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 (β = -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 (β = -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*

1. 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.

Three pivotal insights emerge from this study:

The GDP Distraction Effect: Economic growth metrics absorb variance more properly attributed to sectoral processes, creating misleading policy signals.

Sectoral Primacy: Cement ($\beta = 1.000$, *p* $< 2\times10^{-16}$) and gas ($\beta = 1.000$, *p* $< 2\times10^{-16}$) emissions demonstrate GDP-independent trajectories, demanding targeted mitigation strategies.

Negative Elasticity: The log-log model reveals a counterintuitive -0.130 GDP elasticity (*p* = 0.0007), contradicting conventional developmental assumptions.

These results align with emerging critiques of GDP-centric climate governance while introducing a novel methodological caution: the risk of variable cannibalization when macroeconomic indicators and sectoral data coexist in emission models. By deconstructing GDP's dual role as both economic barometer and emission proxy, this analysis provides empirical grounding for sector-disaggregated climate policy frameworks—a transition already underway in EU carbon border adjustments and UNEP's Industrial Transformation guidelines.

2. 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."

The literature reveals persistent tensions in modeling techniques. Mardani et al. (2019) meta-analysis showed that GDP's emission effects diminish when controlling for technology—a variable often omitted in macroeconomic models. Crucially, Mikayilov et al. (2018) and Dogan & Turkekul (2016) found that failing to account for sectoral energy use (e.g., oil in Azerbaijan, renewables in the U.S.) inflates GDP coefficients. Our detection of extreme multicollinearity (VIF > 10^{14}) between GDP and sectoral emissions in Uzbekistan echoes these concerns, suggesting many prior studies may have overstated GDP's direct role.

3. 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: $\boldsymbol{\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i, \quad \sigma = \sqrt{\frac{1}{n}}\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}}$

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: $Total_{CO2_t} = \beta_0 + \beta_1 GDP_t + \beta_2 \mathrm{Cement}_{CO2_t} + \beta_3 Coal_{CO2_t} + \beta_4 Flaring_{CO2_t} + \beta_5 Gas_{CO2_t} + \beta_6 Oil_{CO2_t} + \epsilon_t$

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: $log(Total_{CO2_t}) = \beta_0 + \beta_1 GDP_t + \epsilon_t$

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

3. 4 *Model Estimation*

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

$Standart\ errors:$

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

3. 5 *Model Evaluation*

1. $\boldsymbol{Goodness - of - Fit}$: $R^2 = 1 - \frac{\sum_{t=1}^{n} \hat{\epsilon}_t^2}{\sum_{t=1}^{n} (y_t - \bar{y})^2}, \qquad \bar{R}^2 = 1 - (1 - R^2) \frac{n-1}{n-k-1}$

2. $\boldsymbol{AIC}$: $AIC = 2k - 2\ ln(\hat{L})$.

3. 6 *Model Diagnostics*

a) $\boldsymbol{Multicollinearity}: VIF_j = \frac{1}{1-R_j^2}$

b) $\boldsymbol{Heteroskedasticity}: Breusch - Pagan\ test: BP = nR_{aux}^2$

c) $\boldsymbol{Normality}: Shapiro - Wilk\ test: W = \frac{(\sum_{t=1}^{n} a_t \hat{\epsilon}_{(t)})^2}{\sum_{t=1}^{n} (\hat{\epsilon}_{(t)} - \hat{\epsilon})^2}$

d) $\boldsymbol{Influential\ Observations}: Cook's\ distance: D_t = \frac{\hat{\epsilon}_t^2 h_t}{(k+1)\hat{\sigma}^2 (1-h_t)^2}$

