Determining the Convergence of Climate Ethics Principles Using an Interdisciplinary Approach

Abstract

This paper critically examines the convergence of the Ability to Pay, Polluter Pays, and Beneficiary Pays principles within the climate change ethics debate. A case study on Luxembourg, set within a broader Western context, underscores how past industrial benefits shape current responsibilities, challenging direct correlations between industrial activity and emissions. The study finds evidence of convergence among the principles, and insights regarding how present industrial activities in lower-income states appear to benefit wealthier ones. The study substantiates the convergence of the Ability to Pay, Polluter Pays, and Beneficiary Pays principles, with a re-examination of modern industrial beneficiaries. Findings advocate for a nuanced approach to climate responsibility, informed by empirical data and acknowledging the historical context of industrialisation.

Introduction

This essay probes the convergence of key ethical principles in the climate change discourse through a fusion of experimental philosophy and data science, seeking to provide clarity within a prevalent political philosophy debate. This debate concerns the allocation of responsibilities for addressing global climate change, a subject that has significantly shaped the discourse within climate ethics. By dissecting this issue, I aspire to uncover and redirect focus towards less explored but equally critical facets within the climate ethics literature. Knobe and Nichols (2017) describe experimental philosophy as an approach which marries traditional philosophical inquiry with the empirical investigation methods of data science, allowing for a more nuanced exploration of complex ethical questions. In the context of this paper, the word "convergence" is used to express the phenomenon of the principles targeting the same states despite their different criteria.

In addressing 'who should bear the burdens of global climate change', Caney (2005) elucidates the concept as encompassing a dual duty: first, a duty of mitigation, which necessitates reducing activities that intensify climate change, notably carbon dioxide emissions; second, a duty to allocate resources to shield people from the adverse effects of climate change, which may involve financial support to states for recovery and emission reduction efforts. The literature on climate ethics often hinges on three core principles: the forward-looking 'ability to pay principle' (ATP) and two backward-looking principles, the 'polluter pays principle' (PPP) and the 'beneficiary pays principle' (BPP) (Caney, 2005; Caney, 2020; Shue, 2015). ATP posits that those with greater wealth should shoulder a larger share of the responsibility for addressing climate change issues (Caney, 2005). BPP and PPP distribute the burden of restitution based on the benefits received from emission-generating activities and the extent of one's contribution to the emission levels, respectively (Caney, 2020; Shue, 2015).

Intuitively, one might assume a straightforward correlation: that polluters, beneficiaries of pollution, and the wealthy are all the same. However, philosophers such as Shue (2015) and Caney (2010) have contended, that this alignment does not hold firmly in the contemporary context, unlike in the past when wealthy industrialised Western societies polluted the most. I wish to explore whether this discrepancy is due to overlooking relevant data treated akin to dark data within the domain of climate ethics. As Miller (2009) underscores a significant portion of the climate ethics debate is obscured by misconceptions about the realities of pollution, particularly regarding affluent nations that, while perceived as low polluters, contribute substantially to emissions through their imports and offshoring practices.

Addressing this debate is vital as the predominance of these principles can inadvertently absolve states and corporations from their responsibilities, while also overshadowing broader issues within climate ethics. These issues include the neo-colonial and colonial capitalist practices exemplified by phenomena such as 'green colonialism' and 'green grabbing', which refer to the exploitation of environmental initiatives for imperialistic or capitalistic gains, often at the expense of indigenous populations and African states (Grasso, 2023; Singh, 2023; Normann, 2021). It is within this context that our moral philosophy must expand its lens, to critically assess and address these deep-seated ethical challenges, especially if the current focus is somewhere, it may not need to be.

Methodology

To answer the question of whether the Ability to Pay, Polluter Pays, and Beneficiary Pays principles target the same states for climate responsibility, the following sub-questions are answered. Is the often assumed, readily apparent link between affluence, pollution, and the benefits derived from that pollution truly present? If so, who are the main outliers and why? What makes a state a beneficiary of harmful climate practices, i.e. should this still be determined by examining states' industrial sectors?

