The Historical Role of Capitalism in Shaping Environmental Justice: A Study of Economic Growth and CO_2 Emissions from 2000 to 2022

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Contents

1 Introduction

Environmental injustice has become a significant issue in the global conversation about climate change. While there is widespread recognition of the need to reduce emissions and address global warming, the debate often stalls when it comes to determining who should bear the costs. This issue arises because the responsibility for climate change is not equally distributed. The countries that have historically emitted the most pollutants are not always the ones most affected by the consequences. In fact, the brunt of climate change often falls on underdeveloped countries that lack the advanced technology and resources to deal with its effects. This uneven distribution of responsibility highlights the unequal nature of climate change and its consequences. In response, the research aims to examine the historical incentives that capitalism has played in shaping environmental progress, particularly in relation to economic growth and CO2 emissions. The study will focus on three groups of countries—low-income countries, newly industrialized nations, and developed countries—to explore how economic growth has influenced emissions patterns within each group. By analyzing these different groups, the research seeks to uncover the complex relationship between economic development and environmental responsibility, as well as to highlight the inequalities that persist in the global response to climate change. The data used for CO2 emissions are sourced from EIA World Data, which is provided by the U.S. Energy Information Administration (EIA). For GDP data by country, the source is the World Bank Open Data, which includes datasets on various aspects of development, such as economic growth and the environment. The GDP figures have been adjusted using the price index from the Consumer Price Index (CPI-U), provided by the U.S. Department of Labor Bureau of Labor Statistics. The datasets cover the period from 2000 to 2022.

2 Capitalism's Role in Environmental Injustice

Economic incentives drive technological efficiency in resource extraction, significantly altering Earth's systems. In the 19th century, steam technology thrived due to British imperialism and global exploitation. The rationale for these advancements was "geared to the opportunities provided by the constellation of a largely depopulated New World" (Malm & Hornborg, 2014). The decline of Indigenous populations left uncultivated lands for European settlers to control resource-rich territories. This created a need for improved production capabilities that steam-powered factories could provide. However, increased extraction efficiency leads to amplified consumption and environmental impact. Modern societies' dependence on technology can "modify the very core processes that drive Earth System dynamics" (López-Corona & Magallanes-Guijón, 2020). Thus, the pursuit of economic profit has historically fueled technological progress in resource over-extraction.

The unequal allocation of resources has exacerbated global inequality through technological development. Limited access to innovations for a wealthy minority prevents equitable distribution of benefits. In capitalist systems, scientific progress "could only be installed by the owners of the means of production" (Malm & Hornborg, 2014). Thus, a privileged class drives environmental exploitation through systematic inequality, leaving the marginalized unaccountable. Similarly, the global technological gap is "predicated on a global division of labour that is geared precisely to abysmal price and wage differences between populations" (Malm & Hornborg, 2014). Scientific prosperity in wealthy nations relies on the exploitation of cheaper labour in less affluent countries. Lacking financial resources to invest in skilled labour, developing nations depend on outdated technologies that hinder growth. Consequently, "[p]erceptions of 'technology' [...] are cultural constructions conditioned by global power structures" (Malm & Hornborg, 2014). Companies with advanced technologies decide which innovations to pursue and promote in favour of the wealthy. Economic disparity thus ensures that the benefits of advanced industries accrue to a small group of nations while leaving others disadvantaged.

3 Classifying Countries Based on GDP Growth

The analysis focuses on three groups of countries to evaluate the differing impacts of CO2 emissions and economic growth: low-income countries, newly industrialized countries (NICs) and developed countries. GDP growth is utilized as the basis for classifying countries into these categories. Countries with an average GDP growth of less than 10% over a span of 22 years and ranking each year among the top 10% globally in GDP are classified as developed countries. Countries with GDP growth exceeding 10% over the same period are categorized as newly industrialized countries. Meanwhile, countries with GDP growth below 10% and a consistent ranking in the bottom 11% of global GDP each year are classified as low-income countries.

During the classification process, Mexico met the criteria for developed countries. However, existing literature indicates that this classification does not align with the study's framework, leading to its exclusion. This results in the identification of eight developed countries: Canada, the European Union, France, Germany, Italy, Japan, the United Kingdom and the United States. For the NIC category, while more than eight countries were eligible, only the top eight with the highest average GDP growth were included to maintain balance across the categories. These countries are Chad, China, Equatorial Guinea, Ethiopia, Ghana, Guyana, Iraq, and the Maldives. In identifying low-income countries, the bottom 10% of GDP rankings initially included Tuvalu. However, due to significant missing data for Tuvalu during the study period, the threshold was adjusted to the bottom 11% of GDP rankings. This adjustment resulted in the selection of the following low-income countries: Belize, Burundi, the Central African Republic, Eswatini, Kiribati, Lesotho, Samoa and Seychelles.

4 Data Cleaning and Variable Construction

The following code prepares a panel dataset linking national carbon dioxide (CO_2) emissions with inflation-adjusted GDP from 2000 to 2022. It begins by importing emissions and GDP data, standardizing country names, and merging the datasets. Year-specific columns are converted to numeric values, and countries are assigned to continents using predefined regional lists. Aggregated entities such as "OECD" and "OPEC" are excluded. The dataset is filtered to remove countries with excessive missing values and reshaped from wide to long format to facilitate time series analysis. Missing continent labels are manually imputed. Emissions and GDP values are then separated into distinct columns, and GDP data is matched to corresponding years and countries. To allow meaningful comparisons across time, GDP values are adjusted for inflation using Consumer Price Index (CPI) data. Countries are subsequently classified into four groups: developed countries, low income countries, newly industrialized countries, and others. Manual adjustments are applied to refine these classifications. The final dataset includes a selected group of countries representing each category. It integrates emissions, real GDP, regional labels, and growth classifications into a single structure suitable for further analysis.

