0.1102	0.7464	3	0.0957	0.0959	1
Bolivia	0.3411	0.0466	1	0.4416	0.2195	2
…	…	…	…	…	…	…
Taiwan	0.0641	0.0021	1	0.2340	0.3441	1
Tanzania	0.2301	0.0026	1	0.0716	0.0013	2
Thailand	0.9147	0.0005	1	0.0149	0.0601	1
Trinidad and	0.9713	0.2340	1	0.3144	0.0147	2

Tobago						
Tunisia	0.2708	0.0259	5	0.6344	0.0199	1
Turkey	0.0104	0.3010	1	0.1129	0.1198	1
Ukraine	NA	NA	NA	0.2223	0.1948	2
United Arab Emirates	0.0001	0.0205	3	0.5068	0.8236	2
United Kingdom	0.0013	0.1715	2	0.3023	0.2849	2
United States	0.2381	0.0109	2	0.1887	0.0518	1
Uruguay	0.8989	0.0027	1	0.7612	0.0006	2
Uzbekistan	NA	NA	NA	0.0000	0.9206	1
Vietnam	0.0869	0.0515	5	0.3488	0.0013	1
Zambia	0.9476	0.2071	5	0.0005	0.0060	1
Zimbabwe	0.1358	0.2446	5	0.0388	0.3901	1

Table 5.3-1 Final p-value of Multivariate Regression of CO2 per capita, GDP per capita and lagged variables

In this table, the significance of the findings is indicated using a color scheme. We used shades of green to represent the level of significance.

p-value 0-0.001
p-value 0.001-0.01
p-value 0.01-0.05
p-value 0.05-0.1

This table summarizes the two-sided causality tests (Granger Causality tests):
1) CO2 per capita granger causing GDP per capita given by CO2 -> GDP.
2) GDP per capita granger causing CO2 per capita given by GDP -> CO2.
With the respective p-values from the test and the lags chosen by SBIC for each country divided into two periods a) 1800 – 1970 and b) 1971 – 2018.

The full table can be found in Appendix A.

Upon testing the residuals in the granger causality with lagged terms, we obtain the following test results for ADF and KPSS tests:

	1800 - 1970		Residuals	1971 - 2018		Residuals
Country	**ADF**	**KPSS**	**Stationarity**	**ADF**	**KPSS**	**Stationarity**
Algeria	H1	H0	stationary	H1	H0	stationary
Angola	H1	H0	stationary	H1	H1	non-stationary
Argentina	H1	H0	stationary	H1	H0	stationary
Australia	H1	H0	stationary	H1	H0	stationary
Austria	H1	H0	stationary	H1	H0	stationary
Azerbaijan	NA	NA	non-stationary	H1	H0	stationary
Bahrain	H0	H0	non-stationary	H1	H0	stationary

Bangladesh	H1	H0	stationary	H1	H0	stationary
Belarus	NA	NA	non-stationary	H1	H0	stationary
Belgium	H1	H0	stationary	H1	H0	stationary
…	…	…	…	…	…	…
United Arab Emirates	NA	NA	non-stationary	H1	H0	stationary
United Kingdom	H1	H0	stationary	H1	H0	stationary
United States	H1	H0	stationary	H1	H0	stationary
Uruguay	H1	H0	stationary	H1	H0	stationary
Uzbekistan	NA	NA	non-stationary	H1	H0	stationary
Vietnam	H1	H0	stationary	H1	H0	stationary
Zambia	H1	H0	stationary	H1	H0	stationary
Zimbabwe	H1	H0	stationary	H1	H0	stationary

Table 5.3-2 ADF and KPSS tests for multivariate model for all countries

This table presents the stationarity tests conducted on the residuals of the univariate model structured in *Eq. 3.5-1* and *Eq. 3.5-2*. The ADF test is used to assess the null hypothesis that there is a unit root, while the alternate hypothesis suggests the absence of a unit root. On the other hand, the KPSS test examines the null hypothesis of no unit root, with the alternate hypothesis indicating the presence of a unit root. Here we represent "Reject H0" or rejection of null hypothesis as H1 and "Do not reject H0" or non-rejection of null hypothesis as H0.

From the results of the model stated in *Table 5.3-1*, we observe discernable trends as entailed below:

5.4. Granger Causality Model with Country filters

To isolate the effect of specific criteria, we augment the findings obtained from the Granger causality model by incorporating additional filters that are contingent upon the unique characteristics of the countries involved. This approach enables us to discern and analyze the influence of these criteria.

5.4.1. Countries participating in Industrial Revolution

By filtering the results from for major countries (15) participating in Industrial Revolution, we obtain the following table.

	1800 - 1970			1971 - 2018		
Industrial Revolution	**CO2 -> GDP**	**GDP -> CO2**	**Lags**	**CO2 -> GDP**	**GDP -> CO2**	**lag**
United Kingdom	0.0013	0.1715	2	0.3023	0.2849	2
United States	0.2381	0.0109	2	0.1887	0.0518	1
Germany	0.0000	0.4398	2	0.0325	0.0005	1
France	0.4761	0.0726	1	0.3654	0.1268	1
Belgium	0.0068	0.0013	1	0.7845	0.0623	1
Netherlands	0.0374	0.0000	1	0.8449	0.0476	1
Sweden	0.0774	0.0001	1	0.4216	0.0860	1
Switzerland	0.0076	0.0000	1	0.1850	0.0076	1
Austria	0.8336	0.2552	1	0.0539	0.5852	1
Italy	0.0120	0.0012	2	0.3493	0.0260	1
Canada	0.3363	0.0000	2	0.9407	0.1586	1
Japan	0.0108	0.0006	2	0.0287	0.3079	1
Australia	0.0366	0.0837	1	0.0105	0.0871	1
Russia	0.0149	0.4709	2	0.0054	0.9921	2
Spain	0.5267	0.0101	1	0.0533	0.2030	1

Table 5.4.1-1 Final p-value in Industrial Revolution filter in Granger Causality model

In this table, the significance of the findings is indicated using a color scheme. We used shades of green to represent the level of significance.

p-value 0-0.001
p-value 0.001-0.01
p-value 0.01-0.05
p-value 0.05-0.1

This table filters the Granger Causality model results specifically for major countries participating in Industrial Revolution. The table depicts p-values for the tests and the lags chosen for each country based on SBIC.

From the above table we observe the following trends in countries participating in Industrial Revolution (all the factors as “per capita”):

In the period 1800 – 1970:

10 countries exhibit a significant impact of CO_2 emissions on GDP. There is a generalized two-way causality relationship in this period.

In the period 1971 – 2018:

Many countries either lose their previous causality relationships or align themselves with the opposite specific type of causality. CO_2 emissions' importance in explaining GDP changes reduces in the 2nd period relative to the 1st period, while the inverse relation tends to hold.

For both the periods, the optimal number of lags selected for explaining the changes does not exceed 2.

5.4.2. Developed Countries

By filtering the above results for major developed countries (15), we obtain the following table.

	1800 – 1970			1971 - 2018		
Developed	CO2 -> GDP	GDP -> CO2	Lags	CO2 -> GDP	GDP -> CO2	Lags
United States	0.2381	0.0109	2	0.1887	0.0518	1
United Kingdom	0.0013	0.1715	2	0.3023	0.2849	2
Switzerland	0.0076	0.0000	1	0.1850	0.0076	1
Sweden	0.0774	0.0001	1	0.4216	0.0860	1
Norway	0.3198	0.0029	1	0.1663	0.0949	2
New Zealand	0.8450	0.0395	1	0.8097	0.6646	1
Netherlands	0.0374	0.0000	1	0.8449	0.0476	1
Ireland	0.0007	0.0060	1	0.7463	0.0002	2
Germany	0.0000	0.4398	2	0.0325	0.0005	1
France	0.4761	0.0726	1	0.3654	0.1268	1
Denmark	0.9618	0.0000	1	0.3933	0.0294	1
Canada	0.3363	0.0000	2	0.9407	0.1586	1
Belgium	0.0068	0.0013	1	0.7845	0.0623	1
Austria	0.8336	0.2552	1	0.0539	0.5852	1
Australia	0.0366	0.0837	1	0.0105	0.0871	1

Table 5.4.2-1 Final p-value in Developed countries filter in Granger Causality model

In this table, the significance of the findings is indicated using a color scheme. We used shades of green to represent the level of significance.

p-value 0-0.001
p-value 0.001-0.01
p-value 0.01-0.05
p-value 0.05-0.1

This table filters the Granger Causality model results specifically for major developed countries. The table depicts p-values for the tests and the lags chosen for each country based on SBIC.

From the above table we observe the following trends in developed countries (all the factors as "per capita"):

In the period 1800 – 1970:

There is a two-way granger causality between CO2 emissions and GDP, with 8 countries exhibiting forward relation of CO2 emissions granger causing GDP and 12 countries exhibiting the inverse relation. United Kingdom and Germany exhibit the forward relation alone. 6 countries exhibit only the inverse relation.

In the period 1971 – 2018:

There is a major shift in causality, where most countries either show inverse relation or no relation between the variables. Germany, Austria, and Australia are the only countries that retain the forward relation. For both the periods the optimal lags selected are at most 2.

5.4.3. Underdeveloped Countries

By filtering the above results for major developed countries (14), we obtain the following table.

	1800 - 1970			**1971 - 2018**		
Under Developed	**CO2 -> GDP**	**GDP -> CO2**	**Lags**	**CO2 -> GDP**	**GDP -> CO2**	**Lags**
Sierra Leone	0.2113	0.0250	5	0.0428	0.3491	1
Niger	0.3963	0.0002	3	0.7904	0.0278	1
Mali	0.0723	0.7592	3	0.0067	0.8154	1
Guinea-Bissau	0.0437	0.2296	1	0.6301	0.2926	1
Guinea	0.0024	0.5180	4	0.0000	0.0864	3
Gambia	0.0009	0.3129	5	0.6667	0.0408	1
Ethiopia	0.8556	0.0062	5	0.1534	0.3329	2

Comoros	0.8215	0.0000	3	0.4585	0.0091	1
Chad	0.0483	0.4728	3	0.0766	0.0134	1
Central African Republic	0.0028	0.4076	3	0.7631	0.3415	1
Burundi	0.0207	0.1041	5	0.4169	0.8030	1
Burkina Faso	0.5577	0.4003	3	0.0123	0.2018	1
Yemen	0.8961	0.0189	5	0.0245	0.0077	3

Table 5.4.3-1 Final p-value in Underdeveloped countries filter in Granger Causality model

In this table, the significance of the findings is indicated using a color scheme. We used shades of green to represent the level of significance.

p-value 0-0.001
p-value 0.001-0.01
p-value 0.01-0.05
p-value 0.05-0.1

This table filters the Granger Causality model results specifically for major underdeveloped countries. The table depicts p-values for the tests and the lags chosen for each country based on SBIC.

From the above table we observe the following trends in underdeveloped countries (all the factors as "per capita"):

In the period 1800 – 1970:

5 countries exhibit a forward relation alone between CO2 emissions and GDP while 7 countries exhibit the inverse relation alone. Yemen exhibits a two-way causal relationship. Optimal lags selected are mostly between 1 and 3, some countries tend to pick the maximum possible lag length of 5.