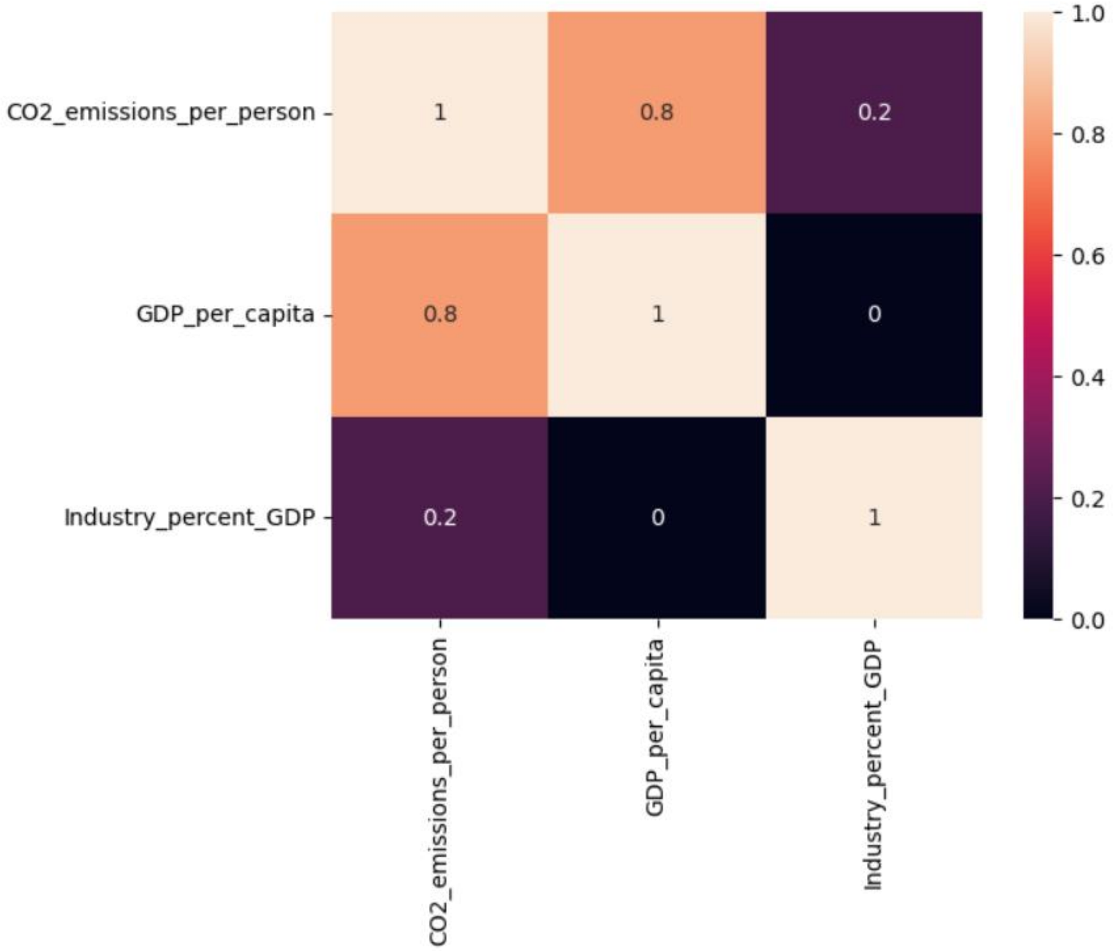
Utilising datasets from Gapminder (2023), sourced from the World Bank, the study analyses 'GDP per capita' as a measure of national wealth and its potential impact on climate change responsibilities. 'Consumption CO2 per capita' data offers insight into the true carbon footprint, adjusting for imports and exports, to identify polluters and beneficiaries in climate talks. While carbon emissions may not show the full picture, this data is selected as Grasso (2023) notes carbon's prominent role in climate discussions and the importance of accounting for carbon offshoring practices. Finally, 'Industry, contribution to economy (% of GDP)' is used to assess industrialisation's impact on wealth and pollution—to further understand the realities of the BPP.

Using Python in Jupyter Lab, the datasets were cleaned to ensure numerical compatibility and merged based on a contemporary and common time frame (1990 to 2017). Correlation heatmaps were then generated to explore and visualise correlations, before carrying out a regression analysis to quantify the relationships between GDP, CO2 emissions, and industrial contribution, providing a statistical foundation for determining the convergence of the three principles. Outliers from the regression analysis were identified, revealing deviations from common patterns. This was followed by a Principal Component Analysis (PCA) and KMeans clustering to simplify the data into discernible clusters. Before concluding, to understand the defining features of each cluster, the centroids were calculated and interpreted in the context of the original variables. Throughout this process, any interesting findings were cross-referenced with relevant academic papers, ensuring that the data-driven insights were placed within a broader academic context. This approach allowed the research to not only rely on quantitative analysis but also to integrate qualitative understanding from existing literature.