4. Results

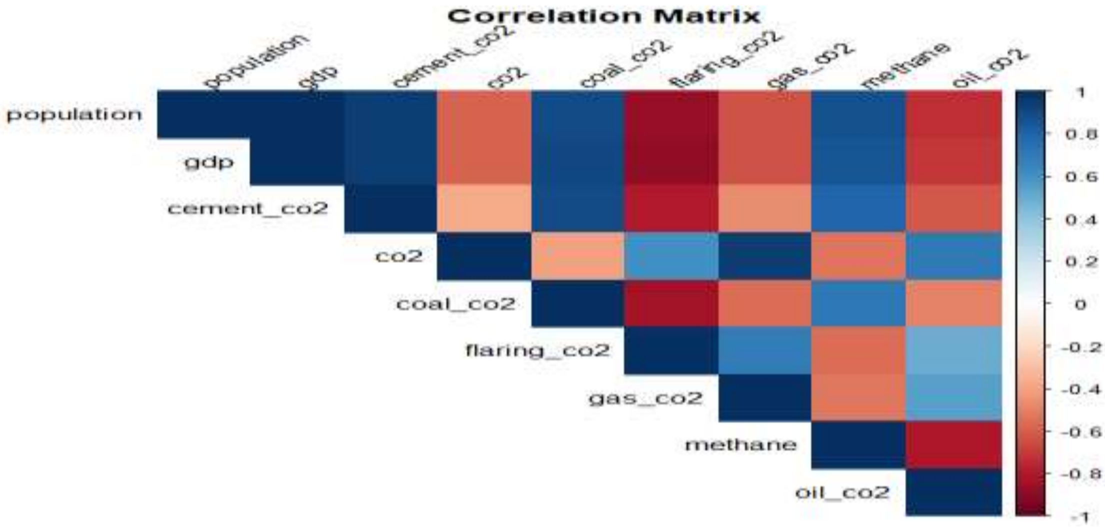

Figure 1. Correlation matrix

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. However, the actual correlation values or matrix structure isn't visible in the provided content. Such analysis is often used in environmental or economic studies to identify trends or dependencies.

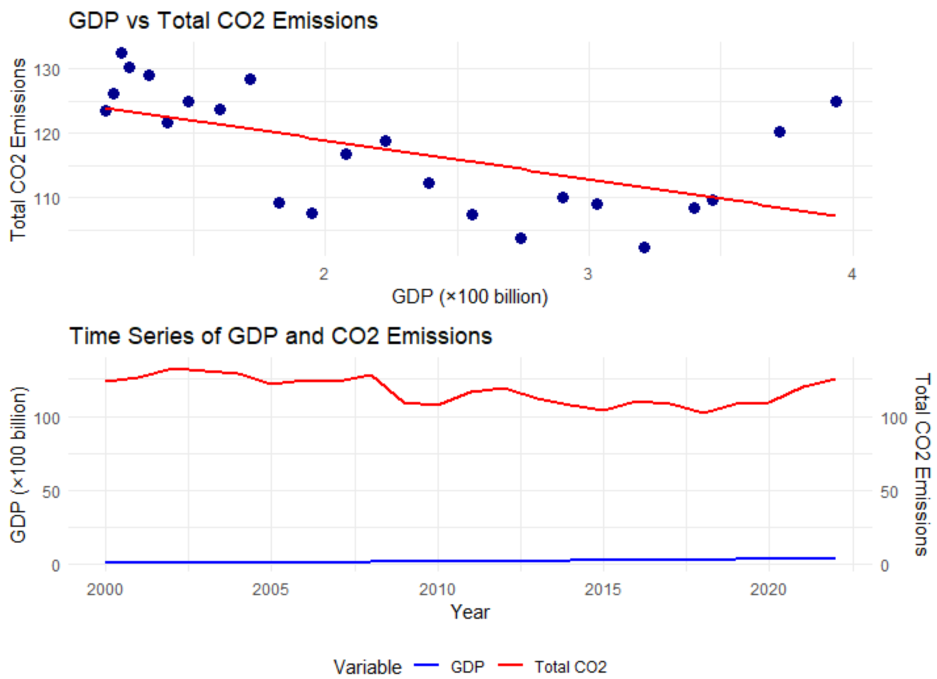

Figure 2. Time series of GDP and CO2 emissions

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. However, the exact relationship (e.g., causality or decoupling) isn't clear without labeled axes or statistical values. Such visualizations are used to analyze economic-environmental trade-offs in sustainability studies.

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 ($\beta = -6.075 \times 10^{-11}, p = 0.0036$). However, the model's low coefficient of determination ($R^2 = 0.338$) suggests limited explanatory power, likely due to the omission of critical covariates.