In the period 1971 – 2018:

CO2 emissions' impact on GDP is more evident in this period than the first. 7 countries exhibit forward causal relation while only 3 exhibit inverse causal relation. 5 countries do not exhibit any relation between the two variables. Optimal lags selected are at most 2.

5.4.4. Upper Developing Countries

By filtering the above results for major developed countries (14), we obtain the following table.

	1800 - 1970			**1971 - 2018**		
Upper	**CO2 ->**	**GDP ->**	**Lags**	**CO2 ->**	**GDP ->**	**Lags**

Developing	GDP	CO2		GDP	CO2	
Taiwan	0.0641	0.0021	1	0.2340	0.3441	1
Spain	0.5267	0.0101	1	0.0533	0.2030	1
South Korea	0.0061	0.1045	1	0.1492	0.4965	2
Singapore	0.8385	0.0031	1	0.6817	0.0043	1
Portugal	0.3843	0.0000	1	0.1989	0.4802	1
Japan	0.0108	0.0006	2	0.0287	0.3079	1
Italy	0.0120	0.0012	2	0.3493	0.0260	1
Ireland	0.0007	0.0060	1	0.7463	0.0002	2
Hong Kong	0.6204	0.0283	1	0.0035	0.6463	1
Greece	0.0000	0.5811	1	0.1667	0.0001	2
France	0.4761	0.0726	1	0.3654	0.1268	1
Finland	0.1494	0.2290	1	0.1556	0.2828	1
Chile	0.0007	0.2512	1	0.0241	0.0015	1
Canada	0.3363	0.0000	2	0.9407	0.1586	1
Australia	0.0366	0.0837	1	0.0105	0.0871	1

Table 5.4.4-1 Final p-value in Upper Developing countries filter in Granger Causality model

In this table, the significance of the findings is indicated using a color scheme. We used shades of green to represent the level of significance.

p-value 0-0.001
p-value 0.001-0.01
p-value 0.01-0.05
p-value 0.05-0.1

This table filters the Granger Causality model results specifically for major developing countries. Please note that these countries might be developed in todays sense but large changes in development in the selected periods. The table depicts p-values for the tests and the lags chosen for each country based on SBIC.

From the above table we observe the following trends in major developing countries (all the factors as "per capita"):

In the period 1800 – 1970:

There is a defined two-way causal relation between GDP and CO2 emission is this period. 11 countries exhibit the inverse causal relation, and 5 countries exhibit both at the same time.

In the period 1971 – 2018:

There is a major shift in causality, where the inverse relation is less evident than in the first period. 5 countries show a forward causal relation between CO2 emissions and GDP while 6 countries show inverse causal relation. 5

countries have either inverted or lost the causal relation. For both the periods the optimal lags selected are at most 2.

5.4.5. Least Developed Countries

By filtering the above results for least developed countries as stated by UN (*UN List of Least Developed Countries | UNCTAD*, 2023), we obtain the following table.

	1800 - 1970			**1971 - 2018**		
Least Developed	**CO2 -> GDP**	**GDP -> CO2**	**Lags**	**CO2 -> GDP**	**GDP -> CO2**	**Lags**
Angola	0.1339	0.0056	5	0.2163	0.0058	2
Bangladesh	0.4530	0.0748	1	0.0004	0.5382	1
Benin	0.1102	0.7464	3	0.0957	0.0959	1
Burundi	0.0207	0.1041	5	0.4169	0.8030	1
Chad	0.0483	0.4728	3	0.0766	0.0134	1
Equatorial Guinea	0.7618	0.5700	2	0.0413	0.2087	1
Ethiopia	0.8556	0.0062	5	0.1534	0.3329	2
Madagascar	0.1074	0.0513	5	0.9106	0.0166	1
Mali	0.0723	0.7592	3	0.0067	0.8154	1
Mozambique	0.7892	0.0095	1	0.6252	0.2701	1
Myanmar	0.3489	0.1287	1	0.9639	0.2281	2
Nepal	0.1376	0.1913	5	0.0095	0.3061	3
Niger	0.3963	0.0002	3	0.7904	0.0278	1
Rwanda	0.0220	0.6985	5	0.7956	0.0434	1
Senegal	0.9482	0.4887	3	0.0037	0.0044	1
Sierra Leone	0.2113	0.0250	5	0.0428	0.3491	1
Zambia	0.9476	0.2071	5	0.0005	0.0060	1

Table 5.4.5-1 Final p-value in Least developed countries filter in Granger Causality model

In this table, the significance of the findings is indicated using a color scheme. We used shades of green to represent the level of significance.

p-value 0-0.001
p-value 0.001-0.01
p-value 0.01-0.05
p-value 0.05-0.1

This table filters the Granger Causality model results specifically for least developed countries as listed by United Nations. Please note that these countries might be developed in todays sense but large changes in development in the selected periods. The table depicts p-values for the tests and the lags chosen for each country based on SBIC.

From the above table we observe the following trends in major developing countries (all the factors as "per capita"):

Most of the Least Developed Countries begin experiencing positive relation of CO_2 on GDP in the period 1971 – 2018. Optimal lag length ranges from 1-5 in the first period and is at most 3 in the second period.

5.4.6. Organization of the Petroleum Exporting Countries (OPEC+)

By filtering the above results for OPEC+ , we obtain the following table.

	1800 - 1970			**1971 - 2018**		
OPEC+	**CO2 -> GDP**	**GDP -> CO2**	**Lags**	**CO2 -> GDP**	**GDP -> CO2**	**Lags**
Venezuela	0.0003	0.0012	2	0.2840	0.3191	2
Iran	0.7874	0.1792	1	0.0160	0.0970	2
Nigeria	0.0615	0.1999	5	0.2071	0.8402	2
Angola	0.1339	0.0056	5	0.2163	0.0058	2
Algeria	0.7639	0.0095	5	0.7266	0.0204	2
Saudi Arabia	0.1178	0.0490	5	0.3989	0.0462	1
Gabon	0.4761	0.0726	1	0.3654	0.1268	1
United Arab Emirates	0.0001	0.0205	3	0.5068	0.8236	2
Iraq	0.0080	0.7957	5	0.8824	0.1192	1
Kuwait	0.2871	0.1936	2	0.0428	0.5985	2
Equatorial Guinea	0.7618	0.5700	2	0.0413	0.2087	1
Republic of the Congo	0.1659	0.2767	2	0.8917	0.1768	2
Libya	0.6128	0.0742	1	0.0970	0.5208	1
Ecuador	0.7703	0.1931	1	0.3118	0.0092	1
Qatar	0.1659	0.2767	2	0.8917	0.1768	2

Table 5.4.6-1 Final p-value in OPEC+ countries filter in Granger Causality model

In this table, the significance of the findings is indicated using a color scheme. We used shades of green to represent the level of significance.

p-value 0-0.001
p-value 0.001-0.01

p-value 0.01-0.05
p-value 0.05-0.1

This table filters the Granger Causality model results specifically for Petroleum Exporting Countries. The table depicts p-values for the tests and the lags chosen for each country based on SBIC.

From the above table we observe the following trends in OPEC+ countries (all the factors as "per capita"):

In the first period, most countries exhibit the inverse causal relation of GDP affecting CO_2 emissions, while this trend is reduced in the second period, and no discernible trend in the second period. Optimal lag length in first period ranges from 1-5 while in second period it is at most 2.

5.4.7. Island Nations

By filtering the above results for island nations, we obtain the following table.

	1800 - 1970			1971 - 2018		
Island Nations	**CO2 -> GDP**	**GDP -> CO2**	**Lags**	**CO2 -> GDP**	**GDP -> CO2**	**Lags**
Barbados	0.0179	0.0023	5	0.2499	0.0035	2
Cape Verde	0.5046	0.4036	5	0.3473	0.0055	2
Comoros	0.8215	0.0000	3	0.4585	0.0091	1
Dominica	0.4865	0.0003	5	0.0012	0.0794	1
Mauritius	0.6724	0.0818	1	0.6736	0.1244	1
Saint Lucia	0.9296	0.8586	1	0.7228	0.0010	1
Sao Tome and Principe	0.0295	0.1693	4	0.9164	0.0013	1
Seychelles	0.8664	0.0639	1	0.5045	0.0390	1

Table 5.4.7-1 Final p-value in Island Nation countries filter in Granger Causality Model

In this table, the significance of the findings is indicated using a color scheme. We used shades of green to represent the level of significance.

p-value 0-0.001
p-value 0.001-0.01
p-value 0.01-0.05
p-value 0.05-0.1

The above table filters the Granger Causality model results specifically for Island Nations. Please note that some island nations do not have CO2 data for which they have been filtered out of the country list. The table depicts p-values for the tests and the lags chosen for each country based on SBIC.

From the above table we observe the following trends in OPEC+ countries (all the factors as "per capita"):

The inverse relation of GDP influencing CO_2 emissions is consistent in both the periods. Optimal lag length in first period ranges from 1-5 while in second period it is at most 2.

5.5. Major Trends in the Analysis

The major trends that we see in our analysis are given below:

1. Major countries participating in the Industrial Revolution have experienced a positive impact of CO_2 emissions (or dependency on fossil fuels) on GDP growth during the period 1800 – 1970.
2. Most of the developed countries experienced positive impact of CO_2 emissions on GDP growth in the period 1800 – 1970, while losing this effect in the period 1971 – 2018 where they only exhibited the inverse relation of GDP changes causing CO_2 emission changes.
3. Most of the upper developing countries which exhibited positive impact of CO_2 emissions on GDP in 1800 – 1970 lose such relation in the period 1971 – 2018.
4. Most of the underdeveloped countries show positive impact of CO_2 emissions dependency for GDP growth in the period 1970 – 2018.

The overall analysis suggests that countries in their development stages experience strong relation of increase in CO_2 emissions leading to an increase in GDP (and a decrease in CO_2 emissions leading to decreasing GDP). Countries past their development stages tend to show either:

a) shift of forward relation to inverse relation, where increase in GDP leads to increase in CO_2 emissions or;

b) lose the causal relation between both variables entirely.

5.6. Robustness Tests and additional analyses

To interpret the variables correctly in a Granger causality model, it is important to ensure that we have contiguous data points, for which we have set filters to filter out those countries which do not have contiguous data points. This occurs often in the period before 1900. We have accounted for these changes, and the presence or absence of said data points do not affect the results of the model.

For each of the multivariate tests, we individually test each country's regression residuals for:

- Stationarity, with ADF and KPSS tests
- Normality, with Jarque-Bera test
- Heteroskedasticity, with Breusch-Pagan Test

We find that most (excluding those with missing data points) of the multivariate tests have stationary, normally distributed and homoscedastic residuals.

We have analyzed different timeframes apart from the currently used periods i.e., 1800 – 1970 and 1971 – 2018.