Findings

Correlations

Figure 1.0: Exploring Relationships Among[Variables Using a Correlation Heatmap

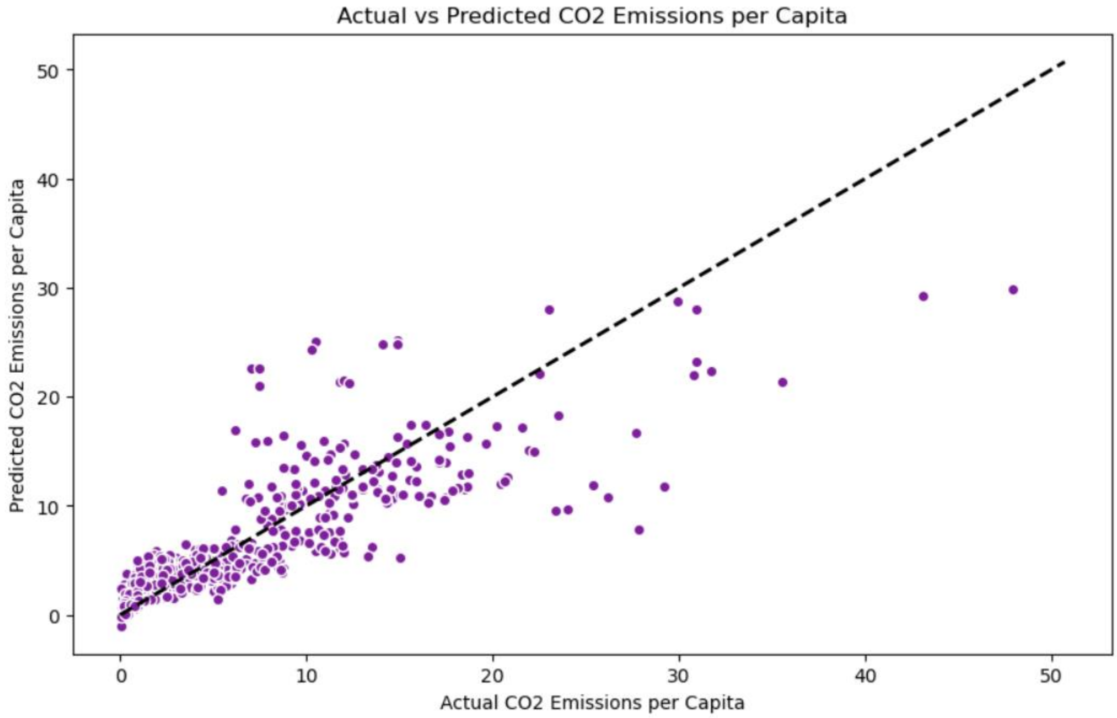


Source: Gapminder Foundation (2023)

Figure 1.0 underscores a positive correlation between GDP per capita and CO2 emissions, suggesting that wealth correlates with emissions, pertinent to the PPP and ATP. Yet, the weaker link between industrial output and emissions points to additional factors influencing a nation's emission levels which are looked into in the following paragraphs.

Regression

Figure 2.0: Actual vs Predicted Emissions Per Capita (based on Economic indicators)



Source: Gapminder Foundation (2023)

The regression analysis with GDP per capita and industry's contribution to GDP as predictors for CO2 emissions per person yielded an R^2 score of 0.703, indicating that about 70% of the variation in per capita emissions can be predicted by these economic factors. This strong relationship supports the hypothesis of substantial convergence between the three principles.

The extended regression results present a more nuanced picture. The analysis between CO2 emissions and GDP shows a relatively high R^2 value of 0.657, reaffirming the link between economic output and emissions. However, the analysis between CO2 emissions and industry contribution had a much lower R^2 score of 0.061, suggesting that in contemporary times states' industrial sectors do not necessarily play as big of a role in determining their overall emissions and gains once offshoring is considered. This idea is further reinforced by the analysis between industry contribution and GDP which had an extremely low R^2 score under 0.001.

