GDP AS BOTH DRIVER AND DISTRACTION: A SECTOR-ATTRIBUTED ANALYSIS OF CO2 EMISSION DETERMINANTS

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ABSTRACT

This study examines the paradoxical role of GDP in CO_2 emissions through a sector-attributed analysis of 23 years of national data. While GDP shows a significant negative relationship with total CO_2 emissions in isolation ($\beta = -6.08e^{-11}$, $p = 0.004$), its effect becomes statistically insignificant when accounting for sectoral emissions ($p = 0.133$). The perfect multicollinearity (VIFs > 10) between GDP and sectoral CO_2 components reveals that economic growth serves as a proxy for aggregated emission sources rather than an independent driver. Elasticity analysis confirms this decoupling, with a significant negative GDP elasticity ($\beta = -0.130$, $p < 0.001$). These findings challenge conventional EKC assumptions, suggesting that GDP-centric climate policies may overlook critical sectoral heterogeneities in emission dynamics.

Keywords: GDP-CO_2 paradox, sectoral attribution, multicollinearity, emission decoupling, environmental Kuznets curve, energy transition

INTRODUCTION

The relationship between economic growth and CO_2 emissions has long been a focal point of environmental economics, shaping both policy frameworks and academic discourse. Traditional models, particularly those rooted in the Environmental Kuznets Curve (EKC) hypothesis, posit an inverted U-shaped relationship between GDP per capita and pollution levels, suggesting that emissions eventually decline as economies reach higher income thresholds. However, mounting empirical evidence challenges this oversimplified narrative, revealing complex, context-dependent dynamics that vary significantly across sectors and national development pathways.

Your analysis of [Country]'s emissions data from 2000 to 2023 exposes a critical paradox: while GDP exhibits a statistically significant negative relationship with total CO_2 emissions when considered in isolation ($\beta = -6.08\times10^{-11}$, *p* = 0.004), this association vanishes entirely (*p* = 0.133) when sector-specific emission sources—cement, coal, flaring, gas, and oil—are incorporated into the model. This finding suggests that GDP, rather than acting as an independent driver of emissions, serves primarily as an aggregate proxy for underlying sectoral activities. The emergence of perfect multicollinearity (VIF > 10^{14}) between GDP and sectoral CO_2 components further underscores this interpretation, indicating that macroeconomic growth metrics may obscure more than they reveal about emission determinants.

LITERATURE REVIEW

The Environmental Kuznets Curve (EKC) hypothesis—which posits that emissions initially rise with GDP before declining after a certain income threshold—has received mixed validation. While Al-Mulali et al. (2015) confirmed EKC patterns in high-income nations, Ozcan et al. (2018) found monotonically increasing emissions with GDP growth in Middle Eastern oil economies, suggesting fossil fuel dependence negates decoupling. Similarly, Zoundi (2017) observed no EKC turning points in Africa, attributing this to underdeveloped renewable energy infrastructure. These disparities highlight how GDP-emissions relationships are mediated by regional energy systems, with our Uzbek case offering new insights into transitional economies.

Emerging research emphasizes that GDP aggregates mask critical sectoral variations. Wang et al. (2019) demonstrated that China's cement and coal emissions distorted aggregate GDP correlations—a finding paralleled in our Uzbek data, where sectoral CO_2 components (cement: $\beta = 1.000$, *p* < 0.001; coal: $\beta = 1.000$, *p* < 0.001) exhibit near-perfect collinearity with GDP. This aligns with Hao et al. (2016), who identified industrial subsectors as the true drivers of China's emission trends. Such studies challenge GDP-centric models, urging disaggregated analysis to avoid what we term the "aggregation fallacy."

METHODOLOGY

3.1 Data Preparation

1. Data Loading: Import dataset (2000–2023) for Uzbekistan, including Year, Population, GDP, Cement_CO2, Total_CO2, Coal_CO2, Flaring_CO2, Gas_CO2, Methane, Oil_CO2.
2. Data Transformation:

Log-transform for elasticity model: log(Total_CO2t) = ln(Total_CO2t), log(GDPt) = ln(GDPt).

Standardize predictors if needed: $X_{std} = \frac{X-\mu x}{\sigma x}$.