[1]:
```python
import pandas as pd
import plotly.graph_objects as go
import plotly.express as px
from plotly.subplots import make_subplots
import os
from IPython.display import display
import numpy as np
import seaborn as sns
import re
```

[2]:
```python
emissions = pd.read_csv('merged_processed_emissions_modified.csv')
emissions['Country'] = emissions['Country'].str.replace(r'(?<=[a-z])(?=[A-Z])',␣
↪' ', regex=True)
emissions = emissions[emissions['Country'] != 'Tuvalu']
gdp = pd.read_excel('GDP2.xls')
```

[3]:
```python
gdp.rename(columns={'Country Name': 'Country'}, inplace=True)


merged_data = emissions.merge(gdp, on='Country', how='left', suffixes=('',␣
↪'_gdp'))


for col in gdp.columns:
    if col != 'Country':
        merged_data.rename(columns={col: f"{col}_gdp"}, inplace=True)



merged_data.to_csv('merged_emissions_with_gdp.csv', index=False)
merged_data = pd.read_csv('merged_emissions_with_gdp.csv')
```

```
[4]: for year in range(2000, 2023):
        merged_data[str(year)] = pd.to_numeric(merged_data[str(year)],␣
     ↪errors='coerce')
        merged_data[f'{year}_gdp'] = pd.to_numeric(merged_data[f'{year}_gdp'],␣
     ↪errors='coerce')


    europe = ['European Union', 'Austria', 'Belgium', 'Bulgaria', 'Croatia',␣
     ↪'Cyprus', 'Czechia', 'Denmark', 'Estonia', 'Finland', 'Former Czechoslovakia',
              'France', 'Germany', 'Germany,East', 'Germany,West', 'Greece',␣
     ↪'Hungary', 'Ireland', 'Italy', 'Latvia', 'Lithuania', 'Luxembourg', 'Malta',
              'Netherlands', 'Poland', 'Portugal', 'Romania', 'Slovakia',␣
     ↪'Slovenia', 'Spain', 'Sweden']
    asia = ['Afghanistan', 'Armenia', 'Azerbaijan', 'Bahrain', 'Bangladesh',␣
     ↪'Bhutan', 'Brunei', 'Burma', 'Cambodia', 'China', 'Georgia', 'India',␣
     ↪'Indonesia',
            'Iran', 'Iraq', 'Israel', 'Japan', 'Jordan', 'Kazakhstan', 'Kuwait',␣
     ↪'Kyrgyzstan', 'Laos', 'Lebanon', 'Malaysia', 'Maldives', 'Mongolia', 'Nepal',
            'North Korea', 'Oman', 'Pakistan', 'Palestinian Territories',␣
     ↪'Philippines', 'Qatar', 'Russia', 'Saudi Arabia', 'Singapore', 'South Korea',␣
     ↪'SriLanka',
            'Syria', 'Taiwan', 'Tajikistan', 'Thailand', 'Timor-Leste',␣
     ↪'Turkmenistan', 'United Arab Emirates', 'Uzbekistan', 'Vietnam', 'Yemen']
    africa = ['Algeria', 'Angola', 'Benin', 'Botswana', 'Burkina Faso', 'Burundi',␣
     ↪'Cameroon', 'CapeVerde', 'Central African Republic', 'Chad', 'Comoros',
              'Congo-Brazzaville', 'Congo-Kinshasa', 'Djibouti', 'Egypt',␣
     ↪'EquatorialGuinea', 'Eritrea', 'Eswatini', 'Ethiopia', 'Gabon', 'Gambia,The',␣
     ↪'Ghana',
              'Guinea', 'Guinea-Bissau', 'IvoryCoast', 'Kenya', 'Lesotho',␣
     ↪'Liberia', 'Libya', 'Madagascar', 'Malawi', 'Mali', 'Mauritania', 'Mauritius',
```

```
         'Morocco', 'Mozambique', 'Namibia', 'Niger', 'Nigeria', 'Rwanda',␣
↪'Senegal', 'Seychelles', 'SierraLeone', 'Somalia', 'SouthAfrica', 'SouthSudan',
         'Sudan', 'Tanzania', 'Togo', 'Tunisia', 'Uganda', 'Zambia', 'Zimbabwe']
north_america = ['Antigua and Barbuda', 'Bahamas', 'Barbados', 'Belize',␣
↪'Canada', 'CostaRica', 'Cuba', 'Dominica', 'DominicanRepublic', 'ElSalvador',␣
↪'Grenada',
                'Guatemala', 'Honduras', 'Jamaica', 'Mexico', 'Nicaragua',␣
↪'Panama', 'SaintKittsandNevis', 'SaintLucia', 'Saint Vincent/Grenadines',␣
↪'Trinidad and Tobago',
                'United States']
south_america = ['Argentina', 'Bolivia', 'Brazil', 'Chile', 'Colombia',␣
↪'Ecuador', 'Guyana', 'Paraguay', 'Peru', 'Suriname', 'Uruguay', 'Venezuela']
oceania = ['Australia', 'Fiji', 'Kiribati', 'Marshall Islands', 'Micronesia',␣
↪'Nauru', 'New Zealand', 'Palau', 'Papua New Guinea', 'Samoa', 'Solomon␣
↪Islands', 'Tonga', 'Tuvalu', 'Vanuatu']

excluded_groups = ['OPEC-South America', 'OPEC-Africa', 'OPEC', 'OECD-North␣
↪America', 'OECD-Europe', 'OECD-Asia And Oceania', 'OECD']

def assign_continent(country):
    if country in europe:
        return 'Europe'
    elif country in asia:
        return 'Asia'
    elif country in africa:
        return 'Africa'
    elif country in north_america:
        return 'North America'
    elif country in south_america:
```

```
        return 'South America'
    elif country in oceania:
        return 'Oceania'
    else:
        return None

merged_data = merged_data[~merged_data['Country'].isin(excluded_groups)].copy() ␣
 ↪# Create a copy here

merged_data.loc[:, 'Continent'] = merged_data['Country'].apply(assign_continent)␣
 ↪ # No warning now
```