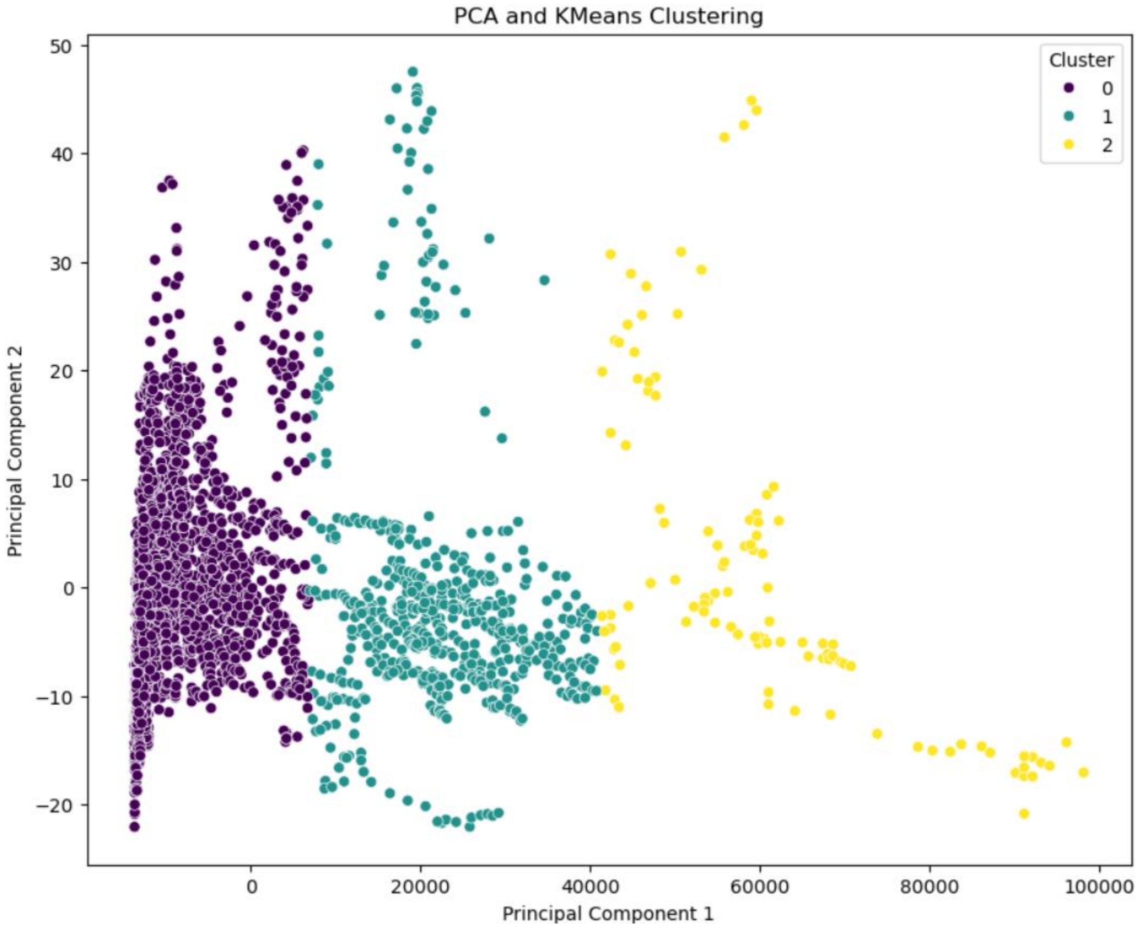
Case study of trends and outliers

To corroborate the findings from our data analysis, detailed examinations of specific states were conducted, with Luxembourg, identified as a significant outlier in 2010 and 2013, serving as an important case study reflective of broader trends among affluent Western states (see Caro et al., 2015; Grasso, 2023). According to Caro et al. (2015), Luxembourg's high import emission levels (35,000–50,000 Gg CO_2e) compared to its exports (18,000–20,000 Gg CO_2e) position it as a net emission importer. This deviation from high emissions in Luxembourg is influenced by its key trading partners (France, Germany, and the Netherlands) who engaged in early decarbonisation efforts under the 1997 Kyoto Protocol and the 2001 directive promoting renewable energy sources (Tremmel, 2002; Grubb, 2004). The 2013 reduction in emissions aligns with Luxembourg and its trading partners; adherence to the 2012 Kyoto targets (Caro et al., 2015), highlighting the cumulative impact of such international commitments.

Furthermore, Luxembourg’s thriving economy predominantly relies on its banking, investment, and manufacturing sectors (Caro et al., 2015). Historically, manufacturing played a key role in Luxembourg's wealth accumulation, but in recent times, its economic landscape has shifted, with banking and investment industries becoming increasingly dominant, supporting the findings of the regression analyses (Caro et al, 2015; Caney, 2010). This trend also suggests that despite the lower correlations between industry contributions to the other factors, affluent states have historically benefitted from industrialisation and gained an advantage because of it. This leads me to suggest that while some correlations may be weak, this does not preclude convergence between beneficiary, polluter, and affluent states or the three principles.