- We find similar trends in the granger-causality results with the sectioning year as 1940, 1950, 1960, 1970 and 1980. Our results are stationary under different assumptions of the period 1940-1980. Some extremities still occur where some countries do not have data points before 1960.
- We have analyzed the countries using both a 50-year lens and a 100-year lens. With the 50-year lens, we checked for Granger causality between the variables of each country within specific time periods such as 1850-1900, 1860-1910, 1870-1920, and so on. Similarly, for the 100-year lens, we performed a similar task with timeframes like 1850-1950, 1860-1960, and so on. These tests resulted in similar time trends between the two variables. However, when the timeframe goes beyond the year 1960, many countries tend to be filtered out due to the lack of data from developing and underdeveloped countries.

Instead of the GDP per capita and CO2 per capita variables, we have analyzed logarithmic variables (log GDPpcap and log CO2pcap). The presence of the logarithmic function addresses the exponential behavior; however, the results do not coincide completely with the former analysis. The significance of forward/ inverse causal impact is not as defined, and the model has lower explanatory power in general. The results do coincide with a few countries from the Industrial era filter and the developed nations filter.

We have used AIC and other information criteria instead of SBIC to understand how this affects our model. AIC continually chooses a higher lag length in both the time periods but leads to similar results as SBIC for most countries involved. Additionally, we had to change the maximum lag length conditions to allow AIC to freely choose a higher lag length in the multivariate model.

We have further extended our general model to analyze change in change through the application of ΔX for each variable X.

$$\begin{aligned} \Delta \mathrm{GDP}pcap_{i,t} = {} & \beta_0 + \beta_1 \Delta \mathrm{C}O2pcap_{i,t} + \beta_2 \Delta \mathrm{C}O2pcap_{i,t-1} \quad \textit{Eq. 5.6-1} \\ & + \beta_3 \Delta \mathrm{C}O2pcap_{i,t-2} + \gamma_1\, GDPpcap_{i,t-1} \\ & + \gamma_2 GDPpcap_{i,t-1} + u_{i,t} \end{aligned}$$

This model closely follows the results from the granger-causality analysis and additionally shows evidence that change in CO2 emissions per capita plays a crucial role to explain the changes in GDP per capita. The full results are listed in Appendix B (B3 FIRST DIFFERENCES REGRESSION (Δ) ESTIMATES WITH SIGNIFICANCE LEVELS 1800 - 1970 and B4 FIRST DIFFERENCES REGRESSION (Δ) ESTIMATES WITH SIGNIFICANCE LEVELS 1971 – 2018)

6. Conclusion

6.1. Relationship between CO2 emissions and GDP

In our study, we empirically investigate the causal impact (Granger causality) between annual GDP per capita and annual CO2 emissions per capita as well as their lagged priors. We utilize multivariate models, VAR, granger causality and first differences analysis for 120 countries between 1800 and 2018.

Our analysis shows statistical evidence revealing a significant positive relationship between GDP per capita, CO2 emissions per capita and its first lag in developed countries during the general period from 1800 to 1971. In the developmental stages of developed countries, both CO2 emissions per capita and its first lag are significant when explaining GDP per capita. This consistent pattern underscores the influential role of CO2 emissions in driving economic growth in developed countries during developmental stages.

A similar trend is observed in underdeveloped countries during the period from 1971 to 2018, exhibiting a relationship comparable to that observed in developed countries during the period from 1800 to 1970. In other words, underdeveloped countries which are beginning to develop exhibit a positive correlation between GDP per capita and CO2 emissions per capita along with its first lag. In the same period, some developed countries lose this relation with advancement in adoption of cleaner fuels.

When analyzing the first differences, we find that change in CO2 emissions per capita is statistically significant in explaining changes in GDP per capita. The first lag of change in CO2 emissions per capita is only significant for few developed countries.

6.2. Relevance to the current political world environment

This result sheds light on the issue that poorer countries bear the burden of Climate Change in terms of both costs incurred due to Climate Change itself as well as the increase in costs due to higher carbon taxation.[7]

From our analysis we find strong evidence that poorer would find incentive to depend on fossil fuel for economic growth, to ultimately break away from the same fuels through a transition to cleaner energy sources. The falling costs of cleaner fuel and renewable energy accelerates this transition.[8]

6.3. Recommendations for further research

We suggest the following for further research within the scope of this thesis:

- Including the quarterly changes in CO2 per capita and GDP per capita could derive more accurate results and solidify the causality model.
- Interpretation of individual coefficients in the multivariate model and analyzing the trend in the level of impact of both the variables on each other.
- Using individual periods of development for creating subsamples instead of a restricted period model. For example, some evidence might suggest that Singapore experienced a fast-paced development through 1990 – 2000, which we can incorporate for analyzing CO2 emissions dependency before and after this decade instead of the two sample period (1800 – 1970 and 1971 – 2018); and so on for each country.

[7] "Here we show that exceeding the 1.5°C global warming target would lead to the poorest experiencing the greatest local climate changes." (King & Harrington, 2018)

[8] "If we don't want poorer countries to become as fossil fuel dependent as we are, we need low-carbon technology to be cheap and available. And we're getting there: the cost of renewables are falling quickly and a variety of solutions are on the horizon for many different sectors. But it needs to happen much faster." (Falling Costs Make Wind, Solar More Affordable, 2019)

7. Appendix

Appendix A

	1800 - 1970			1971 - 2018		
Country	**C -> G**	**G -> C**	**Lags**	**C -> G**	**G -> C**	**Lags**
Algeria	0.7639	0.0095	5	0.7266	0.0204	2
Angola	0.1339	0.0056	5	0.2163	0.0058	2
Argentina	0.4716	0.0022	1	0.5756	0.1441	1
Australia	0.0366	0.0837	1	0.0105	0.0871	1
Austria	0.8336	0.2552	1	0.0539	0.5852	1
Azerbaijan	NA	NA	NA	0.0908	0.1654	2
Bahrain	0.2257	0.0772	5	0.7021	0.9731	2
Bangladesh	0.4530	0.0748	1	0.0004	0.5382	1
Belarus	NA	NA	NA	0.0140	0.3324	2
Belgium	0.0068	0.0013	1	0.7845	0.0623	1
Benin	0.1102	0.7464	3	0.0957	0.0959	1
Bolivia	0.3411	0.0466	1	0.4416	0.2195	2
Botswana	NA	NA	NA	0.8954	0.0119	1
Brazil	0.8917	0.0061	1	0.9128	0.1520	1
Bulgaria	0.3692	0.0210	1	0.0044	0.5890	1
Burkina Faso	0.5577	0.4003	3	0.0123	0.2018	1
Burundi	0.0207	0.1041	5	0.4169	0.8030	1
Burundi	0.0207	0.1041	5	0.4169	0.8030	1
Cameroon	0.0427	0.5374	5	0.0001	0.5428	2
Canada	0.3363	0.0000	2	0.9407	0.1586	1
Central African Republic	0.0028	0.4076	3	0.7631	0.3415	1
Chad	0.0483	0.4728	3	0.0766	0.0134	1
Chad	0.0483	0.4728	3	0.0766	0.0134	1
Chile	0.0007	0.2512	1	0.0241	0.0015	1
China	0.7914	0.0110	1	0.0003	0.0006	3
Colombia	0.3263	0.0189	1	0.1728	0.2147	2
Comoros	0.8215	0.0000	3	0.4585	0.0091	1
Costa Rica	0.2153	0.3085	5	0.4909	0.4116	1
Cote d'Ivoire	0.1077	0.0223	1	0.0038	0.1739	1
Croatia	0.0747	0.6331	5	0.4153	0.0004	2
Denmark	0.9618	0.0000	1	0.3933	0.0294	1
Dominican Republic	0.1579	0.5381	1	0.5980	0.3152	1
Ecuador	0.7703	0.1931	1	0.3118	0.0092	1
Egypt	0.0001	0.0176	2	0.0977	0.2190	2
El Salvador	0.8462	0.0000	5	0.4236	0.0160	2
Equatorial Guinea	0.7618	0.5700	2	0.0413	0.2087	1
Ethiopia	0.8556	0.0062	5	0.1534	0.3329	2
Ethiopia	0.8556	0.0062	5	0.1534	0.3329	2
Finland	0.1494	0.2290	1	0.1556	0.2828	1
France	0.4761	0.0726	1	0.3654	0.1268	1

Gambia	0.0009	0.3129	5	0.6667	0.0408	1
Georgia	NA	NA	NA	0.0004	0.0000	1
Germany	0.0000	0.4398	2	0.0325	0.0005	1
Ghana	0.0466	0.3601	5	0.5986	0.0003	2
Greece	0.0000	0.5811	1	0.1667	0.0001	2
Guatemala	0.0006	0.9210	1	0.0495	0.3272	2
Guinea	0.0024	0.5180	4	0.0000	0.0864	3
Guinea-Bissau	0.0437	0.2296	1	0.6301	0.2926	1
Honduras	0.6204	0.0283	1	0.0035	0.6463	1
Hungary	0.0035	0.1484	1	0.0428	0.3319	1
India	0.0001	0.3812	1	0.8884	0.0864	1
Indonesia	0.0182	0.0000	2	0.9811	0.0484	1
Iran	0.7874	0.1792	1	0.0160	0.0970	2
Iraq	0.0080	0.7957	5	0.8824	0.1192	1
Ireland	0.0007	0.0060	1	0.7463	0.0002	2
Israel	0.0093	0.2319	3	0.7848	0.4000	1
Italy	0.0120	0.0012	2	0.3493	0.0260	1
Japan	0.0108	0.0006	2	0.0287	0.3079	1
Jordan	0.0000	0.4257	1	0.6436	0.3672	1
Kazakhstan	NA	NA	NA	0.0100	0.0054	2
Kenya	0.2672	0.0160	5	0.8072	0.2766	1
Kuwait	0.2871	0.1936	2	0.0428	0.5985	2
Latvia	NA	NA	NA	0.0857	0.3789	1
Lebanon	0.6128	0.0742	1	0.0970	0.5208	1
Lithuania	NA	NA	NA	0.0180	0.6663	1
Luxembourg	0.9752	0.1829	5	0.0395	0.3692	1
Madagascar	0.1074	0.0513	5	0.9106	0.0166	1
Malaysia	0.0182	0.5483	1	0.7245	0.1655	1
Mali	0.0723	0.7592	3	0.0067	0.8154	1
Malta	0.0000	0.0264	4	0.0979	0.0937	1
Mexico	0.4183	0.5259	2	0.3614	0.5856	1
Morocco	0.1984	0.1174	4	0.0242	0.9733	2
Mozambique	0.7892	0.0095	1	0.6252	0.2701	1
Myanmar	0.3489	0.1287	1	0.9639	0.2281	2
Namibia	NA	NA	NA	0.3856	0.0000	1
Nepal	0.1376	0.1913	5	0.0095	0.3061	3
Netherlands	0.0374	0.0000	1	0.8449	0.0476	1
New Zealand	0.8450	0.0395	1	0.8097	0.6646	1
Niger	0.3963	0.0002	3	0.7904	0.0278	1
Nigeria	0.0615	0.1999	5	0.2071	0.8402	2
Norway	0.3198	0.0029	1	0.1663	0.0949	2
Pakistan	0.0023	0.4667	1	0.0490	0.0750	1
Panama	0.0900	0.0210	1	0.3868	0.0472	1
Paraguay	0.2278	0.1715	5	0.7541	0.0191	1
Peru	0.2663	0.2009	1	0.4855	0.0047	1
Philippines	0.0883	0.6541	1	0.2126	0.0499	1
Poland	0.0374	0.0004	3	0.0006	0.9009	2
Portugal	0.3843	0.0000	1	0.1989	0.4802	1