[5]:
```
year_columns = [col for col in merged_data.columns if col.isdigit() and len(col)␣
 ↪== 4]

columns_to_drop = [col for col in year_columns if int(col) < 2000]

merged_2 = merged_data.drop(columns=columns_to_drop)

rows_with_nan = merged_2[merged_2.isna().sum(axis=1) > 10]

merged_2 = merged_2[merged_2.isna().sum(axis=1) <= 10]
```

[6]:
```
year_columns = [col for col in merged_2.columns if col.isdigit() and len(col) ==␣
 ↪4]
gdp_columns = [f"{col}_gdp" for col in year_columns]

melted_df = pd.melt(
    merged_2,
    id_vars=['Country', 'Type of Emission', 'Continent'],
```

```
    value_vars=year_columns + gdp_columns,
    var_name='Variable',
    value_name='Value'
)

melted_df['Year'] = melted_df['Variable'].where(melted_df['Variable'].
↪isin(year_columns)).dropna()
melted_df['Year_gdp'] = melted_df['Variable'].where(melted_df['Variable'].
↪isin(gdp_columns)).dropna()

melted_df = melted_df.drop(columns=['Variable'])

final_melted_df = melted_df.drop_duplicates().copy()

continent_mapping = {
    'Bermuda': 'North America',
    'Dominican Republic': 'North America',
    'El Salvador': 'North America',
    'Equatorial Guinea': 'Africa',
    'Haiti': 'North America',
    'Sierra Leone': 'Africa',
    'South Africa': 'Africa',
    'Sri Lanka': 'Asia',
    'Costa Rica': 'North America',
    'Iceland': 'Europe',
    'Norway': 'Europe',
    'Puerto Rico': 'North America',
    'Switzerland': 'Europe',
    'Turkiye': 'Asia',
```

```
    'United Kingdom': 'Europe'
}

final_melted_df['Continent'] = final_melted_df.apply(
    lambda row: continent_mapping.get(row['Country'], row['Continent']) if pd.
 ↪isna(row['Continent']) else row['Continent'],
    axis=1
)
```

[7]:
```
final_melted_df_co2 = final_melted_df[final_melted_df["Type of Emission"].str.
 ↪strip() == "CO2 emissions (MMtonnes CO2)"].copy()

if final_melted_df_co2.empty:
    print("No data found for 'CO2 emissions (MMtonnes CO2)'. Please check the␣
 ↪filtering condition.")
else:
    final_melted_df_co2.loc[:, 'Emissions'] = final_melted_df_co2.apply(
        lambda row: row['Value'] if pd.isnull(row['Year_gdp']) else None,
        axis=1
    )

    final_melted_df_co2.loc[:, 'GDP'] = final_melted_df_co2.apply(
        lambda row: row['Value'] if pd.isnull(row['Year']) else None,
        axis=1
    )

    final_melted_df_co2.drop(columns=['Value'], inplace=True)
    final_melted_df_cleaned = final_melted_df_co2.drop_duplicates()
```

[8]:
```
final_melted_df_cleaned = final_melted_df_cleaned.copy()
final_melted_df_cleaned['Year_gdp_cleaned'] =␣
↪final_melted_df_cleaned['Year_gdp'].str.extract(r'(\d{4})')[0]
```

[9]:
```
gdp_mapping =␣
↪final_melted_df_cleaned[final_melted_df_cleaned['Year_gdp_cleaned'].
↪notna()][['Year_gdp_cleaned', 'Country', 'GDP']].
↪set_index(['Year_gdp_cleaned', 'Country'])

for index, row in final_melted_df_cleaned[final_melted_df_cleaned['Year'].
↪notna()].iterrows():
    key = (row['Year'], row['Country'])

    if key in gdp_mapping.index:
        final_melted_df_cleaned.at[index, 'GDP'] = gdp_mapping.at[key, 'GDP']

final_melted_df_cleaned = final_melted_df_cleaned.drop(columns=['Year_gdp',␣
↪'Year_gdp_cleaned'], errors='ignore')

final_melted_df_cleaned = final_melted_df_cleaned.dropna(subset=['Emissions'])
```

[10]:
```
cpi_data = {
    'Year': [
        2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009,
        2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019,
        2020, 2021, 2022
    ],
    'CPI': [
        172.2, 177.1, 179.9, 184.0, 188.9, 195.3, 201.6, 207.3, 215.3, 214.5,
        218.1, 224.9, 229.6, 232.9, 236.7, 237.0, 240.0, 245.1, 251.1, 255.7,
```

```
        258.8, 271.0, 292.7
    ]
}

cpi_df = pd.DataFrame(cpi_data)

base_cpi = 100.0

cpi_df['Scaling Factor'] = cpi_df['CPI'] / base_cpi

final_melted_df_cleaned['Year'] = pd.to_numeric(final_melted_df_cleaned['Year'],␣
↪errors='coerce')
final_melted_df_cleaned = final_melted_df_cleaned.dropna(subset=['Year'])

filtered_df = final_melted_df_cleaned[(final_melted_df_cleaned['Year'] >= 2000) &
                                      (final_melted_df_cleaned['Year'] <= 2022)]

updated_df = filtered_df.merge(cpi_df[['Year', 'Scaling Factor']], on='Year',␣
↪how='left')

updated_df['Adjusted GDP'] = updated_df['GDP'] * updated_df['Scaling Factor']
```