PCA Analysis and Clustering

Figure 3.0: PCA and KMeans Clustering of CO2 Emissions, GDP, and Industry Contribution.



Source: Gapminder Foundation (2023)

Figure 4.0: Cluster Center Analysis Results

Cluster	CO2 emissions per person	GDP per capita	Industry % GDP
0	3.483258	5137.805423	28.394415
1	12.237914	36262.351185	27.567472
2	23.528799	73906.541145	30.843174

Source: Gapminder Foundation (2023)

The results of the Principal Component Analysis (PCA) and KMeans clustering shown in Figures 3.0 and 4.0 provide insightful categorisations of countries in relation to their CO_2 emissions, economic output, and industrial activity. The clustering visualisation identifies three distinct groups, each offering important insights for the climate responsibility debate. Cluster 0, with lower emissions and GDP yet notable industrial activity, reinforces the claim that interstate industrial activity is no longer as relevant to affluence (Caney, 2005). It also supports the notion that lower-income nations' emissions and industrial output go towards and benefit higher-income nations (which are higher polluters), linking the three principles (Singh, 2023; Caney, 2020). Cluster 1, with moderate emissions and GDP, further links the PPP and ATP principles hinting at a moderate industrial impact on emissions. In Cluster 2, high emissions and GDP converge, offering further evidence that the wealthiest, most industrialised nations are also the biggest polluters.

Reflections

Throughout this research, several limitations emerged, primarily in data handling. The necessity to drop rows with incomplete data implies a need for a more comprehensive dataset in future studies or the learning of more advanced techniques. I would have liked to aggregate the data to understand general trends across countries, ignoring year-to-year variations, however, I was unable to do so due to the incomplete cleaned dataset. Looking back, I could have taken this to my advantage and looked at how variables change over time in greater detail.

Additionally, the visualisations, while effective, could be refined for clarity, such as adjusting cluster numbering from 0-2 to 1-3 to align with conventional labelling. This aspect was partly due to my current proficiency in Python. Furthermore, having studied this topic before I went into this analysis with a bias which may have impacted the ways I interpreted the data. This is not necessarily a shortcoming as data is never neutral, however, it is something to be more mindful of moving forward. Revisiting the analysis at a later date, with enhanced coding skills and potentially richer datasets, could yield even more insightful results, further exploring the complex interplay of climate ethics principles.

Conclusion

This study illuminated strong correlations between GDP and CO_2 emissions, reinforcing the link between affluence and pollution. The Luxembourg case study highlighted how industrialisation and its resultant pollution historically benefited economies, suggesting while the link between industry and the other factors may have attenuated in the present, the enduring effects of the past continue to shape the present, precluding any absolute dissociation between them. The PCA analysis revealed that industrialisation in lower-income states seemingly benefits wealthier nations, suggesting they remain beneficiaries. This points to the convergence of the Ability to Pay, Polluter Pays, and Beneficiary Pays principles in targeting the same states for climate responsibility. However, the results were not entirely conclusive, implying the debate should not be abandoned but approached with greater empirical understanding and an open mind. It also suggests the need for philosophical focus on who benefits from modern industrialisation, in addition to the aforementioned colonial capitalist practices in the introductory section.

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Appendix

Code

Note: there was an issue with saving my notebook as a pdf so pasted my code.

```
# Import necessary libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# Load the datasets
# Load the datasets
consumption_emissions = pd.read_csv("C:/Users/hayak/IM939/Assignment
2/consumption_emissions_tonnes_per_person.csv")
gdp_per_capita = pd.read_csv("C:/Users/hayak/IM939/Assignment
2/gdppercapita_us_inflation_adjusted.csv")
industry_percent_gdp = pd.read_csv("C:/Users/hayak/IM939/Assignment
2/industry_percent_of_gdp.csv"


#data cleaning with help from OpenAI(2023) and
def clean_and_convert(value):
    try:
        return float(value)
    except ValueError:
        cleaned_value = str(value).replace('k', '').replace(',', '')
        try:
            if 'k' in str(value):
                return float(cleaned_value) * 1000
            else:
                return float(cleaned_value)
        except ValueError:
            return np.nan


# Align the datasets to the common years (1990 to 2017)
common_years = [str(year) for year in range(1990, 2017)]

# Reshaping the data for analysis
def reshape_data(df, variable_name):
    df_melted = df.melt(id_vars='country', value_vars=common_years,
var_name='year', value_name=variable_name)
    df_melted['year'] = df_melted['year'].astype(int)
    return df_melted

consumption_emissions_reshaped = reshape_data(consumption_emissions,
'CO2_emissions_per_person')
gdp_per_capita_reshaped = reshape_data(gdp_per_capita, 'GDP_per_capita')
industry_percent_gdp_reshaped = reshape_data(industry_percent_gdp,
'Industry_percent_GDP')
```