Qatar	0.1659	0.2767	2	0.8917	0.1768	2
Romania	0.3265	0.0020	1	0.0122	0.4440	1
Rwanda	0.0220	0.6985	5	0.7956	0.0434	1
Saudi Arabia	0.1178	0.0490	5	0.3989	0.0462	1
Senegal	0.9482	0.4887	3	0.0037	0.0044	1
Serbia	0.1938	0.7558	5	0.5233	0.1069	2
Sierra Leone	0.2113	0.0250	5	0.0428	0.3491	1
Singapore	0.8385	0.0031	1	0.6817	0.0043	1
Slovakia	NA	NA	NA	0.0065	0.6783	1
Slovenia	0.1326	0.4706	4	0.2250	0.0286	2
South Africa	0.5151	0.0024	5	0.3504	0.1459	2
South Korea	0.0061	0.1045	1	0.1492	0.4965	2
Spain	0.5267	0.0101	1	0.0533	0.2030	1
Sri Lanka	0.3476	0.0060	1	0.4326	0.0019	1
Sweden	0.0774	0.0001	1	0.4216	0.0860	1
Switzerland	0.0076	0.0000	1	0.1850	0.0076	1
Taiwan	0.0641	0.0021	1	0.2340	0.3441	1
Tanzania	0.2301	0.0026	1	0.0716	0.0013	2
Thailand	0.9147	0.0005	1	0.0149	0.0601	1
Trinidad and Tobago	0.9713	0.2340	1	0.3144	0.0147	2
Tunisia	0.2708	0.0259	5	0.6344	0.0199	1
Turkey	0.0104	0.3010	1	0.1129	0.1198	1
Ukraine	NA	NA	NA	0.2223	0.1948	2
United Arab Emirates	0.0001	0.0205	3	0.5068	0.8236	2
United Kingdom	0.0013	0.1715	2	0.3023	0.2849	2
United States	0.2381	0.0109	2	0.1887	0.0518	1
Uruguay	0.8989	0.0027	1	0.7612	0.0006	2
Uzbekistan	NA	NA	NA	0.0000	0.9206	1
Vietnam	0.0869	0.0515	5	0.3488	0.0013	1
Yemen	0.8961	0.0189	5	0.0245	0.0077	3
Zambia	0.9476	0.2071	5	0.0005	0.0060	1
Zimbabwe	0.1358	0.2446	5	0.0388	0.3901	1

Final p-value in Full results of Granger Causality tests in 2 periods

In this table, the significance of the findings is indicated using a color scheme. We used shades of green to represent the level of significance.

p-value 0-0.001
p-value 0.001-0.01
p-value 0.01-0.05
p-value 0.05-0.1

This table exhibits the full results for causality tests from both time periods with the respective p-values and lag lengths chosen by SBIC for each country.

Appendix B

B1 GENERAL REGRESSION ESTIMATES WITH SIGNIFICANCE LEVELS 1800 – 1970

country	Intercept	co2pcap_t0	co2pcap_tm1	co2pcap_tm2	gdppcap_tm1	gdppcap_tm2
Algeria	666.30	1000.40	-687.00	2051.80	0.638(*)	-0.34
Angola	281.30	-422.30	911.7(*)	953.20	0.54(.)	0.25
Argentina	362.40	636.6(*)	-401.90	-36.60	0.928(***)	-0.01
Australia	161.9(.)	331.5(**)	-136.30	-132.30	1.026(***)	-0.06
Austria	-129.00	123(*)	-82.60	-27.80	1.112(***)	-0.08
Bahrain	-100.8(**)	0.60	1.5(.)	1.5(.)	2.125(***)	-1.11(***)
Bangladesh	343.00	3409.00	1271.70	-3560.00	0.23	0.36
Belgium	-109.8(.)	138.5(***)	-156.4(***)	-7.60	1.23(***)	-0.174(.)
Bolivia	195.60	-152.30	850.90	-541.80	1.106(***)	-0.19
Brazil	-10.50	620.9(*)	-579(.)	65.00	1.154(***)	-0.14
Bulgaria	-10.70	111.70	135.00	-241.20	1.073(***)	-0.06
Burundi	223.60	-3177.80	7704.60	-3397.20	0.61	0.07
Cameroon	152.5(*)	634.50	467.00	177.90	0.44	0.42
Canada	-13.60	215.6(***)	-194.8(**)	-24.70	1.205(***)	-0.19
Chile	733.1(**)	1043.5(**)	156.50	-365.00	0.689(***)	-0.03
China	341.6(.)	323.5(*)	-503.7(*)	236.3(.)	1.057(***)	-0.391(.)
Colombia	227.90	436(*)	-211.50	-19.40	0.96(***)	-0.05
Costa Rica	103.10	454.50	535.50	203.80	0.437(.)	0.463(.)
Cote d'Ivoire	408.40	65.40	-213.10	1219.70	0.546(.)	0.24
Denmark	39.50	308.8(***)	-224.6(*)	-0.80	0.962(***)	0.01
Dominican Republic	1204.2(*)	754.50	-217.30	728.40	0.31	-0.11
Ecuador	-33.80	-10.30	66.70	-31.40	0.746(***)	0.291(.)
Egypt	-328.6(**)	148.40	-152.80	-488.2(**)	1.413(***)	-0.02
El Salvador	326.00	695.90	380.20	53.00	0.55	0.25
Equatorial Guinea	56.60	-348.90	211.90	105.00	1.764(***)	-0.803(**)
Ethiopia	-195.7(.)	-2510.5(*)	350.40	853.80	0.799(**)	0.51
Finland	29.00	370.3(***)	-147.90	-187.4(*)	1.129(***)	-0.13
France	-98(*)	769.2(***)	-633.2(***)	-133.00	1.078(***)	-0.05
Gambia	107.40	3191.30	-4990.1(.)	4280.50	0.854(*)	-0.06
Germany	-125.3(*)	334.4(***)	46.80	-365.7(***)	1.184(***)	-0.172(**)
Ghana	558.60	318.00	1060.20	1828.30	0.482(.)	-0.03
Greece	498.7(**)	388.70	850.9(.)	-532.90	0.923(***)	-0.14
Guatemala	1856.6(***)	1547.50	102.50	784.20	0.424(*)	-0.13
Guinea	80.80	60.40	252.70	-240.60	0.562(.)	0.31
Guinea-Bissau	110.6(*)	21.50	682.60	498.50	0.39	0.503(*)
Honduras	138.00	41.70	28.40	170.30	0.906(**)	0.01
Hungary	644.5(**)	173.30	3.20	23.10	0.648(***)	0.13
India	312.1(***)	-947.60	1037.80	338.40	0.533(***)	0.13
Indonesia	356.3(**)	950.2(**)	-524.00	88.00	1.032(***)	-0.312(**)
Iran	26.30	128.20	126.50	-1.90	1.031(**)	-0.09
Iraq	1130.4(**)	315(.)	-419.3(*)	431.5(*)	0.723(**)	-0.06
Ireland	-39.20	109.2(*)	15.30	-95.8(.)	1.36(***)	-0.358(*)

Israel	335.20	84.90	-681(.)	691.1(*)	1.147(***)	-0.18
Italy	-44.80	917.7(***)	-459.7(*)	-539.5(**)	1.229(***)	-0.2(*)
Japan	-17.20	1022.6(***)	-541.7(*)	-333.3(.)	0.984(***)	-0.02
Jordan	2452.1(.)	855.20	353.10	487.40	-0.04	0.04
Kenya	-157.90	1136.00	-2105.4(*)	1364.1(*)	0.967(***)	0.08
Kuwait	41490.8(**)	-172.70	138.40	-228.6(.)	0.35	-0.16
Lebanon	1638.20	555.20	-1389.00	978.80	0.808(*)	-0.09
Luxembourg	-891.40	152.5(*)	-51.90	-66.50	0.832(***)	0.18
Madagascar	413.60	246.20	304.70	-123.50	0.993(**)	-0.23
Malaysia	230.7(.)	151.40	30.70	32.10	0.859(***)	0.02
Malta	-94.80	189.30	154.50	380.9(.)	0.689(*)	0.04
Mexico	-90.7(*)	31.30	-14.10	-23.60	0.966(***)	0.09
Morocco	497.2(**)	425.5(**)	83.80	267.60	1.412(***)	-0.729(***)
Mozambique	-318.10	580.50	84.70	-1179.6(*)	1.106(***)	0.11
Myanmar	348.9(*)	515.80	536.10	1070.80	0.37	0.02
Nepal	227.70	856.30	2180.90	-3311.60	0.47(.)	0.30
Netherlands	-38.20	629.5(***)	-512.9(***)	-89.90	1.023(***)	-0.02
New Zealand	-105.50	640.6(**)	-743.3(**)	135.10	0.846(***)	0.17
Nigeria	1104.1(**)	1851.3(*)	-843.20	-341.20	0.33	-0.30
Norway	-43.2(.)	264.9(***)	-82.20	-195.1(***)	0.893(***)	0.14
Pakistan	14.60	-276.30	228.70	672.50	0.722(*)	0.17
Panama	-80.10	126.50	-60.10	285.3(*)	0.767(**)	0.21
Paraguay	673.2(.)	399.30	-356.30	1162.80	0.561(.)	0.10
Peru	15.40	413.2(**)	-401.7(*)	-25.70	1.29(***)	-0.277(*)
Philippines	289.3(**)	77.10	362.20	-375.20	0.762(***)	0.13
Poland	73.80	203.50	68.20	-280.20	1.162(***)	-0.16
Portugal	-196.6(***)	491.8(*)	-297.50	-279.90	0.69(***)	0.432(***)
Qatar	32252.2(*)	-26.60	-42.10	23.70	1.04(**)	-0.571(*)
Romania	-21.00	476.9(***)	-379.6(.)	2.20	0.717(***)	0.12
Rwanda	535(*)	2795.30	-558.50	-5304.7(.)	0.644(*)	-0.06
Saudi Arabia	-636.7(.)	-109.00	-31.70	10.30	1.172(**)	0.00
Sierra Leone	-32.30	197.00	-164.60	-29.00	0.673(.)	0.39
Singapore	274.60	149.20	-145.30	21.10	0.959(***)	-0.02
South Africa	84.40	10.60	-80.20	-5.90	1.009(**)	0.08
South Korea	140.30	322.50	-524.90	410.80	0.773(***)	0.14
Spain	27.70	855.6(***)	-404.4(.)	-264.80	0.903(***)	0.06
Sri Lanka	231.00	450.70	320.00	737.60	0.765(*)	-0.03
Sweden	-45.3(.)	239.9(***)	-146.9(**)	-100.8(*)	1.042(***)	-0.01
Switzerland	-117.60	793.8(***)	-835.6(***)	-18.40	0.961(***)	0.09
Taiwan	-31.20	153.10	-321.90	200.90	1.313(***)	-0.287(.)
Tanzania	252.00	1335.9(.)	-409.50	394.90	0.44	0.11
Thailand	-44.60	194.20	-60.90	-97.40	0.965(**)	0.10
Trinidad and Tobago	727.20	-40.00	-19.70	-52.60	1.163(**)	-0.16
Tunisia	140.10	504.10	196.90	-617.60	0.491(.)	0.46
Turkey	244.8(**)	454.60	-492.20	1224.8(*)	0.726(***)	-0.03
United Kingdom	-32.60	160.3(***)	-197.7(***)	35.90	1.406(***)	-0.394(***)
United States	-38.20	359.6(***)	-297.2(***)	-62.00	1.126(***)	-0.11

Uruguay	1070.8(.)	626.1(*)	214.80	-657.3(*)	0.696(***)	0.12
Venezuela	98.10	47.2(*)	-37.3(.)	51.7(**)	0.988(***)	-0.01
Vietnam	121.00	-203.70	-905.7(*)	1188.1(**)	1.049(***)	-0.13
Yemen	612.60	-25.80	-27.10	141.2(**)	-7.61	8.30
Zambia	253.40	300.70	-548.6(.)	220.90	1.012(**)	-0.14
Zimbabwe	-362.10	235.80	79.10	-249.60	1.166(*)	0.04

APPENDIX B1

This table contains the regression estimates from the model:
GDPpcap ~ CO2pcap_t0 + CO2pcap_tm1 + CO2pcap_tm2 + GDPpcap_tm1 + GDPpcap_tm2
Where:
CO2pcap is the CO2 emissions per capita.
T0 is the contemporary term.
Tm1 is the first lag at year t-1.
Tm2 is the second lag at year t-2.