[11]:
```
updated_df['Year'] = pd.to_numeric(updated_df['Year'], errors='coerce')
updated_df['Adjusted GDP'] = pd.to_numeric(updated_df['Adjusted GDP'],␣
↪errors='coerce')

updated_df = updated_df.dropna(subset=['Year', 'Adjusted GDP'])
gdp_data = updated_df[updated_df['Year'].between(2000, 2022)]
```

```
gdp_growth = gdp_data.groupby('Country')['Adjusted GDP'].apply(lambda x: x.
↪pct_change() * 100).reset_index()
gdp_growth.rename(columns={'Adjusted GDP': 'GDP Growth'}, inplace=True)

avg_gdp_growth = gdp_growth.groupby('Country')['GDP Growth'].mean().reset_index()
avg_gdp_growth.rename(columns={'GDP Growth': 'Avg GDP Growth 2000-2022'},␣
↪inplace=True)

gdp_2022 = gdp_data[gdp_data['Year'] == 2022].groupby('Country')['Adjusted GDP'].
↪last().reset_index()
top_10_percent_gdp = gdp_2022['Adjusted GDP'].quantile(0.9)
bottom_11_percent_gdp = gdp_2022['Adjusted GDP'].quantile(0.11)

gdp_growth = gdp_growth.merge(avg_gdp_growth, on='Country', how='left')

def classify_country(row):
    all_years_gdp = gdp_data[gdp_data['Country'] == row['Country']].
↪groupby('Year')['Adjusted GDP'].max()
    if row['Avg GDP Growth 2000-2022'] < 10 and all_years_gdp.max() >=␣
↪top_10_percent_gdp:
        return 'Developed countries'

    elif row['Avg GDP Growth 2000-2022'] > 10:
        return 'Newly industrialized countries #2'

    all_years_gdp_bottom = gdp_data[gdp_data['Country'] == row['Country']].
↪groupby('Year')['Adjusted GDP'].max()
    if row['Avg GDP Growth 2000-2022'] < 10 and all_years_gdp_bottom.max() <=␣
↪bottom_11_percent_gdp:
```

```
        return 'Low-income countries'

    return 'Other'

gdp_growth['Country Classification'] = gdp_growth.apply(classify_country, axis=1)
gdp_growth[['Country', 'Country Classification']].drop_duplicates();
```

[12]:
```
newly_industrialized_countries_list = [
    'Guyana', 'Equatorial Guinea', 'Ghana', 'Ethiopia', 'China',
    'Maldives', 'Chad', 'Iraq'
]

gdp_growth.loc[gdp_growth['Country'].isin(newly_industrialized_countries_list),␣
 ↪'Country Classification'] = 'Newly industrialized countries'

gdp_growth.loc[gdp_growth['Country'] == 'Mexico', 'Country Classification'] =␣
 ↪'Other'

unique_classifications = gdp_growth['Country Classification'].unique()
gdp_growth.groupby('Country Classification')['Country'].unique().reset_index();
```

[13]:
```
unique_countries_by_category = gdp_growth.groupby('Country␣
 ↪Classification')['Country'].unique().reset_index()

for index, row in unique_countries_by_category.iterrows():
    print(f"Category: {row['Country Classification']}")
    print(f"Countries: {', '.join(row['Country'])}\n")
```

```
Category: Developed countries
Countries: Canada, European Union, France, Germany, Italy, Japan, United
Kingdom, United States
```

```
Category: Low-income countries
Countries: Belize, Burundi, Central African Republic, Eswatini, Kiribati,
Lesotho, Samoa, Seychelles

Category: Newly industrialized countries
Countries: Chad, China, Equatorial Guinea, Ethiopia, Ghana, Guyana, Iraq,
Maldives

Category: Newly industrialized countries #2
Countries: Algeria, Australia, Bahrain, Bangladesh, Benin, Bolivia, Burkina
Faso, Costa Rica, Dominican Republic, Ecuador, Gabon, Guatemala, Guinea, Guinea-
Bissau, India, Indonesia, Ireland, Jordan, Kenya, Kuwait, Liberia, Malaysia,
Mali, Malta, Mauritania, Nauru, Nepal, New Zealand, Niger, Nigeria, Oman,
Panama, Papua New Guinea, Paraguay, Philippines, Rwanda, Saudi Arabia, Senegal,
Sierra Leone, Singapore, Somalia, Sri Lanka, Sudan, Suriname, Tanzania, Uganda,
Zambia, Zimbabwe

Category: Other
Countries: Austria, Barbados, Belgium, Bermuda, Botswana, Cameroon, Chile,
Colombia, Denmark, El Salvador, Fiji, Finland, Greece, Haiti, Honduras, Hungary,
Iceland, Israel, Jamaica, Libya, Luxembourg, Madagascar, Mauritius, Mexico,
Morocco, Netherlands, Norway, Pakistan, Portugal, Puerto Rico, South Africa,
Spain, Sweden, Switzerland, Thailand, Togo, Tunisia, Turkiye, Uruguay
```

[14]:
```
developed_countries = ['Canada', 'European Union', 'France', 'Germany', 'Italy',␣
↪'Japan', 'United Kingdom', 'United States']
low_income_countries = ['Belize', 'Burundi', 'Central African Republic',␣
↪'Eswatini','Kiribati', 'Lesotho', 'Samoa', 'Seychelles']
```

```
newly_industrialized_countries = ['Chad', 'China', 'Equatorial Guinea',␣
 ↪'Ethiopia', 'Ghana', 'Guyana', 'Iraq', 'Maldives']

selected_countries = developed_countries + low_income_countries +␣
 ↪newly_industrialized_countries

filtered_df = updated_df[updated_df['Country'].isin(selected_countries)]
groups_df = pd.merge(filtered_df, gdp_growth[['Country', 'Country␣
 ↪Classification', 'Avg GDP Growth 2000-2022']], on='Country', how='left')
```