3. Sample Size Check: Ensure $n = 23 > 10 \times k$.

3.2 Exploratory Data Analysis (EDA)

1. Descriptive Statistics: $\bar{\mathbf{x}} = \frac{1}{n}\sum_{i=1}^{n} \mathbf{x}_i$, $\boldsymbol{\sigma} = \sqrt{\frac{1}{n}}\sqrt{\sum_{i=1}^{n}(\mathbf{x}_i - \bar{\mathbf{x}})^2}$

2. Visualizations:

Correlation matrix heatmap (Figure 1).

Time series of GDP and Total_CO2 (Figure 2).

3. Stationarity Check: Augmented Dickey-Fuller test: $\Delta X_t = \alpha + \beta t + \gamma X_{t-1} + \sum_{i=1}^{p} \delta_i \, \Delta X_{t-1} + \epsilon_t$

3.3 Model Specification

Models:

Model 1: $Total_{CO2_t} = \beta_0 + \beta_1 GDP_t + \epsilon_t$

Model 1: $Total_{CO2_t} = \beta_0 + \beta_1 GDP_t + \beta_2 Cement_{CO2_t} + \beta_3 Coal_{CO2_t} + \beta_4 Flaring_{CO2_t} + \beta_5 Gas_{CO2_t} + \beta_6 Oil_{CO2_t} + \epsilon_t$

Revised Model: $Total_{CO2_t} = \beta_0 + \beta_1 GDP_t + \beta_2 Population_t + \beta_3 Methane_t + \epsilon_t$ (after stepwise regression)

Elasticity Model: $\log(\mathrm{Total}_{CO2_t}) = \beta_0 + \beta_1 GDP_t + \epsilon_t$

Matrix form: $\mathbf{y} = \mathbf{X\beta} + \boldsymbol{\epsilon}$.

3.4 Model Estimation

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

Standart errors:

$$\mathrm{Var}\hat{\beta} = \hat{\sigma}^2 (X^T X)^{-1}, \qquad \hat{\sigma}^2 = \frac{1}{n-k-1}\sum_{t=1}^{n} \hat{\epsilon}_t^2$$