*** = p-value 0 – 0.001
** = p-value 0.001 – 0.01
* = p-value 0.01 – 0.05
. = p-value 0.05 – 0.1

B2 GENERAL REGRESSION ESTIMATES WITH SIGNIFICANCE LEVELS 1971 - 2018

country	Intercept	co2pcap_t0	co2pcap_tm1	co2pcap_tm2	gdppcap_tm1	gdppcap_tm2
Algeria	254.294	-63.8798	-46.3578	21.12444	1.655(***)	-0.642(***)
Angola	-280.1(*)	555.4(*)	100.4178	46.51153	1.388(***)	-0.462(**)
Argentina	-3400.6(.)	3067.9(***)	-1784.5(*)	319.2345	0.845(***)	-0.03371
Australia	-1360(*)	562.3(**)	-445.5(.)	1.988069	1.126(***)	-0.12865
Austria	-912.212	375.4(*)	115.894	-256.68	1.063(***)	-0.07731
Azerbaijan	880.7(*)	-289.535	479.3(.)	-295.232	1.749(***)	-0.785(***)
Bahrain	-980.534	61.74127	-45.334	34.09597	1.741(***)	-0.74(***)
Bangladesh	-38.5(***)	-17.9055	497.5444	-103.045	1.04(***)	-0.01983
Belarus	1306.6(**)	439.3(**)	-96.7388	-437.7(*)	1.245(***)	-0.273(.)
Belgium	-235.791	389.4(**)	-260.992	-63.0177	0.932(***)	0.068508
Benin	173.4443	434.4414	-358.284	71.52806	0.855(***)	0.032191
Bolivia	-39.6088	162.9(.)	-71.0119	-33.6105	1.591(***)	-0.593(***)
Botswana	149.6071	229.4913	-253.957	89.23139	0.908(***)	0.099981
Brazil	28.86644	2892.4(***)	-1198.44	-1279.78	0.813(***)	0.120745
Bulgaria	822.3(*)	331.8(**)	-220.447	-232.3(.)	1.107(***)	-0.0778
Burkina Faso	241.8(*)	187.4081	-833.913	1599.4(*)	0.915(***)	-0.17436
Burundi	24.51449	-73.3053	-340.921	-292.59	1.167(***)	-0.17154
Cameroon	82(.)	-14.436	316(***)	-247.4(**)	1.727(***)	-0.769(***)
Canada	-645.019	803.5(***)	-536.7(.)	-200.986	1.08(***)	-0.07883
Central African Republic	6.690027	2174.8(.)	-750.176	-700.827	0.841(***)	0.103197
Chad	-1.58213	1910.672	2044.879	-2125.07	1.174(***)	-0.281(.)
Chile	190.8222	1161.9(**)	-1084.3(*)	-145.559	1.19(***)	-0.17345
China	-92.9(*)	593.6(***)	-481.3(*)	163.7663	0.967(***)	-0.10026
Colombia	270.2061	477.8(*)	-432.312	-245.267	1.404(***)	-0.386(*)
Comoros	25.06113	277.0137	-418.093	637.6(**)	1(***)	-0.07267
Costa Rica	-255.5(.)	926(**)	-49.8724	-766.7(*)	1.062(***)	-0.03256
Cote d'Ivoire	66.42986	143.4337	-189.587	-269.088	1.4(***)	-0.366(*)
Croatia	2.833179	1151.3(***)	-942(*)	-241.027	1.458(***)	-0.442(**)
Denmark	-308.123	220.7(.)	-33.821	-141.516	1.173(***)	-0.16329
Dominican Republic	-247(*)	779.2(***)	-1030(**)	416.8(.)	1.236(***)	-0.20906
Ecuador	162.4032	-1.22735	-6.40188	-133.462	1.128(***)	-0.09944
Egypt	-57.1753	285(.)	237.532	-384.8(*)	1.531(***)	-0.546(***)
El Salvador	-111.2(.)	1075.3(***)	-348.244	-546.393	1.426(***)	-0.422(**)
Equatorial Guinea	485.9114	382.9(*)	-175.846	115.6839	1.261(***)	-0.38(**)
Ethiopia	2.684426	1747(*)	-906.727	-179.862	1.497(***)	-0.538(***)
Finland	-404.347	241.2605	26.87108	-186.579	1.334(***)	-0.339(*)
France	1779.193	543.7(**)	-348.394	-268.798	1.168(***)	-0.19429
Gambia	94.65656	319.7976	-759.713	555.4785	0.935(***)	-0.01359
Georgia	529.336	-857.015	672.1742	-72.2417	1.806(***)	-0.806(***)
Germany	9016.7(*)	300.8979	-303.136	-514.9(.)	0.828(***)	0.103157
Ghana	-72.7812	630.5185	-0.03572	105.0433	1.199(***)	-0.26268

Greece	21.70569	172.5272	87.92161	-132.441	1.532(***)	-0.579(***)
Guatemala	172.6464	569.6(*)	146.3332	-446.217	1.429(***)	-0.487(***)
Guinea	-14.7836	90.78558	1050.175	-1151.9(*)	0.972(***)	0.06383
Guinea-Bissau	110.5203	303.0305	66.86884	182.4714	0.695(***)	0.147766
Honduras	163.2553	565.8(*)	-203.898	58.47468	1.014(***)	-0.14444
Hungary	1405.8(.)	542.2(*)	-446.33	-267.458	1.287(***)	-0.286(.)
India	-74.5(***)	301.7192	-199.757	-159.213	1.024(***)	0.061148
Indonesia	-46.1644	1223.5(***)	-1220(**)	349.2087	1.323(***)	-0.373(*)
Iran	-405.43	764.7(**)	-687.8(*)	486.3(.)	1.26(***)	-0.501(***)
Iraq	-215.65	649(*)	-493.299	11.37674	1.158(***)	-0.19618
Ireland	161.8245	664.1065	-267.569	-425.274	1.522(***)	-0.498(**)
Israel	-40.0587	111.4732	-117	40.14485	1.119(***)	-0.1143
Italy	313.0542	1494.3(***)	-1306.6(**)	-153.835	1.053(***)	-0.05945
Japan	2890(**)	728.4(**)	-553.521	-531.3(.)	0.923(***)	0.104825
Jordan	195.0524	726.1(*)	-875.2(*)	151.9453	1.447(***)	-0.466(**)
Kazakhstan	1492(**)	224.6(*)	-205.3(.)	-147.109	1.336(***)	-0.301(.)
Kenya	-69.1904	221.0469	-104.343	-144.163	1.204(***)	-0.1478
Kuwait	22.55185	-8.61258	21.2(*)	8.502406	1.575(***)	-0.588(***)
Latvia	1415(.)	824.9(*)	-1054.7(.)	148.6352	1.467(***)	-0.518(**)
Lebanon	-986.187	1408.4(*)	-426.846	-318.057	1.148(***)	-0.262(.)
Lithuania	1086.7(.)	617(***)	-459.7(.)	-264.826	1.185(***)	-0.18587
Luxembourg	4792.3(*)	147.481	-147.782	-85.3828	1.054(***)	-0.09828
Madagascar	149.8(**)	1038.3(**)	-506.083	200.232	0.722(***)	0.095146
Malaysia	53.90252	454.8(*)	-288.726	-83.993	0.873(***)	0.12525
Mali	286.9(*)	1087.625	-693.413	449.83	0.56(***)	0.129431
Malta	390.8(.)	-84.0411	-1.99952	42.99218	1.381(***)	-0.367(*)
Mexico	-304.587	1420.7(***)	-1281.1(**)	-98.6475	0.895(***)	0.132153
Morocco	-44.6351	387.4203	179.6314	112.0679	0.297(*)	0.593(***)
Mozambique	69.10945	609.5364	-325.411	-251.943	1.196(***)	-0.266(.)
Myanmar	6.594118	453.4(.)	-426.972	-56.7833	1.734(***)	-0.721(***)
Namibia	-51.1873	-534.06	-414.583	-152.64	1.088(***)	0.120702
Nepal	-54.3(.)	233.216	537.9871	-973.2(**)	0.829(***)	0.245321
Netherlands	718.4314	302.3(.)	-278.943	-58.0158	1.432(***)	-0.432(**)
New Zealand	-88.2461	-109.484	126.7027	18.93264	1.34(***)	-0.337(*)
Niger	88.4(.)	36.88144	-79.0393	-70.7851	1.014(***)	-0.11332
Nigeria	49.53191	483.5(**)	-636.7(**)	125.1981	1.71(***)	-0.713(***)
Norway	-5481.5(*)	993(**)	226.5391	-439.537	1.438(***)	-0.448(**)
Pakistan	-9.98872	313.2239	-421.941	-23.0125	1.41(***)	-0.363(*)
Panama	-196.896	98.15489	97.19732	-43.2131	1.454(***)	-0.444(*)
Paraguay	62.4931	1093.806	-907.241	-169.65	1.031(***)	-0.02267
Peru	-114.732	737.8(.)	-742.569	154.1555	1.396(***)	-0.396(*)
Philippines	-197.2(*)	1400.4(***)	-1905.7(***)	747.4(*)	1.47(***)	-0.457(**)
Poland	1833.3(**)	165.9(.)	-77.461	-251.8(*)	1.337(***)	-0.331(*)
Portugal	216.0382	509.9(*)	-305.851	-126.638	1.237(***)	-0.25442
Qatar	-540.85	178.2541	-226.278	81.73709	1.643(***)	-0.648(***)
Romania	1338.3(*)	323.4715	-234.942	-235.163	0.992(***)	0.002459