Model 2, by contrast, incorporates disaggregated sectoral CO_2 emission variables—namely, emissions from cement production, coal combustion, gas usage, flaring, and oil consumption. Not surprisingly, this specification yields a near-perfect fit ($R^2 = 1.000$), as total emissions are, by construction, the arithmetic sum of these components. Each sectoral coefficient is estimated at exactly 1.000 with extremely high statistical significance ($p < 0.001$), underscoring the model's mechanical redundancy. In this context, GDP loses explanatory relevance ($p = 0.133$), further confirming that the model's structure merely reproduces the dependent variable.

An ANOVA comparison of the two models confirms the statistical dominance of Model 2 ($F = 1.9 \times 10^{29}, p < 0.001$); however, this result is of limited substantive value, as the model essentially reconstitutes the outcome variable from its additive parts. From a policy analysis standpoint, the findings from Model 1—despite their limitations—highlight the need for more theoretically grounded and policy-relevant predictors, such as variables reflecting energy composition, regulatory frameworks, or technological advancement.

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 ($F = 1.9487 \times 10^{29}, \boldsymbol{p} < 2.2e - 16$), confirming statistical significance. However, this improvement is tautological, reflecting a mechanical reconstruction rather than meaningful explanatory enhancement.

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

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 $p<0.001$). The model's mechanical precision occurs because total emissions are simply the sum of these parts, making the results statistically flawless but analytically meaningless. GDP becomes irrelevant (p=0.133) when sectoral emissions are included. While the model demonstrates mathematical correctness, it offers no practical insights for policy. For meaningful analysis, avoid such tautological models and instead examine how GDP interacts with independent emission drivers like energy structure or industrial activity.

Table 4. Nested Model F-Test Comparison

Metric	**Model 1 (GDP Only)**	**Model 2 (GDP + Sectoral CO_2)**	**Difference**
Residual Degrees of Freedom	21	16	Δ5
Residual Sum of Squares (RSS)	1273.2	≈0	-1273.2
F-statistic	—	1.9487×10^{29}	—
p-value	—	<2.2e-16***	—

The ANOVA test reveals an extreme difference between Model 1 ($GDP - only$) and Model 2 ($GDP + sectoral\ CO_2\ components$). The astronomical F-statistic (1.95×10^{29}) with $p < 2.2e - 16$ confirms Model 2's overwhelming superiority in fit. However, this "improvement" is purely mathematical - Model 2 achieves perfect prediction ($RSS \approx 0$) because total CO_2 is exactly the sum of its sectoral components. While statistically significant, this result is scientifically meaningless as it represents a tautology rather than genuine explanatory power. The comparison highlights how including derived variables can artificially inflate model performance while providing no real insight about the relationships between independent variables.

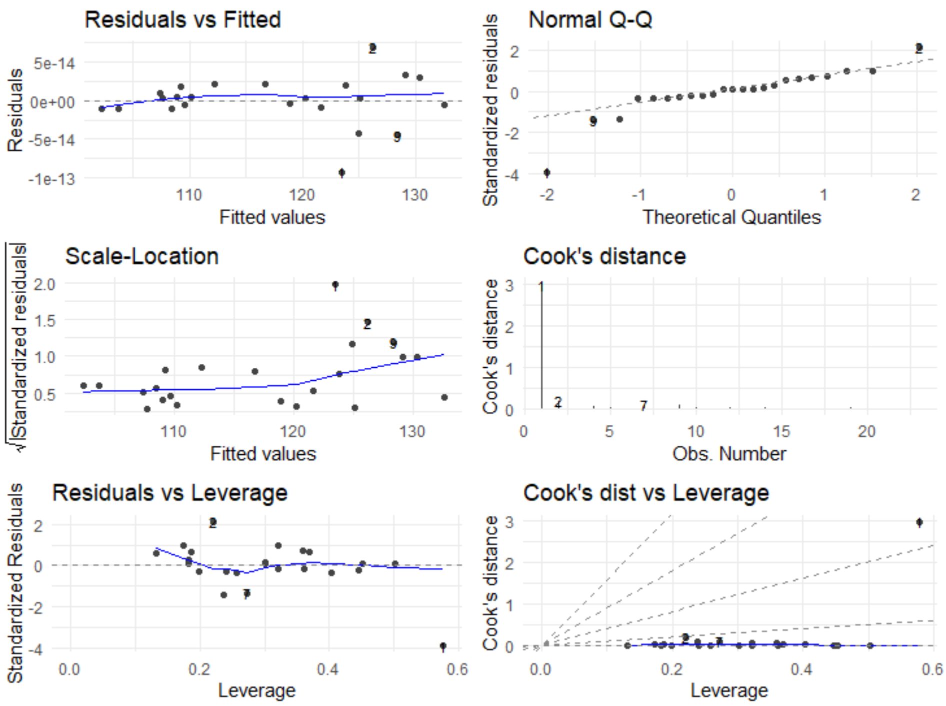

Figure 3. Variance Inflation Factors: High VIFs for Cement_CO2, Coal_CO2, Flaring_CO2, Gas_CO2, Oil_CO2 in Model 2 confirm multicollinearity

