“The impact of industrial CO_2 emissions on PM2.5 air pollution in Central Asian countries: A panel data analysis”

AUTHORS	Sobirjon S. Ruziyev Hulkar R. Turobova Sokhibmalik Khomidov Dilnoza Djuraeva Shaxnoz B. Boltayeva Fozil Xolmurotov

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Sobirjon S. Ruziyev (Uzbekistan), **Hulkar R. Turobova** (Uzbekistan), **Sokhibmalik Khomidov** (Uzbekistan), **Dilnoza Djuraeva** (Uzbekistan), **Shaxnoz B. Boltayeva** (Uzbekistan), **Fozil Xolmurotov** (Uzbekistan)

THE IMPACT OF INDUSTRIAL CO_2 EMISSIONS ON PM2.5 AIR POLLUTION IN CENTRAL ASIAN COUNTRIES: A PANEL DATA ANALYSIS

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Sobirjon S. Ruziyev, Ph.D., Associate Professor, Department of Green Economy and Agribusiness, Faculty of Economics and Tourism, Bukhara State University, Uzbekistan.

Hulkar R. Turobova, Ph.D., Associate Professor, Department of Green Economy and Agribusiness, Faculty of Economics and Tourism, Bukhara State University, Uzbekistan.

Sokhibmalik Khomidov, Ph.D., Associate Professor, Department of Accounting and Statistics, Faculty of Economics and Tourism, Bukhara State University, Uzbekistan.

Dilnoza Djuraeva, DSc, Professor, Department of Green Economy and Agribusiness, Faculty of Economics and Tourism, Bukhara State University, Uzbekistan.

Shaxnoz B. Boltayeva, Ph.D., Associate Professor at the Department of Green Economy and Agribusiness, Faculty of Economics and Tourism, Bukhara State University, Uzbekistan.

Fozil Xolmurotov, DSc., Department of Economics, Faculty of Economics, Mamun University, Uzbekistan. (Corresponding author)

Abstract

Central Asian countries face acute air quality challenges, with PM2.5 concentrations in major cities exceeding World Health Organization guidelines several times over, while industrial CO_2 emissions continue to rise alongside economic development. Understanding the empirical linkage between these pollutants is essential for designing integrated environmental policies. The purpose of this study is to assess the impact of industrial CO_2 emissions on PM2.5 air pollution in five Central Asian countries – Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan – using balanced panel data for the period 2000–2020 ($N = 105$) obtained from the World Bank's World Development Indicators. Pooled OLS, fixed effects, and random effects estimators were applied, with GDP per capita, urbanization, and energy intensity as control variables. Model selection was based on the Hausman test, and robustness was verified through ten alternative specifications. The random effects model (Hausman $\chi2 = 0.412$, $p = 0.521$) reveals a statistically significant positive relationship: a one million metric ton increase in industrial CO_2 emissions is associated with a 0.87–0.89 μg/m³ rise in mean annual PM2.5 concentration ($p < 0.01$). The coefficient remains stable across all robustness checks (0.823–0.923). GDP per capita shows a significant negative effect (–1.92, $p < 0.05$), supporting the Environmental Kuznets Curve hypothesis, while energy intensity has a positive effect ($p < 0.05$). Country-specific effects reveal substantial heterogeneity, with Tajikistan exhibiting the highest baseline PM2.5 (+26.25 μg/m³ above Kazakhstan) and Turkmenistan the lowest (+7.49 μg/m³). These findings confirm the co-pollutant hypothesis and justify integrated climate-air quality policies with country-specific strategies.

Keywords PM2.5, CO_2 emissions, air pollution, panel data, Central Asia, environmental policy

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INTRODUCTION

The increase in CO_2 emissions is one of the primary drivers of global climate change. This process leads to the degradation of air, water, soil, and biological systems, exerting severe negative impacts on the social and economic life of society. In parallel, the worsening of atmospheric pollution – particularly the concentration of fine particulate matter (PM2.5) – has emerged as one of the most pressing environmental challenges of the twenty-first century, threatening global environmental sustainability and public health.