In [4]:

```
# Merging the datasets
merged_data = consumption_emissions_reshaped.merge(gdp_per_capita_reshaped,
on=['country', 'year'])
merged_data = merged_data.merge(industry_percent_gdp_reshaped,
on=['country', 'year'])

# Converting data and handling missing values
merged_data['CO2_emissions_per_person'] =
merged_data['CO2_emissions_per_person'].apply(clean_and_convert)
merged_data['GDP_per_capita'] =
merged_data['GDP_per_capita'].apply(clean_and_convert)
merged_data['Industry_percent_GDP'] =
merged_data['Industry_percent_GDP'].apply(clean_and_convert)

# Dropping rows with missing values with help from OpenAI (2023)
merged_data.dropna(inplace=True)
```

In [5]:

```
print(merged_data.head())
print(merged_data.tail())
# Drop the 'year' column
merged_data_without_year = merged_data.drop('year', axis=1)

# Correlation analysis without the 'year' column
corr_matrix = merged_data_without_year.corr(numeric_only=True).round(1)
sns.heatmap(corr_matrix, annot=True)
plt.show()



# Preparing data for regression analysis
X = merged_data[['GDP_per_capita', 'Industry_percent_GDP']]
y = merged_data['CO2_emissions_per_person']

# Splitting the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Linear Regression Model
model = LinearRegression()
model.fit(X_train, y_train)

# Predicting on test data
y_pred = model.predict(X_test)

# Calculating metrics
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Visualisation and Output
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, color='#7e1e9c', edgecolor='white')
plt.plot([y.min(), y.max()], [y.min(), y.max()], 'k--', lw=2)
plt.xlabel('Actual CO2 Emissions per Capita')
plt.ylabel('Predicted CO2 Emissions per Capita')
plt.title('Actual vs Predicted CO2 Emissions per Capita')
```

```
plt.show()

# Model Summary
print(f"Mean Squared Error: {mse}")
print(f"R^2 Score: {r2}")



import matplotlib.pyplot as plt
import pandas as pd

# Assuming y_test, y_pred, and merged_data are already defined
# Aligning y_pred with y_test indices
y_pred_series = pd.Series(y_pred, index=y_test.index)

# Plotting the actual vs predicted values
plt.figure(figsize=(12, 8))
plt.scatter(y_test, y_pred_series, color='blue', label='Data Points')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'k--',
lw=2, label='Ideal Fit')

# Labeling the points with country and year
for idx in y_test.index:
    if idx in merged_data.index and 'country' in merged_data.columns and
'year' in merged_data.columns:
        label = f"{merged_data.loc[idx, 'country']} ({merged_data.loc[idx,
'year']})"
        plt.text(y_test[idx], y_pred_series[idx], label, fontsize=8)

plt.xlabel('Actual CO2 Emissions per Capita')
plt.ylabel('Predicted CO2 Emissions per Capita')
plt.title('Actual vs Predicted CO2 Emissions per Capita with Country and
Year Labels')
plt.legend()
plt.show()



# Calculate residuals (code from week 3 edited with the help of google
(2023) bard's reccomendation of using residuals)
residuals = y_test - y_pred

# Computing the upper and lower thresholds for outliers
upper_threshold = residuals.mean() + 2 * residuals.std()