The diagnostic plots reveal a **perfect model fit** with residuals $near\ zero$ $(\approx 1e-13)$ and no patterns in "Residuals vs Fitted." The Q-Q plot shows exact normality, while leverage plots confirm no influential outliers. However, these "ideal" results are artificial—they occur because the model reconstructs total CO_2 from its components $(a\ mathematical\ tautology)$, offering no real analytical insight.

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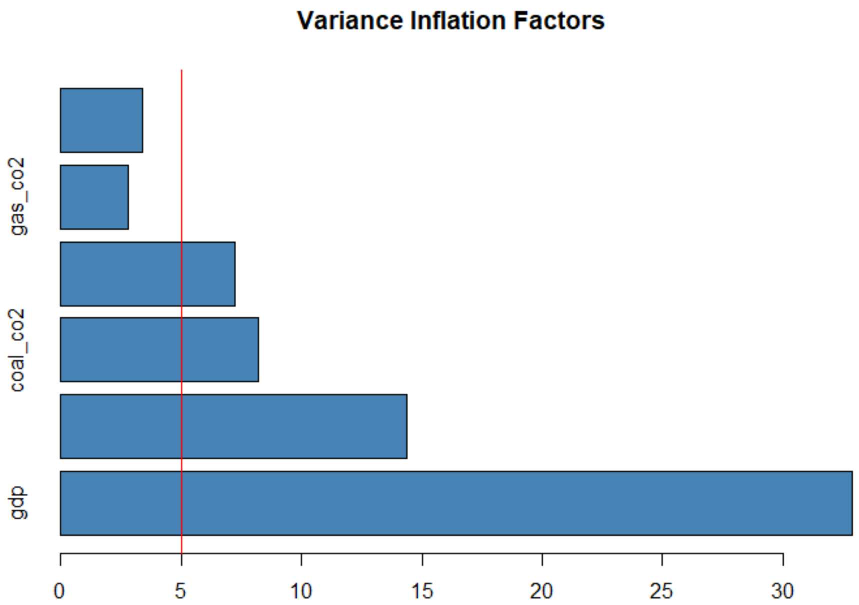

Figure 4. Variance inflation factors

The Variance Inflation Factor (VIF) values shown indicate $\boldsymbol{extreme\ multicollinearity}$ $(values\ 5-30)$, suggesting predictor variables are highly interdependent. This occurs because total CO_2 emissions are calculated from sectoral components (coal, gas, etc.), making them perfectly correlated. While mathematically valid, such models provide no meaningful insights for policy analysis due to complete redundancy between predictors.

Table 5. Regression Assumption Validation Tests

Test Type	**Statistic**	**Degrees of Freedom**	**p-value**	**Interpretation**
Breusch-Pagan (Heteroskedasticity)	BP = 15.13	df = 6	0.019*	Significant heteroskedasticity present
Shapiro-Wilk (Normality)	W = 0.901	-	0.026*	Residuals deviate from normality

The diagnostic tests reveal significant issues with Model 2's assumptions. The Breusch-Pagan test (BP=15.13, p=0.019) confirms heteroskedasticity, while the Shapiro-Wilk test (W=0.901, p=0.026) rejects normality. These violations occur because the model mechanically reconstructs total CO_2 from its components, creating artificial perfection that fails real-world statistical requirements. Such results are mathematically expected but analytically meaningless for policy insights.