5 Trends in Emissions and Economic Growth Across Country Groups

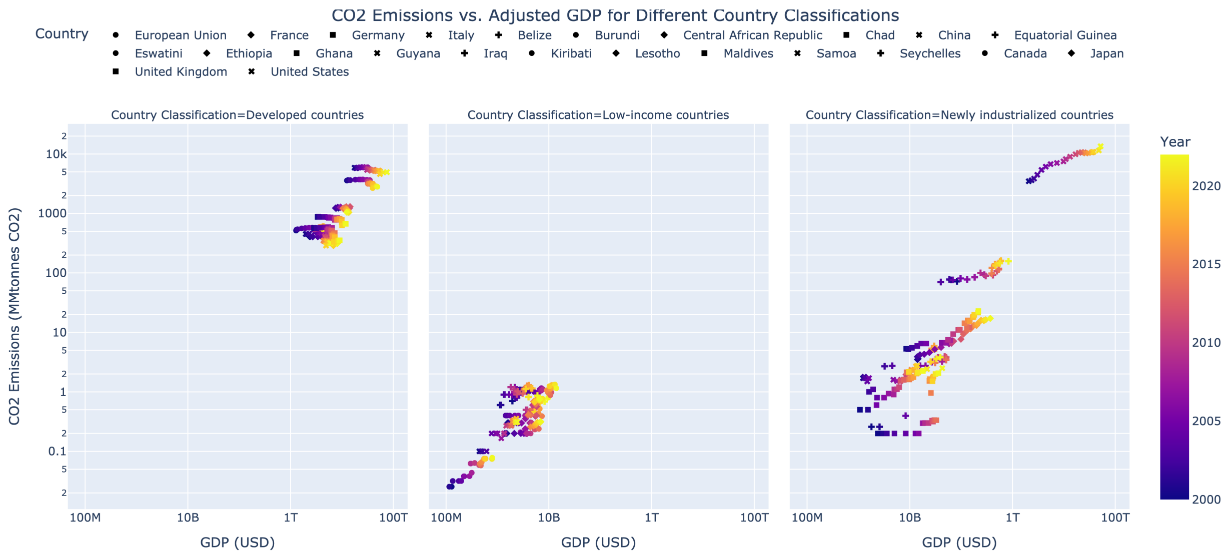
In developed countries, as GDP increases, the data shows an overall trend of decreasing emissions. This phenomenon suggests that "marginal impacts of economic growth on carbon emissions decline as average income increases"(Ravallion et al., 2000). For instance, developed countries' emissions appear to decrease within their borders (territorial emissions) because production and the associated emissions are outsourced to lower-income countries (consumption emissions). It reflects the dynamic where production, and its environmental costs, are offloaded to less developed regions to sustain consumption patterns in wealthier states (Soener, 2019).

For both NICs and low-income countries, it shows an upward trend, where an increase in GDP is associated with a rise in emissions. For these countries, the focus on economic growth outweighs environmental concerns, which pushed them to undergo rapid industrialization. The environmental impact of coal, particularly its contribution to CO2 emissions and local air pollution, is often a secondary concern for these countries. Although coal is a more significant source of pollution compared to other energy sources, "the concern is often of secondary importance to many people in developing countries living in utter poverty" (Mikulska, 2019). The lack of access to clean energy, food and healthcare makes it difficult for the public to prioritize long-term environmental issues over immediate economic and energy needs. As Mikulska (2019) highlights, "in developed countries, wealthy populations are more likely to express their preferences for clean environment (water, air, food) and climate change," but this is not the case in developing nations, where energy security and development take precedence. Thus, low-income counties and NICs prioritize industrialization and economic growth over environmental considerations, and the transition to cleaner energy sources remains a challenging task.

For low-income countries, the tightly clustered points in the data suggest these countries generally exhibit lower economic output and lower levels of emissions, creating a dense grouping in the lower-left corner of the logarithmic plot. The limited variability in economic and industrial activity could explain this clustering. Low-income countries often have more homogenous economies, typically driven by subsistence agriculture or small-scale industries (Angelsen et al., 2014). On the other side, NICs values are more dispersed which implies varying levels of emissions depending on their stage of industrial growth and dependence on energy-intensive industries. The variation in emissions could reflect differences in energy policies, resource availability and the adoption of technologies across NICs. While most NICs show an upward trend, the relationship is more variable. NICs are in a transitional phase, striving to balance industrial growth with environmental sustainability. These countries exhibit a broad spectrum of industrial capabilities, from heavy manufacturing to advanced technology sectors, contributing to the greater dispersion of data points.

[16]:
```
fig = px.scatter(
    groups_df[groups_df["Country Classification"].isin(["Newly industrialized␣
↪countries", "Developed countries", "Low-income countries"])],
    x="Adjusted GDP",
    y="Emissions",
    log_x=True,
    log_y=True,
    symbol="Country",
    color="Year",
    facet_col="Country Classification",
    facet_col_wrap=3,
```

```
    height=500
)

fig.update_layout(
    title="CO2 Emissions vs. Adjusted GDP for Different Country Classifications",
    title_x=0.5,
    title_y=1.0,
    legend=dict(
        orientation="h",
        yanchor="bottom",
        y=1.1,
        xanchor="right",
        x=1
    ),
    yaxis_title="CO2 Emissions (MMtonnes CO2)",
    xaxis_title="GDP (USD)",
    height=700
)

fig.update_xaxes(title_text="GDP (USD)")

fig.show()
```