CO_2 emissions are primarily generated by industrial production, energy generation, transportation, and extractive industries. These contribute to the rising concentration of greenhouse gases in the atmosphere. This, in turn, leads to increased global temperatures, changes

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in climate patterns, more extreme weather events, and deteriorating air quality indicators. From this perspective, the increase in CO_2 emissions is closely linked not only to global climate change but also to local air pollution challenges, including the rise in PM2.5 concentrations. This issue is especially acute for developing countries, where industrialization is accelerating, and carbon-intensive energy sources remain dominant.

The rise in PM2.5 concentration has severe adverse effects on human health. Fine particulate matter penetrates deep into the respiratory system, contributing to asthma, bronchitis, pneumonia, reduced lung function, and an elevated risk of lung cancer. PM2.5 also constricts blood vessels, raises blood pressure, and accelerates blood clotting, thereby increasing the risks of heart attacks, heart failure, and strokes. Scientific evidence further indicates that PM2.5 particles can reach the brain, intensifying inflammatory processes and raising the risk of dementia and depression. Children are particularly vulnerable, as exposure slows lung development, weakens the immune system, and negatively affects fetal growth. Overall, elevated PM2.5 reduces labor productivity, increases healthcare expenditures, and shortens life expectancy.

From the perspective of environmental economics, CO_2 emissions are viewed as a negative externality arising from economic activity. Under market conditions, producers make decisions based on their private costs, while the damage caused to the environment – that is, the social costs – is often not taken into account. This leads to excessive carbon emissions and the disruption of ecological balance. The scientific problem, therefore, lies in the absence of robust empirical evidence on how industrial CO_2 emissions shape air quality – specifically PM2.5 concentrations – in developing regions where carbon-intensive industries coexist with weak pollution control mechanisms. Central Asia represents precisely such a region: despite facing some of the highest PM2.5 levels in the world and rapidly expanding industrial activity, it remains largely overlooked in the environmental economics literature, leaving a critical gap in the empirical foundation required to synchronize climate mitigation efforts with local air quality management in transition economies.

1. LITERATURE REVIEW

The interrelationship between carbon dioxide (CO_2) emissions and air quality has emerged as one of the most extensively investigated topics in environmental economics over the past three decades. As global climate change intensifies and atmospheric pollution continues to threaten environmental sustainability, scholarly interest in the co-pollutant nexus has expanded considerably. Existing research can be broadly organized into four interrelated strands:

(i) the Environmental Kuznets Curve (EKC) framework applied to particulate pollution;

(ii) the empirical co-benefits between CO_2 mitigation and PM2.5 reduction;

(iii) the role of urbanization and socioeconomic drivers; and

(iv) the influence of energy consumption patterns and renewable energy transition.

Each of these strands offers valuable insights, yet significant gaps remain regarding the regional specificity of the CO_2 – PM2.5 relationships.

The theoretical foundation of most empirical studies in this field rests on the EKC hypothesis, which posits an inverted U-shaped relationship between economic growth and environmental degradation, with pollution levels initially rising with income before declining beyond a certain development threshold (Grossman & Krueger, 1991, 1995; Panayotou, 1997; Stern, 2004). The applicability of this framework to PM2.5 pollution has been confirmed in several Chinese studies, where inverted U-shaped patterns between income and particulate matter concentrations have been documented at both the regional and city levels (Hao & Liu, 2016; Ding et al., 2019; Chang et al., 2022). Cross-country evidence further suggests that urbaniza-

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tion initially exacerbates PM2.5 emissions but eventually contributes to their reduction as countries achieve higher development stages (Dong et al., 2020; Qodirov et al., 2024). Taken together, these findings lend empirical credibility to the EKC framework while underscoring the importance of country- and region-specific validation.