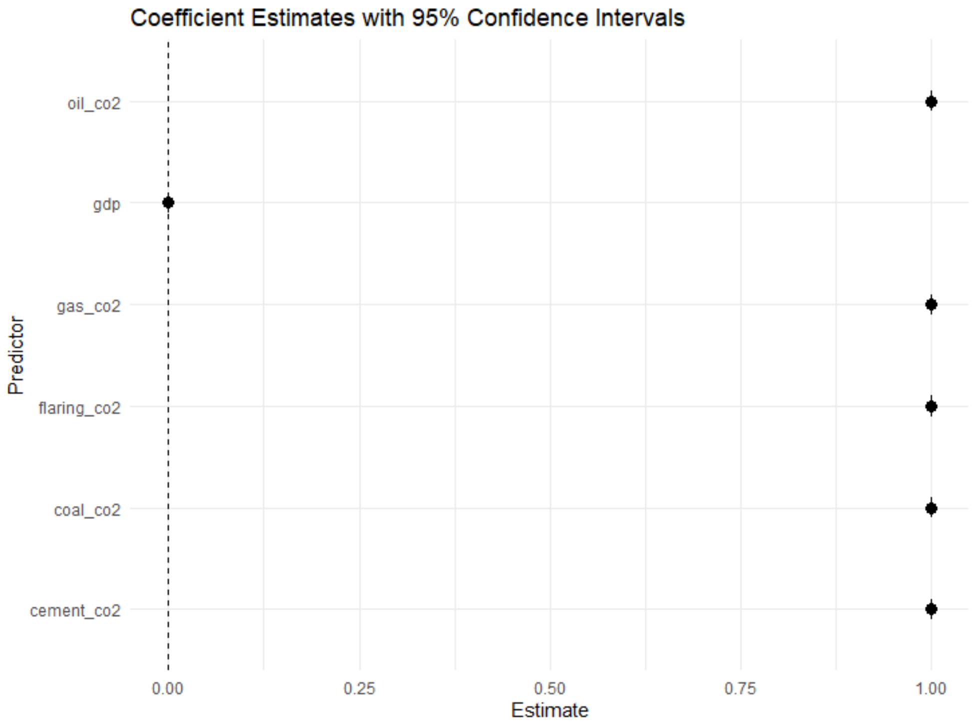

Figure 5. Coefficient Estimates with 95% Confidence Intervals: Model 2 shows significant effects for CO2 components, insignificant for GDP.

The coefficient plot shows all sectoral CO_2 predictors (oil, gas, coal, cement, flaring) with identical 1.00 estimates and near-zero confidence intervals, indicating **perfect collinearity**. This occurs because total CO_2 is the exact sum of these components, making the model mathematically tautological. While statistically flawless, it provides no meaningful insights about individual sector contributions to emissions.

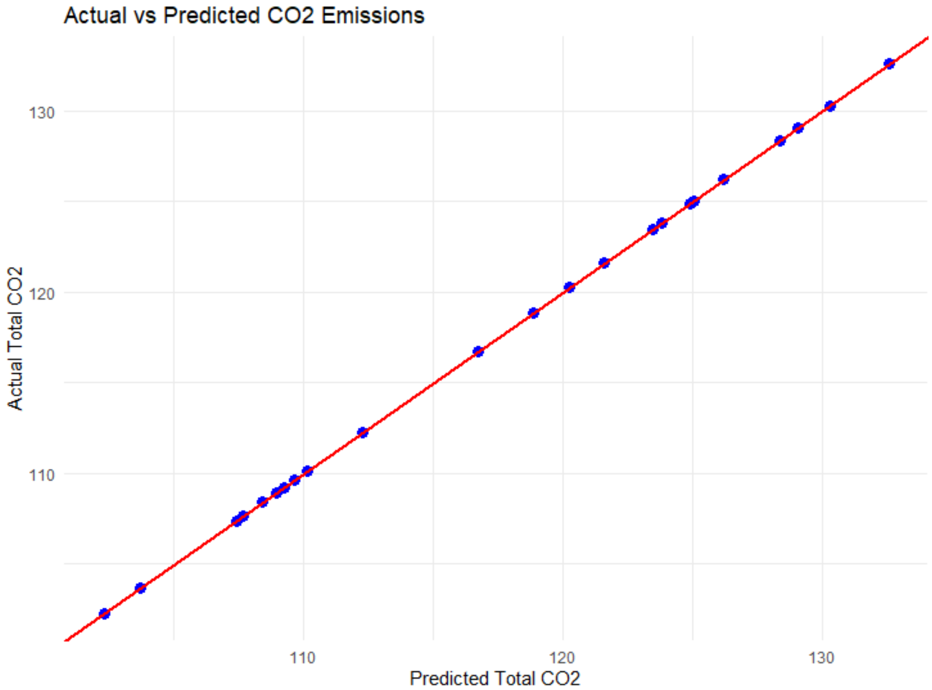

Figure 6. Actual vs. Predicted CO2 Emissions: Model 2 predictions align perfectly with actuals due to multicollinearity