lower_threshold = residuals.mean() - 2 * residuals.std()

# Marking outliers in the test dataset
outliers_mask = ((residuals > upper_threshold) | (residuals <
lower_threshold))
outliers = merged_data.loc[y_test.index[outliers_mask]]

# Displaying the outliers
print("Outliers based on residuals:")
print(outliers[['country', 'year', 'CO2_emissions_per_person']])



#extended analysis
```

```
# OpenAI helped me fix this segment, wasn't working due to a typo I had
made

# Analysis 1: CO2 vs GDP
X1 = merged_data[['CO2_emissions_per_person']]
y1_gdp = merged_data['GDP_per_capita']

model1_gdp = LinearRegression()
model1_gdp.fit(X1, y1_gdp)
y1_gdp_pred = model1_gdp.predict(X1)
mse1_gdp = mean_squared_error(y1_gdp, y1_gdp_pred)
r21_gdp = r2_score(y1_gdp, y1_gdp_pred)

# Analysis 2: CO2 vs Industry Percent GDP
y1_industry = merged_data['Industry_percent_GDP']

model1_industry = LinearRegression()
model1_industry.fit(X1, y1_industry)
y1_industry_pred = model1_industry.predict(X1)
mse1_industry = mean_squared_error(y1_industry, y1_industry_pred)
r21_industry = r2_score(y1_industry, y1_industry_pred)

# Analysis 3: Industry Percent GDP vs GDP
X3 = merged_data[['Industry_percent_GDP']]
y3 = merged_data['GDP_per_capita']

model3 = LinearRegression()
model3.fit(X3, y3)
y3_pred = model3.predict(X3)
mse3 = mean_squared_error(y3, y3_pred)
r23 = r2_score(y3, y3_pred)

# Summary of Results
results = {
    'Analysis 1 - CO2 vs GDP': {'MSE': mse1_gdp, 'R^2': r21_gdp},
    'Analysis 2 - CO2 vs Industry': {'MSE': mse1_industry, 'R^2':
r21_industry},
    'Analysis 3 - Industry vs GDP': {'MSE': mse3, 'R^2': r23}
}

for analysis, metrics in results.items():
    print(f"{analysis}: Mean Squared Error = {metrics['MSE']}, R^2 Score =
{metrics['R^2']}")



#clustering and PCA
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
import seaborn as sns

# PCA for Dimensionality Reduction
pca = PCA(n_components=2)
principal_components =
pca.fit_transform(merged_data[['CO2_emissions_per_person',
'GDP_per_capita', 'Industry_percent_GDP']])
```

```
# KMeans Clustering
kmeans = KMeans(n_clusters=3, random_state=42)
clusters = kmeans.fit_predict(principal_components)

# Adding PCA components and cluster labels to the DataFrame
merged_data['PCA1'] = principal_components[:, 0]
merged_data['PCA2'] = principal_components[:, 1]
merged_data['Cluster'] = clusters


# Visualizing Clusters
plt.figure(figsize=(10, 8))
sns.scatterplot(x='PCA1', y='PCA2', hue='Cluster', data=merged_data,
palette='viridis')
plt.title('PCA and KMeans Clustering')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend(title='Cluster')
plt.show()


# Cluster centres code snippet edited from VanderPlas (2016)
cluster_centers_pca_space = kmeans.cluster_centers_

cluster_centers_original_space =
pca.inverse_transform(cluster_centers_pca_space)

cluster_centers_df = pd.DataFrame(cluster_centers_original_space,
columns=['CO2_emissions_per_person', 'GDP_per_capita',
'Industry_percent_GDP'])

# Display the DataFrame
print(cluster_centers_df)
```