A growing body of literature has explored the co-benefits between CO_2 emission reduction and air quality improvement, demonstrating that climate mitigation policies often deliver substantial secondary gains in terms of reduced particulate pollution. Using Input–Output Analysis and gridded spatial data, scholars have identified strong correlations between CO_2 reduction policies and air quality outcomes in major Chinese urban agglomerations, particularly Beijing–Tianjin–Hebei, the Yangtze River Delta, and the Pearl River Delta (Yang et al., 2016; Li et al., 2020). More recent evidence applying spatiotemporal and machine-learning techniques has confirmed that industrial emissions, vehicle exhaust, and coal combustion represent the primary common sources of both pollutants, with reductions in industrial activity generating the largest synergistic effects (Chung & Liu, 2024; Cai et al., 2024; Xu et al., 2025). Global-scale analyses covering thousands of urban areas have shown that more than half of cities worldwide exhibit positive correlations across CO_2 and PM2.5 pairs, although the direction and magnitude vary systematically with income level and environmental policy stringency (Kim et al., 2025). Interestingly, a study of 186 countries identified a negative correlation between CO_2 and PM2.5 at the global level, attributable to heterogeneity in energy mixes – oil and natural gas consumption weakens the positive link, while coal intensifies it (Wu et al., 2025). These divergent findings highlight that the CO_2–PM2.5 relationship is highly context-dependent and cannot be generalized across development stages or energy regimes.

The socioeconomic determinants of PM2.5 concentrations have been systematically examined using various panel data techniques. Evidence drawn from large cross-country samples indicates that urbanization, income, and service sector development exert significant influences on particulate pollution, with the magnitude of these effects varying markedly across development categories (Wang et al., 2019; Ji et al., 2018). In developing economies specifically, a 1% increase in energy use, economic growth, industrialization, and urbanization has been associated with corresponding increases in CO_2 emissions ranging from 0.17% to 2.32% (Sikder et al., 2022). Regional studies of South Asian economies have likewise identified statistically significant cointegrating relationships between PM2.5 concentrations and key macroeconomic indicators (Musa et al., 2024). Complementary evidence from Uzbekistan confirms that economic growth, energy consumption, and trade openness are central drivers of environmental outcomes in transition economies (Halmuratov et al., 2025a, 2025b; Yulduz et al., 2025; Xolmuratov et al., 2025). Collectively, this literature establishes that PM2.5 dynamics are shaped by a complex interplay of economic, demographic, and structural factors that operate differently across countries.

Energy consumption patterns and the transition toward renewable sources constitute another critical dimension of the CO_2–air quality nexus. Panel cointegration and regional analyses consistently show that renewable energy adoption and energy-sector innovation reduce emission levels and improve air quality, while non-renewable energy consumption produces the opposite effect (Zoundi, 2017; Alvarez-Herranz et al., 2017; Chen et al., 2019; Inglesi-Lotz & Dogan, 2018). Evidence from Uzbekistan reinforces this finding, indicating that renewable energy consumption has favorable effects on export performance, employment, and broader macroeconomic outcomes (Xolmurotov et al., 2025a, 2025b; Nurjanov et al., 2025). Forward-looking simulations for Europe project that aggressive climate mitigation scenarios could reduce population-weighted PM2.5 concentrations by more than half by mid-century relative to 2014 baselines (Clayton et al., 2024). These studies collectively suggest that energy transition policies can serve as a unified lever for simultaneously addressing climate change and air pollution.

Despite the extensive body of research reviewed above, Central Asia remains strikingly underrepresented in the environmental economics literature. The World Bank's (2024) comprehensive regional assessment revealed that PM2.5 concentrations in major Central Asian cities exceed

WHO guidelines by six to twelve times, with 50–80% of total exposure attributable to anthropogenic sources amenable to policy intervention. Nevertheless, no study has yet applied a systematic panel data framework to quantify how industrial CO_2 emissions shape PM2.5 concentrations across all five Central Asian republics over a prolonged period. This represents a significant empirical and policy gap, given the region's acute air quality challenges, its ongoing industrial expansion, and its heavy reliance on fossil-fuel-intensive production (WHO, 2021; World Bank, 2024).

In summary, the existing literature provides robust evidence that CO_2 and PM2.5 emissions are linked through common anthropogenic sources and that this relationship is moderated by income, urbanization, energy mix, and institutional capacity. However, the magnitude and even the direction of the CO_2–PM2.5 nexus vary considerably across regions, making country- and region-specific evidence indispensable for effective environmental policy design. The absence of dedicated panel data evidence for Central Asia, therefore, constitutes a meaningful research gap that this study seeks to fill.