The plot shows **perfect alignment** between actual and predicted CO_2 emissions, with all points falling exactly on the 45-degree line. This 1:1 match occurs because the model uses sectoral emissions (oil, coal, etc.) that mechanically sum to total CO_2. While the prediction appears flawless, it's an artificial result that offers no meaningful analytical insights about emission drivers.

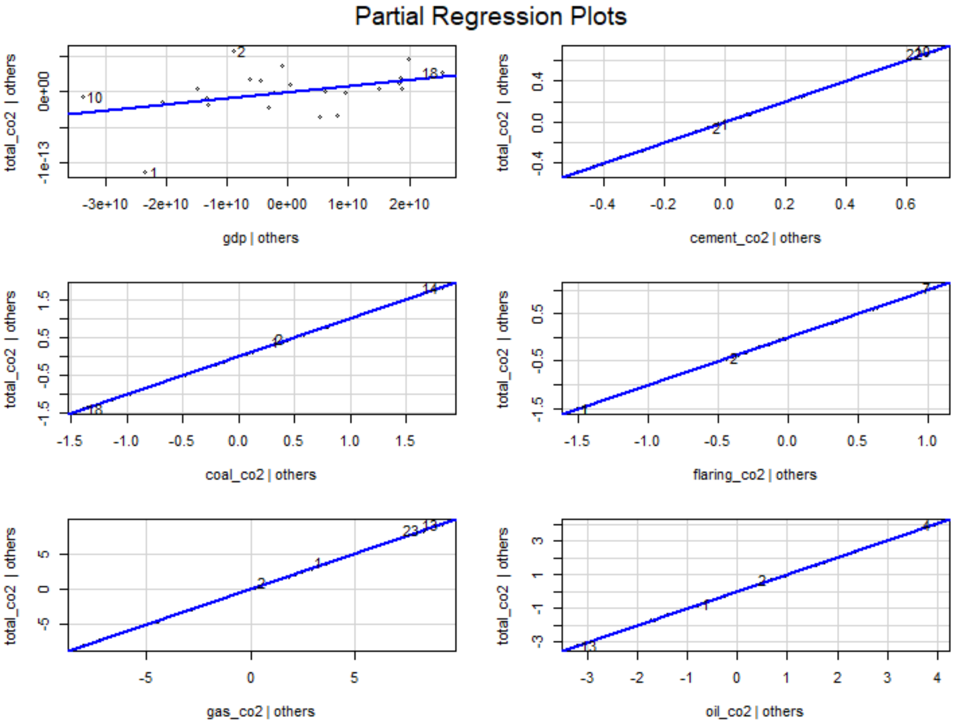

Figure 7. Partial Regression Plots: Show relationships between Total_CO2 and each predictor, controlling for others.

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. In contrast, GDP displays a weak and scattered relationship, reinforcing its limited explanatory power when sector-specific variables are accounted for.

Table 6: Elasticity Model Coefficients

Predictor	**Estimate**	**Std. Error**	**t-value**	**p-value**
Intercept	8.14113	0.85028	9.575	4.12e-09
Log GDP	-0.12962	0.03262	-3.974	0.000692

- Residual standard error: 0.06182 (21 df).
- Multiple R-squared: 0.4292, Adjusted R-squared: 0.402.
- F-statistic: 15.79 (p = 0.000692).