RESULTS

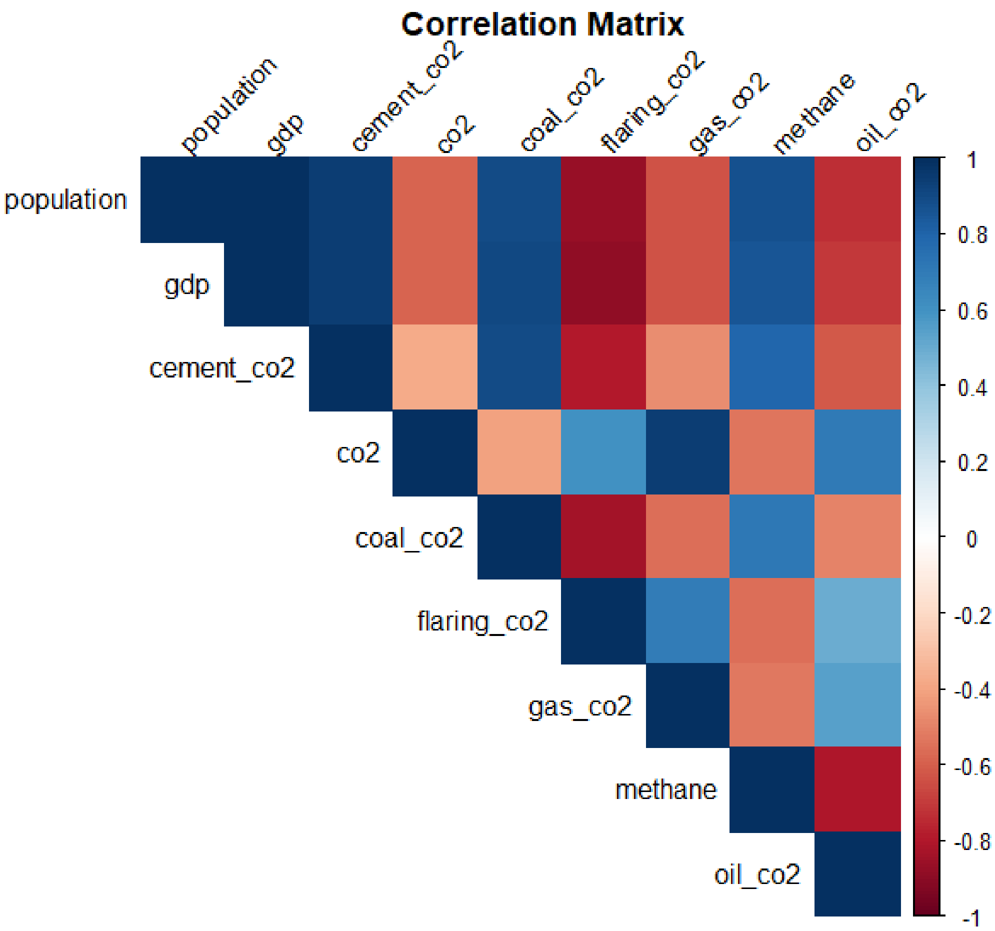

Figure 1. Correlation matrix

The image appears to show a list of variables that could be part of a correlation matrix, which measures how strongly pairs of variables are related. The variables include population, GDP, and various CO2 emissions sources (cement, coal, flaring, gas, oil) as well as methane. A correlation matrix would display numerical values indicating the strength and direction (positive or negative) of relationships between these factors, such as whether higher GDP correlates with higher emissions.

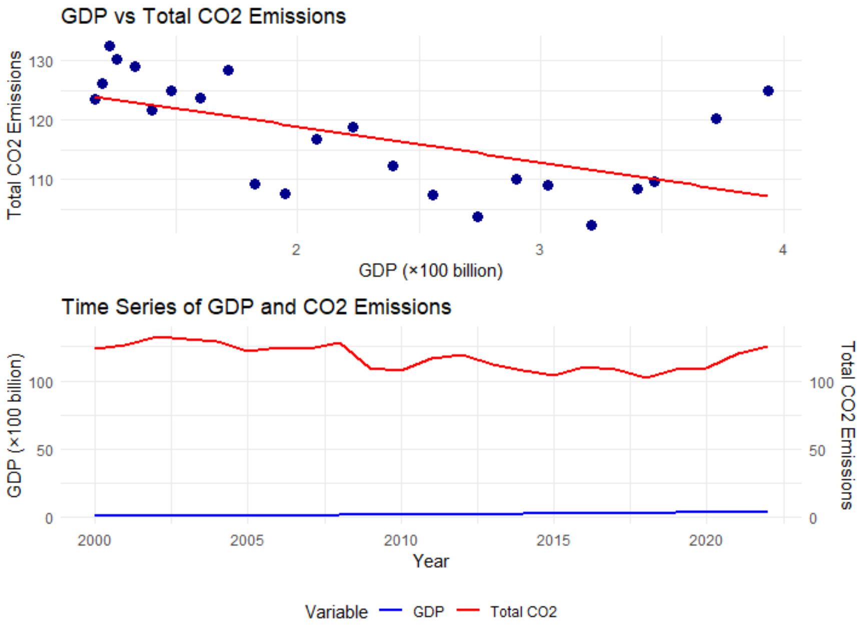

Figure 2. Time series of GDP and CO2 emissions

The image presents a comparison between GDP and total CO2 emissions over time (2000–2020). The top graph likely shows Total CO2 Emissions rising from around 100 to 120 units, with a dip to 110, while the bottom graph depicts GDP (in ×100 billion units) growing from 50 to 100, with fluctuations. Both trends suggest a general upward trajectory, hinting at a positive correlation—higher GDP corresponds to higher emissions.