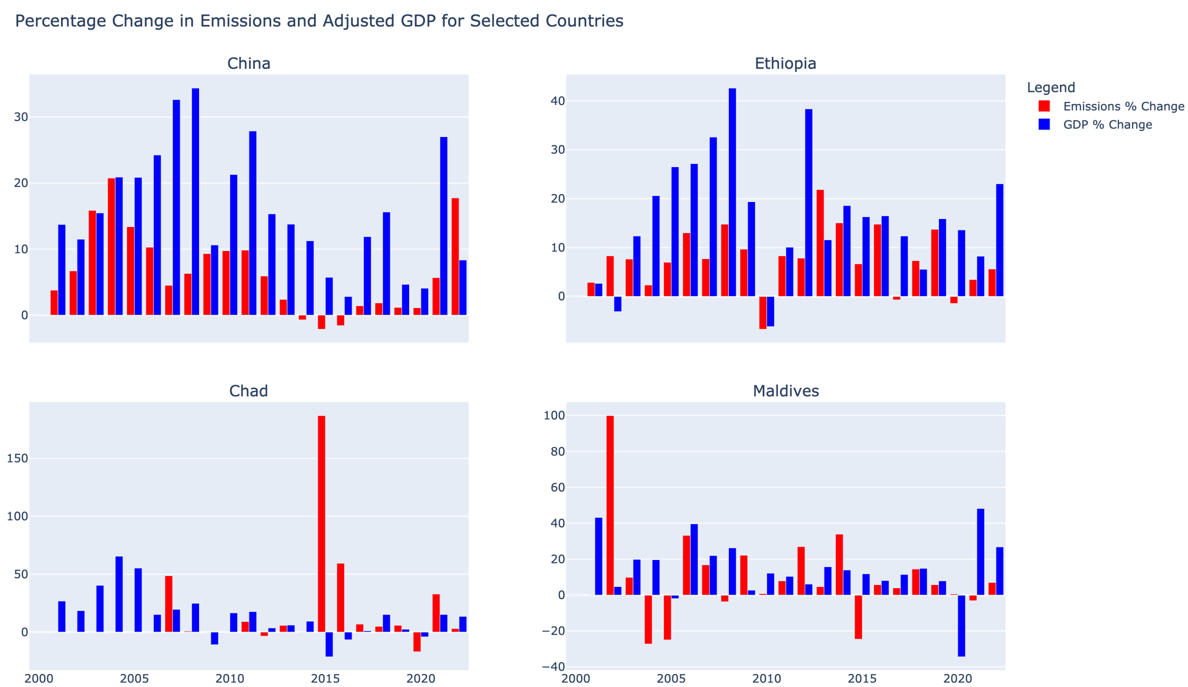


6 Variation in GDP Growth and Emissions Across NICs

[18]:
```python
groups_df['Emissions Intensity'] = groups_df['Emissions'] / groups_df['Adjusted GDP']



intensity_by_classification = groups_df.groupby(['Country Classification', 'Year']).agg(
    avg_emissions_intensity=('Emissions Intensity', 'mean')
).reset_index()


low_income_df = intensity_by_classification[intensity_by_classification['Country Classification'] == 'Low-income countries']
newly_industrialized_df = intensity_by_classification[intensity_by_classification['Country Classification'] == 'Newly industrialized countries']
developed_df = intensity_by_classification[intensity_by_classification['Country Classification'] == 'Developed countries']
```

```
fig = go.Figure()

fig.add_trace(go.Scatter(
    x=low_income_df['Year'], y=low_income_df['avg_emissions_intensity'],
    mode='lines+markers', name='Low-income countries',
    line=dict(color='red')
))

fig.add_trace(go.Scatter(
    x=newly_industrialized_df['Year'],␣
 ↪y=newly_industrialized_df['avg_emissions_intensity'],
    mode='lines+markers', name='Newly industrialized countries',
    line=dict(color='blue')
))

fig.add_trace(go.Scatter(
    x=developed_df['Year'], y=developed_df['avg_emissions_intensity'],
    mode='lines+markers', name='Developed countries',
    line=dict(color='green')
))

fig.update_layout(
    title='Emissions Intensity by Country Classification Over Time',
    xaxis_title='Year',
    yaxis_title='Emissions Intensity (MMtonnes CO2/USD)',
    yaxis=dict(type='log'),
    legend_title='Country Classification',
    height=700,
```

```
    width=1000
)

fig.show()
```



7 China's GDP Growth and Emissions vs. Low-Income Countries' Energy-Driven Growth

While most NICs show a positive correlation, where an increase in GDP leads to an increase in emissions, China exhibits a much stronger connection. For instance, China is responsible for the majority of the total emissions. Yuan et al. (2014) demonstrate that in China, income and energy consumption are interconnected through a bilateral Granger causality, while emissions exhibit a unilateral causality influencing income. This indicates that China's rapid economic growth and energy consumption are heavily related to its emissions growth, contrasting with the less pronounced relationships observed in other NICs.

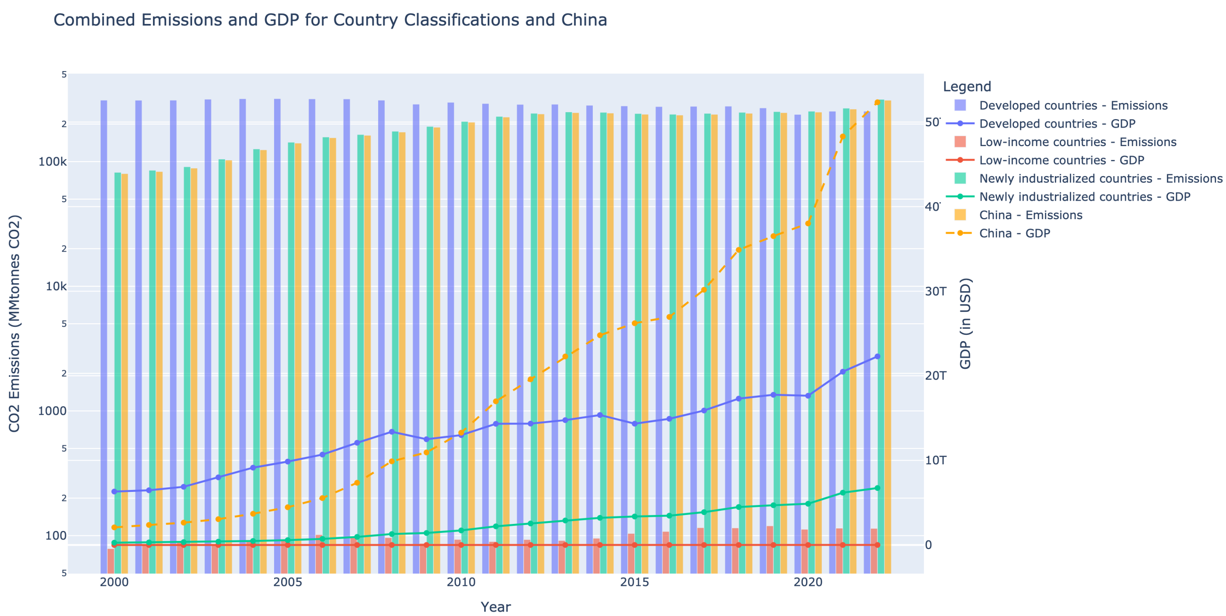
On the other hand, for low-income countries, the rise in emissions is more pronounced than the increase in GDP. This can be attributed to their heavy reliance on energy-intensive resources, meaning that while their economic growth may not be as pronounced, emissions increase significantly due to energy consumption. Many low-income countries rely heavily on fossil fuels, particularly coal, for industrial activities due to a combination of economic, technological and resource constraints. As Mikulska (2019) highlights, coal is the cheapest energy source for many developing nations and is often more accessible than alternatives. Furthermore, coal mining is a labor-intensive industry, providing employment opportunities in these regions where cheap labor is abundant due to booming populations. As a result, without a major technological breakthrough or significant policy intervention, these countries will continue to rely on fossil fuels for their energy needs and industrial activities. While fossil fuel consumption may temporarily enrich economies, especially in industrialized nations, it may not support sustained growth. In some cases, nations relying heavily on fossil fuels face long-term economic risks due to environmental degradation and the eventual necessity to shift towards cleaner, more sustainable energy sources (Bhuiyan et al., 2022).