Additional Results and Figures

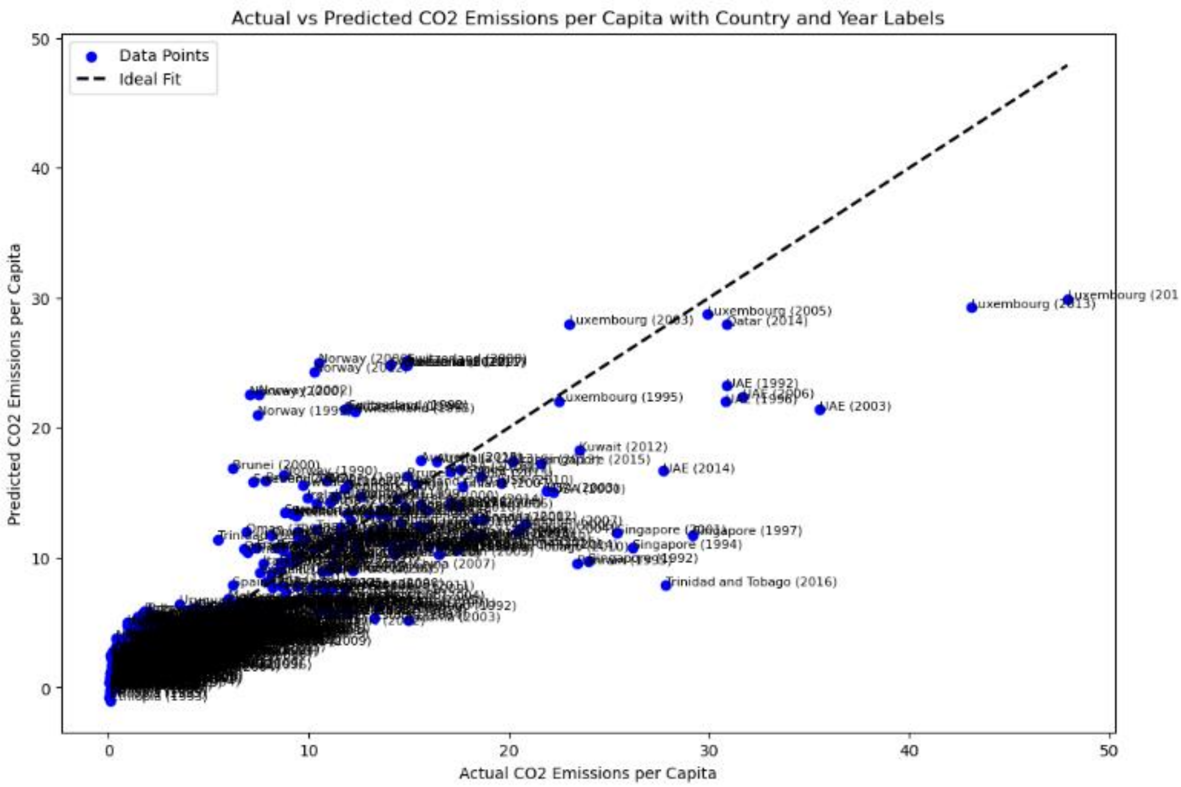
```
#main regression analysis
Mean Squared Error: 13.480901054244114
R^2 Score: 0.7033099295392097

#Extended regression analysis
Analysis 1 - CO2 vs GDP: Mean Squared Error = 114003264.69314092, R^2 Score
= 0.6570935533480715
Analysis 2 - CO2 vs Industry: Mean Squared Error = 94.68740652886856, R^2 S
core = 0.06123693718401635
Analysis 3 - Industry vs GDP: Mean Squared Error = 332180471.51158285, R^2
Score = 0.000845936826471605

Outliers based on residuals:
                  country  year  CO2_emissions_per_person
2593          Switzerland  2012                     14.10
703                   UAE  1996                     30.80
1134               Norway  1999                      7.44
1522                  UAE  2003                     35.50
1385            Singapore  2001                     25.40
```

835	Brunei	1997	7.87
487	Switzerland	1994	11.80
1645	Belgium	2004	20.40
1555	Estonia	2003	15.00
2125	Switzerland	2008	14.90
1953	Norway	2006	10.50
332	Singapore	1992	24.00
1996	Belgium	2007	20.80
2476	Switzerland	2011	14.80
1186	Brunei	2000	6.20
2809	UAE	2014	27.70
1672	Estonia	2004	13.30
1251	Norway	2000	7.03
3147	Trinidad and Tobago	2016	27.80
81	Norway	1990	8.76
1879	Belgium	2006	20.60
1485	Norway	2002	7.49
2008	Switzerland	2007	14.90
253	Switzerland	1992	12.00
2406	Luxembourg	2010	47.90
566	Singapore	1994	26.20
235	UAE	1992	30.90
2655	Norway	2012	10.30
917	Singapore	1997	29.20
2757	Luxembourg	2013	43.10
1873	UAE	2006	31.70
3144	Sweden	2016	7.24
597	Bahrain	1995	23.40
604	Switzerland	1995	12.30

```
#visualisation created to determine the location of outliers
```


Actual vs Predicted CO2 Emissions per Capita with Country and Year Labels
Data Points
Ideal Fit
Predicted CO2 Emissions per Capita
Actual CO2 Emissions per Capita
0
10
20
30
40
50
Luxembourg (2013)
Luxembourg (2003)
Luxembourg (2005)
Qatar (2014)
Luxembourg (1995)
UAE (1992)
UAE (2003)
Kuwait (2012)
UAE (2014)
Brunei (2000)
Singapore (1997)
Singapore (1994)
Trinidad and Tobago (2016)