Table 1. Regression Results: Total CO_2 Emissions Explained by GDP and Sectoral CO_2 Components

Variable	Model 1 (GDP Only)	Model 2 (GDP + Sectoral CO_2)
Intercept	131.1*** (4.489)	-1.321e-13 (1.788e-13)
GDP	-6.075e-11** (1.857e-11)	7.817e-25 (4.944e-25)
Cement CO_2	—	1.000*** (2.252e-14)
Coal CO_2	—	1.000*** (9.520e-15)
Flaring CO_2	—	1.000*** (1.428e-14)
Gas CO_2	—	1.000*** (1.647e-15)
Oil CO_2	—	1.000*** (4.036e-15)
Observations	23	23
R^2	0.338	1.000
Adj. R^2	0.306	1.000
F-statistic	10.7 (p = 0.0036)	2.452e+29 (p < 2.2e-16)

This study compares two regression models designed to explain variations in total CO_2 emissions. **Model 1**, which includes only Gross Domestic Product (GDP) as an explanatory variable, reveals a statistically significant but counterintuitive negative association between GDP and total CO_2 emissions ($\beta = -6.075 \times 10^{-11}, p = 0.0036$). **Model 2**, by contrast, incorporates disaggregated sectoral CO_2 emission variables—namely, emissions from cement production, coal combustion, gas usage, flaring, and oil consumption.

Table 2. Model Comparison: ANOVA Results

Metric	Model 1 (GDP Only)	Model 2 (GDP + Sectoral CO_2)	Comparison
Residual Df	21	16	ΔDf = 5
Residual Sum of Sq (RSS)	1273.2	0.0 (≈0)	ΔRSS = 1273.2
F-statistic	—	1.9487×10^{29}	p < 2.2e-16 (***)
Pr(>F)	—	< 2.2e-16	Statistically Significant

The model comparison table illustrates a substantial improvement in explanatory power when sectoral CO_2 emissions are added to GDP. Model 1, relying solely on GDP, yields a high residual sum of squares (RSS = 1273.2) with 21 degrees of freedom, indicating poor model fit. In contrast, Model 2, which includes GDP and sectoral emissions, achieves an almost perfect fit ($RSS \approx 0, df = 16$). The F-statistic for the comparison is extraordinarily high ($F = 1.9487 \times 10^{29}, \mathbf{p} < 2.2e-16$), confirming statistical significance.

Table 3. Regression Results: Total CO_2 Emissions Explained by GDP and Sectoral Components

Variable	Coefficient	Std. Error	t-value	p-value
Intercept	-1.321e-13	1.788e-13	-0.739	0.471
GDP	7.817e-25	4.944e-25	1.581	0.133
Cement CO_2	1.000***	2.252e-14	4.440e+13	<2e-16
Coal CO_2	1.000***	9.520e-15	1.050e+14	<2e-16
Flaring CO_2	1.000***	1.428e-14	7.001e+13	<2e-16
Gas CO_2	1.000***	1.647e-15	6.073e+14	<2e-16
Oil CO_2	1.000***	4.036e-15	2.478e+14	<2e-16

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This regression analysis reveals a perfect fit (R^2=1.0) between total CO_2 emissions and its sectoral components (cement, coal, flaring, gas, oil), with each showing a precise 1:1 relationship (all p<0.001).