[17]:
```
grouped_data = groups_df.groupby(['Country Classification', 'Year']).agg(
    combined_emissions=('Emissions', 'sum'),
    avg_adjusted_gdp=('Adjusted GDP', 'mean')
).reset_index()

china_data = groups_df[groups_df['Country'] == 'China'].groupby(['Year']).agg(
    combined_emissions=('Emissions', 'sum'),
    avg_adjusted_gdp=('Adjusted GDP', 'mean')
).reset_index()

fig = go.Figure()

for classification in grouped_data['Country Classification'].unique():
    classification_df = grouped_data[grouped_data['Country Classification'] ==␣
 ↪classification]
```

```
    fig.add_trace(go.Bar(
        x=classification_df['Year'],
        y=classification_df['combined_emissions'],
        name=f'{classification} - Emissions',
        marker=dict(color=px.colors.qualitative.Plotly[grouped_data['Country␣
↪Classification'].unique().tolist().index(classification)]),
        opacity=0.6,
        showlegend=True
    ))

    fig.add_trace(go.Scatter(
        x=classification_df['Year'],
        y=classification_df['avg_adjusted_gdp'],
        mode='lines+markers',
        name=f'{classification} - GDP',
        line=dict(color=px.colors.qualitative.Plotly[grouped_data['Country␣
↪Classification'].unique().tolist().index(classification)]),
        showlegend=True,
        yaxis='y2'
    ))

fig.add_trace(go.Bar(
    x=china_data['Year'],
    y=china_data['combined_emissions'],
    name='China - Emissions',
    marker=dict(color='orange'),
    opacity=0.6,
    showlegend=True
```

```
))

fig.add_trace(go.Scatter(
    x=china_data['Year'],
    y=china_data['avg_adjusted_gdp'],
    mode='lines+markers',
    name='China - GDP',
    line=dict(color='orange', dash='dash'),
    showlegend=True,
    yaxis='y2'
))

fig.update_layout(
    height=700,
    width=1000,
    title='Combined Emissions and GDP for Country Classifications and China',
    xaxis_title='Year',
    yaxis=dict(
        title='CO2 Emissions (MMtonnes CO2)',
        showgrid=True,
        type='log',
    ),
    yaxis2=dict(
        title='GDP (in USD)',
        overlaying='y',
        side='right',
        showgrid=True
    ),
    legend_title='Legend'
```

```
)

fig.show()
```



8 Energy Intensity Trends

Based on the importance of renewable energy, the energy intensity ratio is presented for the three groups of countries. It is important to understand the concept of energy intensity, which is the ratio of emissions to GDP, essentially providing a measure of how much emissions are produced per dollar of economic output. Energy intensity reflects how efficiently a country uses energy to generate economic value. A lower energy intensity indicates that less energy is required to produce each unit of economic output, which is a sign of improving energy efficiency (Energy.gov, 2016). The graph suggests that, for each group of countries, the energy intensity ratio is decreasing, potentially indicating that energy efficiency is improving. However, further research is needed to determine whether this decline in energy intensity is primarily due to decreasing emissions or increasing GDP. This will help to better assess whether countries are truly becoming more energy-efficient on a global scale.