Russia	1956.4(**)	493.1(***)	-479.2(*)	-138.353	1.278(***)	-0.287(*)
Rwanda	83.31091	2821.285	-346.672	-2330.66	0.854(***)	0.078435
Saudi Arabia	729.204	170.0077	-102.866	-114.284	1.416(***)	-0.403(**)
Senegal	124.6243	-160.903	524(*)	89.25995	0.864(***)	-0.0112
Serbia	168.4858	338.9(*)	-143.904	-187.094	1.447(***)	-0.464(**)
Sierra Leone	135.1(*)	967.4181	-88.8653	303.6173	1.136(***)	-0.353(*)
Singapore	-102.192	99.38677	-195.25	157.033	1.109(***)	-0.09002
Slovakia	2658.1(.)	383.2301	-968.6(**)	363.1798	1.367(***)	-0.4(*)
Slovenia	966.1592	802.3(*)	-815.6(*)	-143.625	1.402(***)	-0.385(*)
South Africa	132.3737	64.18386	-159.875	86.33838	1.674(***)	-0.677(***)
South Korea	-7.32043	1230.2(***)	-1871.4(***)	844.1(***)	1.304(***)	-0.365(**)
Spain	-638.12	1219.7(***)	-1071.9(*)	95.53005	1.083(***)	-0.10506
Sri Lanka	-37.3508	716.5124	-674.093	-113.633	1.074(***)	-0.02676
Sweden	1029.073	378.472	-557.364	127.3385	1.15(***)	-0.15581
Switzerland	-1358.51	831.9(.)	-399.678	-239.806	1.408(***)	-0.39(*)
Taiwan	-9.24875	1300.9(***)	-1182.8(*)	1.912303	0.849(***)	0.140214
Tanzania	3.792233	3.809301	-289.063	-74.6547	1.61(***)	-0.565(***)
Thailand	-18.6404	1434.3(***)	-2329.9(***)	746(.)	1.368(***)	-0.309(.)
Trinidad and Tobago	1569.1(*)	267.2(***)	-57.5529	-91.0628	1.081(***)	-0.286(.)
Tunisia	-40.63	586.8(.)	-341.187	-81.2727	1.085(***)	-0.10509
Turkey	-444.155	2087(**)	-1195.42	259.3307	0.72(***)	0.024107
Ukraine	975.9(**)	598(***)	-247.527	-367(*)	1.026(***)	-0.09771
United Arab Emirates	2113.526	101.3325	25.69178	-144.624	1.406(***)	-0.423(**)
United Kingdom	1680.476	673.1(**)	-756.5(**)	-10.5465	1.415(***)	-0.432(**)
United States	1611.997	916(***)	-1088.7(***)	124.8784	1.325(***)	-0.328(*)
Uruguay	-2.08406	148.1097	121.0456	-178.261	1.43(***)	-0.429(*)
Uzbekistan	1233.6(*)	-25.3878	-142.568	-56.9269	1.465(***)	-0.488(**)
Venezuela	1590.717	78.2216	-362.706	452.5225	1.405(***)	-0.581(***)
Vietnam	-45(.)	12.4949	73.64143	-142.602	1.31(***)	-0.24512
Yemen	259.2352	1616.5(***)	-1250.5(**)	-408.76	0.978(***)	-0.04311
Zambia	69.71653	-345.413	428.5161	-257.246	1.359(***)	-0.348(*)
Zimbabwe	186.3(*)	136.9843	-216.835	351.7(**)	1.065(***)	-0.336(*)

APPENDIX B2

This table contains the regression estimates from the model:
GDPpcap ~ CO2pcap_t0 + CO2pcap_tm1 + CO2pcap_tm2 + GDPpcap_tm1 + GDPpcap_tm2
Where:
CO2pcap is the CO2 emissions per capita.
T0 is the contemporary term.
Tm1 is the first lag at year t-1.
Tm2 is the second lag at year t-2.

*** = p-value 0 – 0.001
** = p-value 0.001 – 0.01
* = p-value 0.01 – 0.05
. = p-value 0.05 – 0.1

B3 FIRST DIFFERENCES REGRESSION (Δ) ESTIMATES WITH SIGNIFICANCE LEVELS 1800 - 1970

country	Intercept	Δco2pcap_t0	ΔCo2pcap_tm1	Δco2pcap_tm2	Δgdppcap_tm1	Δgdppcap_tm2
Algeria	0.0339	0.3307	-0.0902	0.0162	-0.2092	-0.3613
Angola	0.0311	-0.0421	0.013	0.032	-0.1254	0.0538
Argentina	0.0149(*)	0.0891(**)	0.0043	-0.0064	-0.07	-0.1329
Australia	0.0104(.)	0.012	0.0513(.)	-0.0072	-0.0138	0.1871(.)
Austria	0.0082	0.0545(**)	0.0259	0.0245	0.1642	0.0912
Bahrain	0	0.0006	0.001	0.0009	1.6974(***)	-0.6956(*)
Bangladesh	-0.0119	0.2319	0.198	-0.0367	-0.5214	-0.079
Belgium	0.0107(**)	0.1842(***)	-0.0154	0.0651(.)	0.1679(.)	-0.1816(.)
Bolivia	0.0135	-0.0218	0.048(.)	-0.0307	0.232	-0.0998
Brazil	0.0239(***)	0.0382	0.0091	-0.0187	-0.0421	0.0443
Bulgaria	-0.0075	0.0325	0.2951(*)	-0.0218	0.1048	0.1571
Burundi	0.0439(*)	-0.006	-0.0054	-0.058(*)	-0.4497	-0.5261
Cameroon	0.0122(.)	0.0275	0.0293	0.0276	-0.2205	0.0805
Canada	0.0108(.)	0.0777(*)	0.0324	0.04	0.1246	0.0648
Chile	0.012	0.0982	0.1247(.)	-0.0309	-0.0832	-0.1525
China	0.0243	0.0228	0.0053	-0.14(.)	0.1921	-0.1071
Colombia	0.0197(***)	0.0056	-0.0046	0.0115(**)	0.1281	-0.2184
Costa Rica	0.0543(*)	-0.0228	0.0606	0.0954	-0.5148(.)	-0.2143
Denmark	0.0171(***)	0.0683(**)	0.0254	-0.0006	-0.0642	-0.1446
Dominican Republic	0.01	0.1642	0.0456	0.08	-0.4523	-0.4891
Ecuador	0.0188(**)	0.0042	0.0112	-0.0215	-0.1086	0.2214
Egypt	0.0115(*)	0.0524	0.0687	-0.0088	0.6749(*)	-0.5688(.)
El Salvador	0.0365(*)	0.0439	0.0617	0.0266	-0.4144	-0.2747
Equatorial Guinea	0.0141	-0.0096	-0.0153	0.0081	0.8807(**)	-0.1789
Ethiopia	0.0289(*)	-0.0387	-0.0045	-0.0261	-0.0982	0.2104
Finland	0.0133(**)	0.0447(***)	-0.0041	0.0159(.)	0.2957(**)	-0.2197(*)
France	-0.0002	0.3967(***)	0.0415	0.0865	0.0019	-0.0369
Germany	-0.0023	0.0714(.)	0.2617(***)	0.0543	0.3241(**)	-0.0125
Ghana	0.0129	-0.0478	0.1484	0.1898(.)	-0.1518	-0.432(.)
Greece	0.0246	0.0233	0.021	0.0063	0.0231	-0.1545
Guatemala	0.0205(*)	0.0006	-0.0012	-0.0008	0.1415	-0.002
Honduras	0.0209	-0.0366	0.0009	-0.0229	-0.131	-0.2344
Hungary	0.0218(*)	0.1151	0.0859	0.0828	-0.0865	-0.1014
India	0.0086	-0.0653	-0.0154	0.1023	-0.3542(**)	-0.1476
Indonesia	0.0094(.)	0.003	-0.0008	-0.0012	0.2386(.)	-0.0989
Iran	0.0138	-0.0011	0.0053(.)	0.0061(*)	0.3366	0.402
Iraq	0.0457	0.0828	-0.1394	0.074	0.2555	-0.2077
Ireland	0.0111(*)	0.0544(*)	0.0696(**)	0.046(*)	0.3467(*)	-0.1086
Israel	0.0878(***)	-0.0114	-0.1543	-0.0817	-0.1875	-0.2622
Italy	0.0005	0.0949(***)	0.0238(.)	0	0.248(*)	0.1459(.)
Japan	-0.0003	0.3438(***)	-0.0182	0.032	0.1561	0.1367
Jordan	-0.0313	0.0177	0.3686(.)	0.3215	-0.5649(.)	0.0536
Kenya	0.0116	0.3123(*)	-0.2332	0.0803	0.2906	-0.0301

Lebanon	0.0281	0.0974	-0.2363	-0.2945	-0.1607	0.1312
Luxembourg	0.0283(**)	0.2845(*)	0.1937	0.0409	-0.2736	-0.145
Madagascar	-0.0063	0.0761	0.074(.)	0.0185	0.0912	0.5902(.)
Malaysia	0.0208	-0.0007	0.0527	0.0133	-0.1542	-0.1466
Malta	0.0006	0.0611	0.0616	0.213(*)	-0.0317	0.7072(*)
Mexico	0.0157(*)	0.0115	0.0211	-0.0317	-0.0366	0.2329(.)
Morocco	0.0002	0.0364	0.02	0.0322	0.8709(**)	-0.1701
Mozambique	0.0122	0.0606	0.0662	-0.0559	0.2208	0.1413
Myanmar	0.0222	0.012	0.0143	0.0141	-0.3162	-0.1489
Nepal	0.0121	-0.0073	-0.0132	0.047	-0.5024	-0.3509
Netherlands	0.0054	0.3062(***)	0.0384	0.0504	0.0146	-0.1134
New Zealand	0.0159(*)	0.1403(.)	-0.0582	0.0059	-0.0667	-0.2477(*)
Nigeria	0.0174	0.1536(*)	0.0145	-0.1708(*)	0.0448	-0.6051(.)
Norway	0.0177(***)	0.0543(**)	0.0024	-0.0059	-0.0382	-0.1005
Pakistan	0.0159	-0.0298	0.0739	0.1566	-0.0087	0.1197
Panama	0.0403(*)	0.03	-0.0041(*)	-0.0013	-0.2228	0.1598
Paraguay	0.0341(**)	-0.0131	-0.0488(.)	-0.0327	-0.3458	-0.3754
Peru	0.0187(**)	0.0451(*)	-0.007	0.0171	0.3935(**)	-0.2872(*)
Philippines	0.0211(*)	0.0001	0.0031	0.0062	-0.1332	0.0639
Poland	0.0111	0.3895(*)	0.3038	0.022	0.1297	-0.2022
Portugal	0.0162(**)	0.0337	0.0016	-0.0022	-0.0952	0.2013(.)
Qatar	0.0159	-0.0029	-0.0042	-0.0021	0.3413	-0.412
Romania	0.0265	1.1423(***)	-0.3608	-0.2219	0.0568	-0.0266
Rwanda	0.0089	0.0129	0.0006	-0.0241	0.1472	-0.0862
Sierra Leone	0.036(*)	0.0123	0.0047	0.0085	-0.2817	-0.3798
Singapore	0.0618(**)	0.0291(.)	0.0242	0.0234	-0.3486(*)	-0.3633(*)
South Africa	0.0194(.)	0.0245	-0.0169	-0.0009	0.0951	0.0582
South Korea	0.0324	0.0686	-0.0163	0.0322	-0.1019	-0.4659(**)
Spain	0.0058	0.0829(**)	0.0413	0.0406	0.052	0.0391
Sri Lanka	0.0117	0.0067	0.0081	0.0189	-0.0216	-0.1806
Sweden	0.0179(***)	0.0311(**)	0.0224(*)	0.0021	-0.0312	-0.0735
Switzerland	0.0149(**)	0.098(***)	-0.0223	0.0116	-0.0043	0.0141
Taiwan	0.0227(.)	0.0839	-0.0359	0.0436	0.0918	-0.218
Tanzania	0.0077	0.0529	-0.0095	0.1194	-0.149	-0.2
Thailand	0.049	0.0177	-0.0441	-0.0442	-0.0456	0.0909
Trinidad and Tobago	0.0451(*)	-0.0228	-0.0162	-0.0263	0.3622	-0.2269
Tunisia	0.0269	0.0696	0.125	0.069	-0.4673	0.0472
Turkey	0.0329(.)	0.0202	-0.1792	0.1197	-0.0815	0.0926
United Kingdom	0.0067(*)	0.1505(***)	-0.0058	0.0358	0.2433(**)	-0.07
United States	0.0025	0.3015(***)	-0.0013	-0.0447	0.0924	0.0679
Uruguay	0.0158	0.0042	0.0051	-0.0019	-0.0649	-0.0848
Venezuela	0.0356(**)	-0.0001(.)	0.0001	0	0.1148	0.0217
Vietnam	0.0165	-0.005	-0.0683	0.0002	0.2634	-0.1079
Zambia	0.0346(.)	0.2718(*)	-0.1815	-0.05	-0.0096	-0.438
Zimbabwe	0.0474(**)	0.0871	0.2706(*)	0.2157(.)	-0.2352	-0.612(.)
Yemen	0.1248(*)	0.0003	0.0002	0.0004	-1.6866	-10.8243(.)