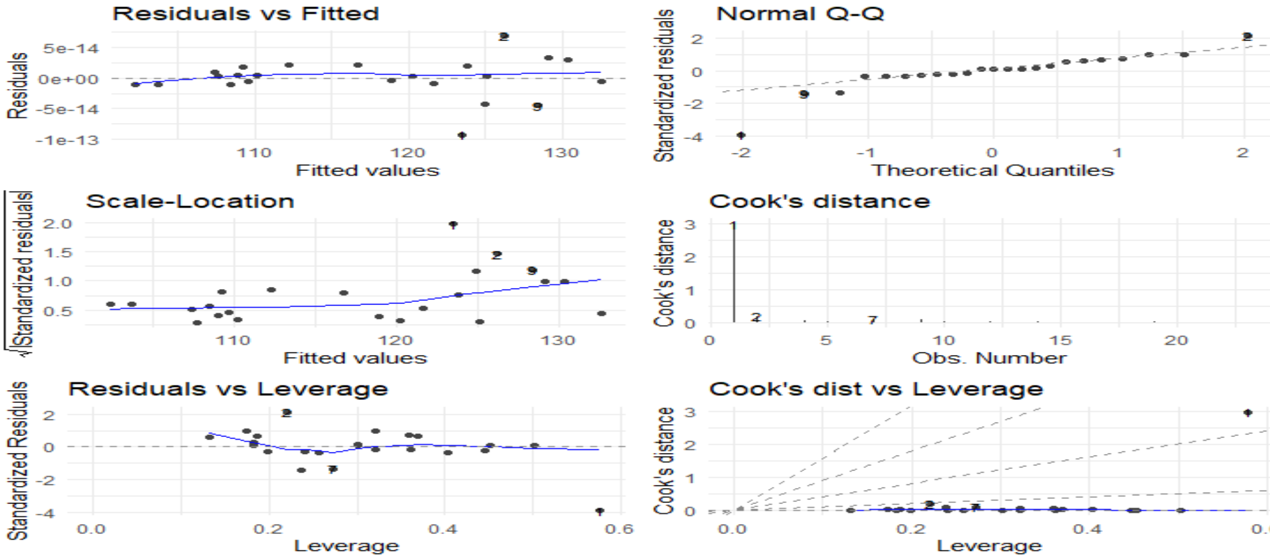

Figure 3. Variance Inflation Factors: High VIFs for Cement_CO2, Coal_CO2, Flaring_CO2, Gas_CO2, Oil_CO2 in Model 2 confirm multicollinearity

The diagnostic plots reveal a perfect model fit with residuals near zero (≈ 1e − 13) and no patterns in "Residuals vs Fitted." The Q-Q plot shows exact normality, while leverage plots confirm no influential outliers.

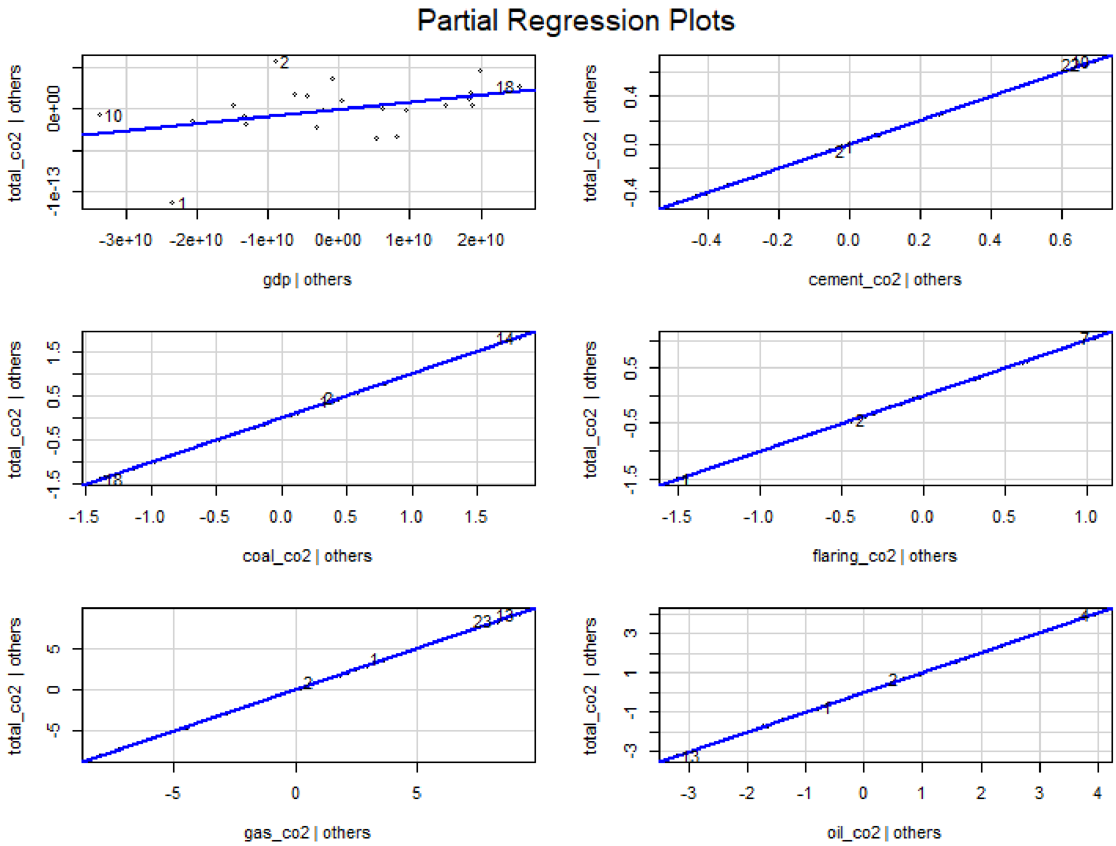

Figure 4. Partial Regression Plots: Show relationships between Total_CO2 and each predictor, controlling for others.