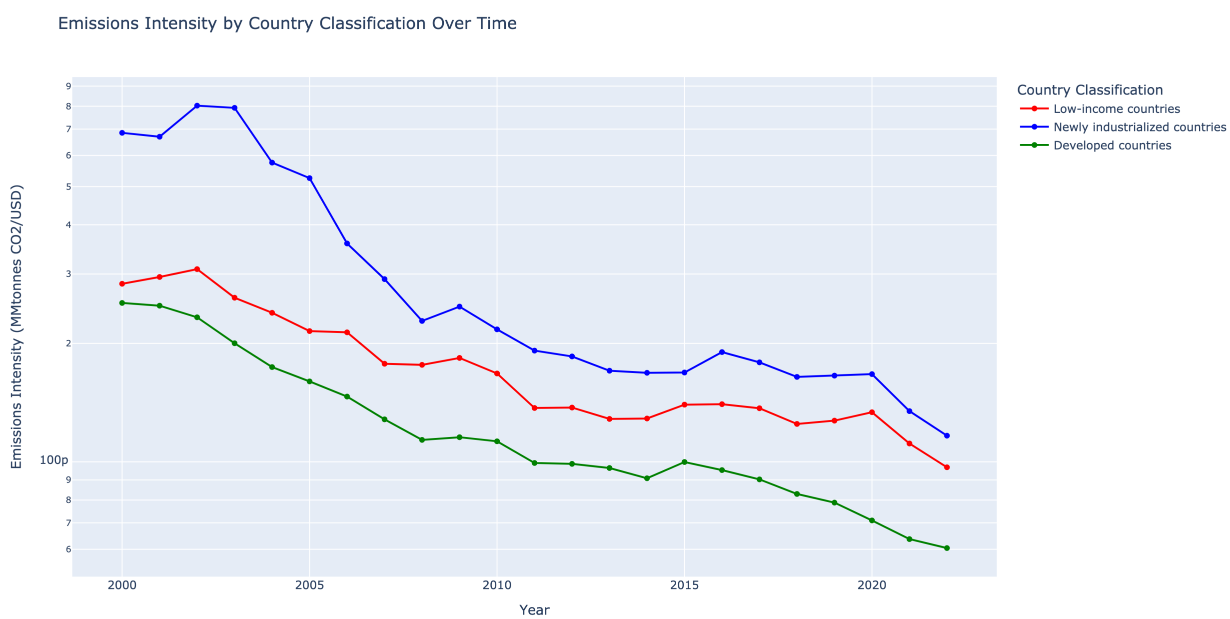
Developed countries, due to their access to more renewable energy, are the most energy-efficient, followed by low-income countries. As a country attains higher income levels, emissions resulting from consumption may turn into "an inferior good as a result of preferences for a cleaner environment at higher levels of income" (Barassi & Spagnolo, 2012). Preference for greener technology encourages developed countries to invest in technological innovations aimed at reducing CO2 emissions. Research and development (R&D) investments often focus on implementing sustainable practices (Apanasovich & Apanasovich, 2024). Thus, countries with higher GDP and R&D spending tend to exhibit decreased CO2 emissions over time, suggesting that advancements in technology and efficient practices are integral to this trend.

Renewable energy also offers a path to sustainable growth. As countries shift towards more renewable sources, they can potentially decouple economic growth from fossil fuel reliance, ensuring long-term development without the negative environmental impact (Bhuiyan et al., 2022). However, low-income countries and NICs face challenges in transitioning to greener resources and meeting global climate goals due to limited financial resources and technology. They lack the means to integrate widespread use of renewable energy into their industries. While renewable energy technologies like solar power are "already far cheaper," developing nations still struggle with scaling them due to "intermittency" and the high costs of energy storage solutions (Tongia, 2022). As such, reliance on fossil fuels remains essential in the short term. Therefore, low-income countries and NICs are less likely to adopt renewable energy alternatives to replace fossil fuels, leading to higher energy intensity.

[17]:
```
groups_df['Emissions Intensity'] = groups_df['Emissions'] / groups_df['Adjusted␣
↪GDP']



intensity_by_classification = groups_df.groupby(['Country Classification',␣
↪'Year']).agg(
    avg_emissions_intensity=('Emissions Intensity', 'mean')
).reset_index()
```

```
low_income_df = intensity_by_classification[intensity_by_classification['Country␣
↪Classification'] == 'Low-income countries']
newly_industrialized_df =␣
↪intensity_by_classification[intensity_by_classification['Country␣
↪Classification'] == 'Newly industrialized countries']
developed_df = intensity_by_classification[intensity_by_classification['Country␣
↪Classification'] == 'Developed countries']

fig = go.Figure()

fig.add_trace(go.Scatter(
    x=low_income_df['Year'], y=low_income_df['avg_emissions_intensity'],
    mode='lines+markers', name='Low-income countries',
    line=dict(color='red')
))

fig.add_trace(go.Scatter(
    x=newly_industrialized_df['Year'],␣
↪y=newly_industrialized_df['avg_emissions_intensity'],
    mode='lines+markers', name='Newly industrialized countries',
    line=dict(color='blue')
))

fig.add_trace(go.Scatter(
    x=developed_df['Year'], y=developed_df['avg_emissions_intensity'],
    mode='lines+markers', name='Developed countries',
    line=dict(color='green')
))
```

```python
fig.update_layout(
    title='Emissions Intensity by Country Classification Over Time',
    xaxis_title='Year',
    yaxis_title='Emissions Intensity (MMtonnes CO2/USD)',
    yaxis=dict(type='log'),
    legend_title='Country Classification',
    height=700,
    width=1000
)

fig.show()
```



9 Conclusion

The relationship between economic growth, technological progress and CO2 emissions highlights the unequal distribution of responsibility for climate change. Developed countries, with their advanced technologies and access to renewable energy, show a trend of decreasing emissions as their economies grow. In contrast, low-income countries and newly industrialized nations prioritize economic growth, often at the expense of environmental sustainability, leading to rising emissions. The trade-off between economic growth and climate change presents a complex challenge, particularly for developing countries. While reducing emissions is critical to mitigating the impacts of climate change, it is unfair to demand that developing nations immediately curb their emissions. Historically, these countries have contributed far less to global emissions compared to their developed counterparts. The recent surge in emissions from developing nations can largely be attributed to their economic growth, which is still heavily reliant on fossil fuels for industrialization. Developed countries, having industrialized early, had access to cleaner technologies and renewable energy sources. Consequently, expecting rapid shifts to renewable energy in developing countries is unrealistic, given the limited financial resources, technological infrastructure and institutional capacity they face.

Some may argue that wealth redistribution could offer a solution by providing developing countries with the resources to transition to cleaner energy. While this could potentially alleviate some immediate financial barriers, it would not address the underlying structural drivers of emissions. If these countries are still economically incentivized to produce goods cheaply, often through high-emission energy sources, a redistribution of wealth would likely only serve as a bandage rather than a long-term solution. Without altering the economic incentives that drive emissions growth, even wealth redistribution will not halt environmental degradation. Low-income countries, in particular, may simply escalate their production efforts to catch up economically, continuing the cycle of rising emissions. Therefore, addressing the root causes of emissions requires more than just wealth redistribution—it necessitates a fundamental shift in the structural drivers of economic growth, energy consumption and technological advancement to create a sustainable future for all nations.

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