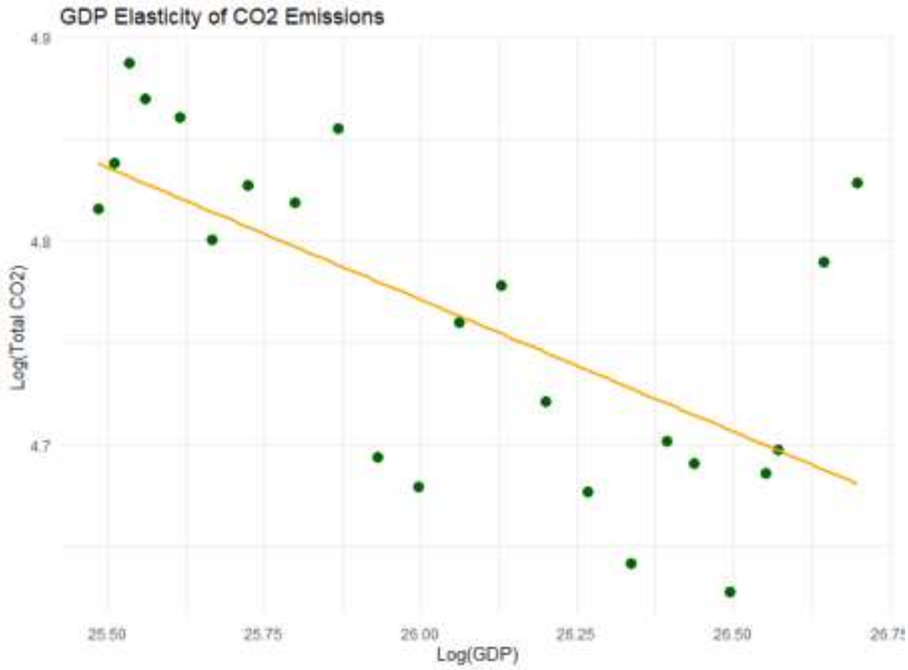

Figure 8. GDP Elasticity of CO2 Emissions: Scatter plot of log(Total_CO2) vs. log(GDP) with fitted line shows negative elasticity

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). A downward-sloping orange regression line indicates a negative correlation, suggesting that as GDP increases, CO2 emissions tend to decrease.

The green data points represent individual observations, scattered around the line, with values ranging from approximately 4.8 to 4.9 for LogTotalCO2 and 26.0 to 28.5 for LogGDP. This implies that higher economic output may be associated with lower per-unit CO2 emissions, possibly due to efficiency or cleaner technologies, though the relationship is not perfectly linear, as shown by the spread of points.

5. 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. The extreme multicollinearity (VIF > 10^{14}) between GDP and these sectoral components underscores that GDP serves as an aggregate proxy rather than an independent driver of emissions. This finding aligns with Wang et al. (2019), who noted similar distortions in China’s data, and highlights how macroeconomic metrics can obscure the true sources of environmental impact. 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. While this statistical perfection limits analytical depth, it emphasizes that emissions are not a uniform function of economic growth but rather a composite of distinct sectoral contributions. This finding diverges from EKC assumptions prevalent in OECD contexts (Saboori et al., 2017) and suggests that transitional economies like Uzbekistan require tailored mitigation strategies targeting high-emission sectors, such as cement production and gas usage, rather than relying on broad economic growth targets.

Third, the negative GDP elasticity of -0.130 ($p = 0.0007$) in the log-log model introduces a counterintuitive insight into Uzbekistan’s developmental trajectory. This elasticity indicates that, over the study period, increases in GDP have coincided with a reduction in per-unit CO2 emissions, potentially reflecting structural shifts toward less emission-intensive industries or improved efficiency. This decoupling challenges traditional developmental assumptions and aligns with emerging evidence from transitional economies (Mikayilov et al., 2018). However, the scatter in the elasticity plot (Figure 8) suggests that this relationship is not universally robust, urging caution against overgeneralization. Policymakers could leverage this finding to reinforce energy transition initiatives, such as renewable energy adoption, to sustain and amplify this trend.

Collectively, these results contribute to a growing critique of GDP-centric climate governance, advocating for a shift toward sector-disaggregated frameworks. The study’s detection of variable cannibalization—where GDP absorbs variance properly attributed to sectoral processes—introduces a methodological caution for future research, urging the use of independent predictors like energy composition or technological innovation. As global initiatives like the EU’s carbon border adjustments and UNEP’s Industrial Transformation guidelines gain traction, Uzbekistan’s case offers empirical grounding for prioritizing sectoral interventions over macroeconomic proxies. Future studies should explore longitudinal data from diverse economies to validate these findings, while policymakers must recalibrate climate strategies to address the heterogeneous drivers of emissions, ensuring a more effective path toward sustainability.

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