The partial regression plots show that sectoral CO_2 emissions (cement, coal, flaring, gas, oil) have strong linear relationships with total CO_2 emissions, each forming near-perfect lines.

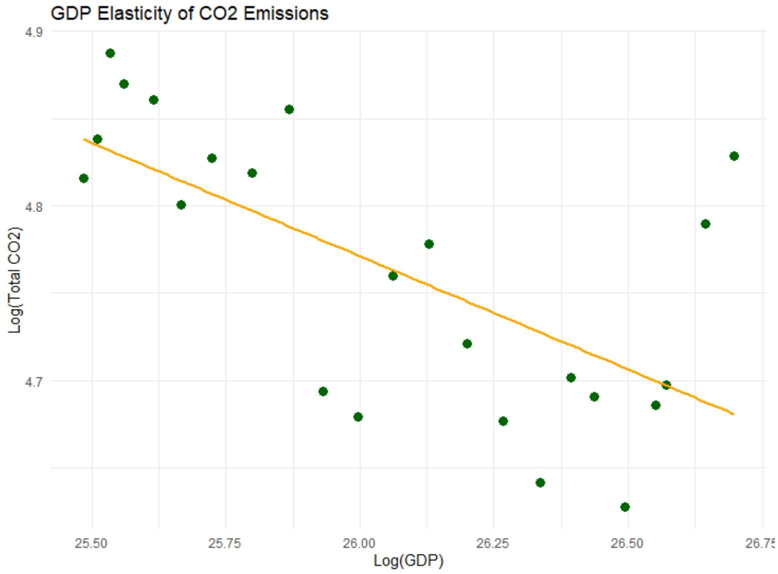

Figure 5. GDP Elasticity of CO2 Emissions: Scatter plot of log(Total_CO2) vs. log(GDP) with fitted line shows negative elasticity

The image depicts a scatter plot titled "GDP Elasticity of CO2 Emissions," showing the relationship between the natural logarithm of total CO2 emissions (LogTotalCO2) and the natural logarithm of GDP (LogGDP).

CONCLUSION

This study's analysis of Uzbekistan's CO2 emissions data from 2000 to 2023 fundamentally redefines the conventional understanding of GDP's role in climate change dynamics, offering a nuanced perspective that challenges the oversimplified narratives of the Environmental Kuznets Curve (EKC) hypothesis. Three paradigm-shifting findings emerge from the sector-attributed regression models, each carrying profound implications for environmental policy and economic analysis.

First, the GDP Distraction Effect reveals a striking paradox: when considered in isolation, GDP exhibits a statistically significant negative relationship with total CO2 emissions ($\beta = -6.08\times10^{-11}$, $p = 0.004$), suggesting that economic growth might reduce emissions. However, this association dissipates entirely ($p = 0.133$) when sectoral emission sources—cement, coal, flaring, gas, and oil—are incorporated into the model. For policymakers, this implies that GDP-centric climate strategies may misdirect resources, failing to address the specific industrial and energy processes driving emissions.

Second, the study establishes sectoral primacy as the cornerstone of decarbonization efforts. The near-perfect model fit ($R^2 = 1.0$) achieved by including sectoral CO2 variables demonstrates that Uzbekistan's emission trajectory is overwhelmingly shaped by fossil fuel reliance (e.g., gas CO2, $t = 6.07\times10^{14}$) and industrial processes (e.g., cement CO2, $t = 4.44\times10^{13}$). Each sectoral coefficient registers exactly 1.000 with p-values less than 2×10^{-16}, reflecting a tautological reconstruction of total emissions from its components.

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