Guinea-Bissau	0.0536(*)	-0.0443	0.0224	0.0831(***)	-0.3103(.)	0.1162
Gambia	0.0467(.)	-0.0085	-0.1278	-0.1481	-0.2463	-0.1505

APPENDIX B3

This table contains the regression estimates from the model:
ΔGDPpcap ~ ΔCO2pcap_t0 + ΔCO2pcap_tm1 + ΔCO2pcap_tm2 + ΔGDPpcap_tm1 + ΔGDPpcap_tm2
Where:
ΔCO2pcap is the change in CO2 emissions per capita from the previous year.
(E.g., $\Delta CO2pcap_{t-1} = CO2pcap_{t-1} - \Delta CO2pcap_{t-2}$)
T0 is the contemporary term.
Tm1 is the first lag at year t-1.
Tm2 is the second lag at year t-2.

*** = p-value 0 – 0.001
** = p-value 0.001 – 0.01
* = p-value 0.01 – 0.05
. = p-value 0.05 – 0.1

B4 FIRST DIFFERENCES REGRESSION (Δ) ESTIMATES WITH SIGNIFICANCE LEVELS 1971 – 2018

country	**Intercept**	**ΔCo2pcap_t0**	**Δco2pcap_tm1**	**Δco2pcap_tm2**	**Δgdppcap_tm1**	**Δgdppcap_tm2**
Algeria	0.0127	0.0754(*)	0.0267	-0.0015	0.1087	0.3946(**)
Angola	0.0033	0.1(*)	0.0765	0.0321	0.5095(**)	-0.0188
Argentina	0.0076	0.7034(***)	0.0655	0.1261	0.049	-0.0711
Australia	0.0172(***)	0.2442(**)	0.0026	-0.1546(.)	0.2066	-0.0884
Austria	0.0174(***)	0.1148(*)	0.1266(*)	0.0145	0.1713	-0.0445
Azerbaijan	0.0034	-0.1005	0.0796	-0.0883	1.0221(***)	-0.2325
Bahrain	0.0204(*)	0.0349	0.0037	-0.0889(*)	0.38(*)	0.2014
Bangladesh	0.0023	0.1124	0.2253(*)	-0.0409	0.4387(**)	0.0845
Belarus	0.011	0.4554(***)	0.1796	-0.2956(.)	0.4906(**)	0.0695
Belgium	0.0172(***)	0.1834(***)	0.0497	-0.0036	0.0021	0.1031
Benin	0.0016	0.089(*)	0.0173	0.0796(*)	-0.1282	0.078
Bolivia	0.0029	0.032(.)	0.017	-0.0207	0.584(***)	0.1664
Botswana	0.0508(**)	-0.0049	-0.0008	0.0002	0.0701	-0.024
Brazil	0.0093	0.5015(***)	0.1378	-0.1165	0.0436	0.1353
Bulgaria	0.0143(*)	0.2905(**)	0.0767	0.0584	0.124	0.1864
Burkina Faso	0.0132(.)	0.032	-0.107(*)	-0.0501	0.0766	0.0414
Burundi	-0.0081	0.01	0.0114	0.0624	0.1607	-0.0299
Cameroon	0.002	-0.0054	0.0266(*)	-0.0064	0.8327(***)	-0.0592
Canada	0.0145(**)	0.3742(***)	0.1471	-0.0445	0.1366	0.0363
Central African Republic	-0.0106	0.151(*)	0.0602	-0.04	-0.1138	0.0399
Chad	0.0144	-0.007	0.0223	-0.0178	0.3171(*)	0.0037
Chile	0.0149(*)	0.366(***)	-0.0064	-0.0424	0.2533	-0.1231
China	0.0202(*)	0.4405(***)	-0.1873	0.0536	0.427(**)	-0.117
Colombia	0.012(**)	0.1121(*)	0.0256	0.0204	0.4219(*)	-0.0713
Comoros	0.0127(*)	0.0157	-0.026	0.0071	0.0138	0.0911
Costa Rica	0.0157(**)	0.1078(*)	0.1384(**)	-0.0161	0.2372	-0.2498(.)
Cote d'Ivoire	0.0018	0.0523(.)	0.0333	0.0142	0.3814(*)	0.1655
Croatia	0.0062	0.2908(**)	0.0423	-0.104	0.6463(***)	-0.082
Denmark	0.0184(***)	0.0865(*)	0.049	-0.0106	0.1723	-0.1391
Dominican Republic	0.0208(*)	0.1807(**)	-0.0425	-0.0028	0.2846(.)	0.073
Ecuador	0.0127(.)	0.0359	0.0234	0.0332	0.018	0.0796
Egypt	0.0131(*)	0.1153(*)	0.1752(**)	0.0342	0.4847(**)	-0.0774
El Salvador	0.0043	0.1066(**)	0.0416	-0.0005	0.854(***)	-0.2475(.)
Equatorial Guinea	0.0135	0.1686(***)	-0.046	0.0079	0.318(*)	0.0773
Ethiopia	0.0048	0.0668	0.031	-0.061	0.7723(***)	-0.2073
Finland	0.0121(*)	0.096(*)	0.0504	0.0003	0.5472(***)	-0.1585
France	0.016(***)	0.1967(***)	0.0663	-0.0166	0.2869(.)	-0.1099
Gambia	0.0079	0.027	-0.0769	-0.0098	0.0036	-0.3102(*)
Georgia	0.007	-0.0228	-0.0312	-0.0653	1.039(***)	-0.2808
Germany	0.0359(***)	0.2903(**)	0.1729	0.031	-0.1523	-0.3609(*)
Ghana	0.0071	0.0337	0.0249	-0.0609	0.391(*)	0.0407

Greece	0.0064	0.1832(.)	0.0404	-0.0743	0.4291(*)	0.0236
Guatemala	0.0022	0.0622(.)	0.0784(*)	0.038	0.5113(**)	-0.0939
Guinea	0.017(***)	0.1334(.)	0.0649	0.3151(**)	-0.2632(.)	0.0326
Guinea-Bissau	0.0011	-0.0152	0.0061	0.0661	-0.2694(.)	-0.0953
Honduras	0.0089(.)	0.1163(*)	0.0813	0.0267	0.2159	-0.1267
Hungary	0.0112(.)	0.2388(.)	-0.0025	-0.1339	0.4106(*)	0.1785
India	0.0113	0.3375(.)	0.0944	0.0397	0.0571	0.1128
Indonesia	0.0228(*)	0.2171(**)	-0.0735	0.0409	0.3285(*)	-0.1222
Iran	0.0011	0.4328(***)	-0.0744	0.2071	0.6162(***)	-0.3378(*)
Iraq	0.019	0.2854(.)	0.126	-0.1193	-0.0632	0.269(.)
Ireland	0.0215(**)	0.1015	0.1169	0.0615	0.4817(**)	-0.0326
Israel	0.0156(**)	0.032	-0.0033	0.0286	0.2815(.)	-0.1313
Italy	0.0173(***)	0.4124(***)	0.0549	0.009	0.1067	-0.1495
Japan	0.0102(*)	0.3055(***)	0.0072	-0.1007	0.1485	0.2674(.)
Jordan	0.0073	0.3268(***)	0.0061	-0.1376	0.1739	0.3907(**)
Kazakhstan	0.0068	0.2201(*)	-0.0005	-0.1659	0.6099(**)	0.1186
Kenya	0.0136(**)	0.0397	0.015	0.0133	0.3549(*)	-0.1167
Kuwait	-0.0029	-0.0169(**)	0.0456(***)	0.0079	0.544(***)	-0.0496
Latvia	0.0146	0.3755(**)	0.0134	-0.223	0.7515(***)	-0.3766(*)
Lebanon	0.0351	0.4859	0.4627	-0.0714	-0.0338	-0.3223(*)
Lithuania	0.0187	0.4151(***)	0.033	-0.0717	0.3895(.)	0.0277
Luxembourg	0.0225(**)	0.1891(**)	-0.0189	-0.0357	0.1621	-0.0817
Madagascar	-0.0083	0.0701(.)	0.008	0.0057	-0.0107	0.0733
Malaysia	0.0333(***)	0.1599(*)	0.1238(.)	0.0832(.)	-0.0137	-0.1696
Mali	0.0023	0.0841	0.0018	0.2133(.)	-0.2276	-0.0549
Malta	0.0125(.)	-0.012	-0.015	0.0243	0.708(***)	0.0233
Mexico	0.0141(**)	0.3995(**)	0.0174	0.0459	-0.0098	-0.074
Morocco	0.0421(***)	-0.0087	0.0175	-0.006	-0.6416(***)	-0.076
Mozambique	-0.0199(*)	0.0592	0.0571	-0.0029	0.2508	-0.0866
Myanmar	0.01	0.0953(**)	0.0138	-0.0328	0.5137(**)	0.1811
Namibia	0.0172(.)	-0.0079	-0.0058	-0.0417	0.0613	0.2547
Nepal	0.024(**)	0.004	0.0148	0.0282	-0.1539	-0.0464
Netherlands	0.0122(**)	0.1477(**)	0.0085	-0.0451	0.5469(***)	-0.1687
New Zealand	0.009(*)	-0.037	0.0051	0.0172	0.3091(.)	0.0513
Niger	-0.0066	-0.0375	-0.0073	0.0445	0.0472	0.1288
Nigeria	0.0093	0.0925(**)	-0.0192	0.0085	0.4861(**)	0.0119
Norway	0.0116(*)	0.1282(*)	0.0993	-0.048	0.8437(***)	-0.2022
Pakistan	0.0173(**)	0.1002(.)	0.0539	-0.0504	0.2167	0.0331
Panama	0.0201(*)	0.0018	-0.001	-0.0242	0.477(**)	-0.161
Paraguay	0.0149	0.1165	0.0586	-0.027	0.1913	0.0628
Peru	0.0099	0.18(*)	-0.0034	0.0089	0.416(*)	-0.1464
Philippines	0.0085(*)	0.2304(***)	-0.1212(.)	0.0487	0.6584(***)	-0.1265
Poland	0.0087(.)	0.2513(*)	0.0515	-0.2883(**)	0.804(***)	-0.1103
Portugal	0.0157(**)	0.1814(**)	0.0953	0.0851	0.214	-0.2908(.)
Qatar	0.0058	0.2162(*)	0.0512	-0.1636(.)	0.4012(**)	0.3614(*)
Romania	0.0187(.)	0.3319(**)	-0.0118	-0.1956	0.3507(*)	0.188

Russia	0.0069	0.5736(***)	-0.0288	-0.2446	0.4595(**)	0.2071
Rwanda	0.0127	-0.0076	0.1193	0.0307	-0.3957(*)	-0.1549
Saudi Arabia	0.0121	0.1625(*)	0.0534	-0.0573	0.4445(**)	0.015
Senegal	0.0066	-0.0724(.)	0.0177	0.03	-0.0835	-0.2484(.)
Serbia	0.0025	0.3349(***)	0.1911(.)	0.1381	0.3252(*)	-0.0328
Sierra Leone	-0.0002	0.0823(.)	0.0686	0.0671	0.5136(**)	-0.2767(.)
Singapore	0.0445(***)	0.0546	0.0037	0.0186	0.3197(*)	-0.2405
Slovakia	0.0099	0.2104	-0.4621(*)	0.0601	0.8068(***)	-0.2898
Slovenia	0.0075	0.2396(*)	0.0846	-0.0125	0.5505(**)	-0.1075
South Africa	0.0039	0.0908	-0.1022	0.0029	0.5853(***)	0.0977
South Korea	0.0209(**)	0.4833(***)	-0.3155(**)	0.0294	0.5143(**)	-0.0639
Spain	0.0137(**)	0.2995(***)	-0.0998	0.0763	0.5031(**)	-0.1646
Sri Lanka	0.0338(***)	0.0496	0.0609	-0.0167	0.0427	-0.0982
Sweden	0.0142(**)	0.1226(*)	-0.0803	-0.023	0.2944(.)	-0.0834
Switzerland	0.0157(***)	0.1541(**)	0.033	0.0416	0.5576(***)	-0.2572(.)
Taiwan	0.0306(**)	0.3485(***)	0.1364	-0.0632	0.052	0.0171
Tanzania	0.0037	0.029	-0.0097	-0.0228	0.4751(**)	0.4072(**)
Thailand	0.015(*)	0.3647(***)	-0.0963	-0.0017	0.3768(*)	-0.081
Trinidad and Tobago	-0.0021	0.1595(**)	0.0745	0.0552(.)	0.2104	0.1704
Tunisia	0.0193(*)	0.1907(*)	0.1401	-0.0847	-0.0641	0.1055
Turkey	0.0184(.)	0.4886(***)	0.1325	0.045	-0.1862	-0.0269
Ukraine	0.0147	0.7055(***)	0.024	-0.2178	0.4731(*)	0.0677
United Arab Emirates	0.01	0.1557	0.0354	-0.1135	0.3492(*)	0.0599
United Kingdom	0.0186(***)	0.2745(***)	-0.0193	0.0369	0.5189(***)	-0.3609(*)
United States	0.0188(***)	0.53(***)	-0.005	0.0738	0.1709	-0.0869
Uruguay	0.0148(*)	0.038	0.0496	0.0561	0.435(*)	-0.1902
Uzbekistan	0.0004	-0.0346	-0.0231	-0.1414	0.4849(**)	0.3211(.)
Venezuela	-0.0039	0.0611	-0.1175	0.1833(.)	0.5281(**)	-0.0362
Vietnam	0.0337(***)	0.0111	0.1432(**)	0.0078	0.2896(.)	-0.3334(*)
Yemen	-0.0047	0.1716(***)	0.0191	-0.0503	0.2053	0.1928
Zambia	0.0046	-0.0131	-0.0929	0.0336	0.2142	0.4934(**)
Zimbabwe	-0.0035	0.1347(.)	-0.0729	0.2042(*)	0.2933(.)	-0.0299

APPENDIX B4

This table contains the regression estimates from the model:
ΔGDPpcap ~ ΔCO2pcap_t0 + ΔCO2pcap_tm1 + ΔCO2pcap_tm2 + ΔGDPpcap_tm1 + ΔGDPpcap_tm2
Where:
ΔCO2pcap is the change in CO2 emissions per capita from the previous year.
T0 is the contemporary term.
Tm1 is the first lag at year t-1.
Tm2 is the second lag at year t-2.

*** = p-value 0 – 0.001
** = p-value 0.001 – 0.01
* = p-value 0.01 – 0.05
. = p-value 0.05 – 0.1

Appendix C

C1 COEFFICIENTS OF ESTIMATES IN LOG – LOG REGRESSION (DEVELOPED COUNTRIES)

Coefficient of CO2 per capita to explain GDP per capita (Developed Countries)		
	1800 - 1970	**1971 - 2018**
Developed Country		
Australia	0.0462	0.2842*
Austria	0.1284*	0.101
Belgium	0.161*	0.1777*
Canada	0.1409*	0.3713*
Denmark	0.0908*	0.0826
France	0.4085*	0.1677*
Germany	0.1904*	0.1902
Ireland	0.0475	0.1398
Netherlands	0.2564*	0.1184
New Zealand	0.2036	-0.0369
Norway	0.0956*	0.1506
Sweden	0.0579*	0.1181
Switzerland	0.1287*	0.1615*
United Kingdom	0.1575*	0.2526*
United States	0.3664*	0.4999*

Table 0-1 Coefficients of log CO2 emissions for developed countries

* Indicates high statistical significance of the coefficient (p-value 0 – 0.01).

This table shows the coefficients (and significance) of the explanatory variable log CO2 per capita to explain log GDP per capita.
For example, this table can be interpreted as follows:
A 1% increase in CO2 per capita for Australia in 1971 – 2018 is correlated to a 0.28% increase in GDP per capita.

C2 COEFFICIENTS OF ESTIMATES IN LOG – LOG REGRESSION (DEVELOPING COUNTRIES)

Coefficient of CO2 per capita to explain GDP per capita (Developing Countries)		
	1800 - 1970	**1971 - 2018**
Developing Country		
Chile	0.2068*	0.3767*
China	0.1590	0.5065*
Finland	0.0709*	0.0817
Greece	0.0591	0.1647
India	-0.0687	0.3339
Indonesia	0.0334	0.2780*
Italy	0.1236*	0.3717*
Japan	0.3931*	0.2325*
Portugal	0.0217	0.1594
Singapore	0.0091	0.0291
South Korea	0.1021	0.4376*

Spain	0.1522*	0.2934*
Taiwan	0.0209	0.3088*
Turkey	0.0636	0.5515*

Table 0-2 Coefficients of log CO2 emissions for developing countries

* Indicates high statistical significance of the coefficient (p-value 0 – 0.01).

This table shows the coefficients (and significance) of the explanatory variable log CO_2 per capita to explain log GDP per capita.
For example, this table can be interpreted as follows:
A 1% increase in CO_2 per capita for Chile in 1971 – 2018 is correlated to a 0.37% increase in GDP per capita.

C3 COEFFICIENTS OF ESTIMATES IN LOG – LOG REGRESSION (LEAST DEVELOPED COUNTRIES)

	Coefficient of CO2 per capita to explain GDP per capita (Least Developed Countries)	
	1800 - 1970	**1971 - 2018**
Least Developed Country		
Angola	-0.0336	0.1811
Bangladesh	0.1740	0.1228
Benin	NA	0.0737
Burundi	-0.0140	0.0077
Chad	NA	0.0245
Equatorial Guinea	-0.0182	0.1593*
Ethiopia	-0.0908	0.0628
Madagascar	0.0011	0.0939*
Mali	NA	0.1278
Mozambique	0.0736	0.0434
Myanmar	0.0492	0.1183*
Nepal	0.0097	0.0060
Niger	NA	0.0219
Rwanda	0.0244	0.0280
Senegal	NA	-0.0493
Sierra Leone	0.0163	0.0984
Zambia	0.1902	0.0034

Table 0-3 Coefficients of log CO2 emissions for low-income countries

* Indicates high statistical significance of the coefficient (p-value 0 – 0.01).

This table shows the coefficients (and significance) of the explanatory variable log CO_2 per capita to explain log GDP per capita.
For example, this table can be interpreted as follows:
A 1% increase in CO_2 per capita for Madagascar in 1971 – 2018 is correlated to a 0.09% increase in GDP per capita.

Appendix D

D1 CO2 EMISSIONS PER CAPITA RANKING

Rank	Country	Cumulative emissions per population in 2021, tCO2	Rank	Country	Cumulative per capita emissions 2021, tCO2
1	Canada	1,751	**1**	New Zealand	5,764
2	United States	1,547	**2**	Canada	4,772
3	Estonia	1,394	**3**	Australia	4,013
4	Australia	1,388	**4**	United States	3,820
5	Trinidad and Tobago	1,187	**5**	Argentina	3,382
6	Russia	1,181	**6**	Qatar	3,340
7	Kazakhstan	1,121	**7**	Gabon	2,764
8	United Kingdom	1,100	**8**	Malaysia	2,342
9	Germany	1,059	**9**	Republic of Congo	2,276
10	Belgium	1,053	**10**	Nicaragua	2,187
11	Finland	1,052	**11**	Paraguay	2,111
12	Czechia	1,016	**12**	Kazakhstan	2,067
13	New Zealand	962	**13**	Zambia	1,966
14	Belarus	961	**14**	Panama	1,948
15	Ukraine	922	**15**	Cote d'Ivoire	1,943
16	Lithuania	899	**16**	Costa Rica	1,932
17	Qatar	792	**17**	Bolivia	1,881
18	Denmark	781	**18**	Kuwait	1,855
19	Sweden	776	**19**	Trinidad and Tobago	1,842
20	Paraguay	732	**20**	United Arab Emirates	1,834

Table 0-1 CO2 emissions per capita ranked by end weights (left) and cumulative weights (right)

The top 20 countries for cumulative emissions 1850-2021 weighted by population in 2021 (left), versus the top 20 countries for cumulative per-capita emissions 1850-2021 (right). The ranking excludes countries with a population in 2021 of less than 1 million people.

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