Against this background, the purpose of this study is to assess the impact of industrial CO_2 emissions on PM2.5 air pollution in five Central Asian countries – Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan – using panel data covering the period 2000–2020. To achieve this purpose, the following hypotheses are formulated and tested:

H1: *Industrial CO_2 emissions exert a statistically significant positive effect on PM2.5 concentrations in Central Asian countries.*

H2: *GDP per capita is negatively associated with PM2.5 concentrations, consistent with the Environmental Kuznets Curve hypothesis.*

H3: *Energy intensity is positively associated with PM2.5 concentrations, reflecting the adverse environmental consequences of energy-inefficient production.*

H4: *Baseline PM2.5 levels vary significantly across Central Asian countries due to differences in geographic, economic, and structural conditions.*

2. METHODS

This study employs balanced panel data covering five Central Asian countries – Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan – over the period 2000–2020, yielding 105 country-year observations. All variables were obtained from the World Bank's World Development Indicators database (World Bank, 2025), a widely recognized source of internationally comparable development statistics. The study period ends in 2020 to exclude the structural break caused by COVID-19-related disruptions to industrial production and mobility, which temporarily altered both CO_2 and PM2.5 patterns in ways that do not reflect the underlying long-run relationship (Forster et al., 2020; Helm, 2020; Hepburn et al., 2020). The 21-year window provides sufficient temporal variation to capture the structural co-pollutant nexus under normal economic conditions.

The dependent variable is PM2.5 – the mean annual population-weighted exposure to fine particulate matter with an aerodynamic diameter below 2.5 micrometers, measured in micrograms per cubic meter ($\mu g/m^3$). The key explanatory variable is industrial CO_2 emissions, measured in million metric tons of CO_2 equivalent (Mt CO_2e). Three control variables are included: GDP per capita in constant 2015 year US dollars (proxying economic development), urban population as a share of total population (capturing urbanization), and energy use per USD 1,000 of GDP (representing energy intensity). Descriptive statistics for all variables are presented in Table 1.

The empirical analysis follows a four-step procedure. First, pairwise correlations and variance inflation factors are computed to examine potential multicollinearity among regressors. Second, the Pesaran (2007) cross-sectionally augmented IPS (CIPS) panel unit root test is applied to verify the stationarity of all variables and avoid spurious regression. Third, three panel estimators – pooled OLS, fixed effects (FE), and random effects (RE) – are estimated, and the appropriate model is selected using the Hausman (1978) specification test. Fourth, diagnostic tests are conducted for cross-sectional dependence (Pesaran, 2004), heteroskedasticity (Modified Wald test), and serial correla-

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Table 1. Descriptive statistics

Variable	Mean	Median	Std. Dev.	Min	Max	Obs
PM2.5 (μg/m³)	26.07	23.10	7.86	15.70	44.80	105
CO_2 (Mt CO_2e)	3.66	2.00	3.82	0.20	14.60	105
GDPpc (USD)	3,842.56	2,156.32	4,125.78	356.42	15,678.90	105
Urban (%)	45.23	44.50	12.45	26.30	57.80	105
EnergyInt	285.67	267.45	145.32	98.56	612.34	105

tion (Wooldridge, 2010), and robustness is verified through ten alternative specifications.

The baseline empirical model is specified as follows:

$$PM2.5_{it} = \alpha_i + \beta_1 CO2_{it} + \beta_2 \ln(GDPpc)_{it} + \beta_3 Urban_{it} + \beta_4 EnergyInt_{it} + \lambda_t + \varepsilon_{it}, \quad (1)$$

where $PM2.5_{it}$ denotes the concentration of fine particulate matter in country i at time t, α_i captures country-specific effects, λ_i represents time fixed effects controlling for common temporal shocks, and ε_{it} is the idiosyncratic error term. The pooled OLS estimator assumes homogeneity across cross-sectional units and is consistent only when country-specific effects are absent or uncorrelated with the regressors (Wooldridge, 2010). The fixed effects estimator allows correlation between unobserved country-specific effects and the explanatory variables and yields consistent estimates via within-transformation even when this correlation is nonzero (Baltagi, 2021). The random effects estimator treats country-specific effects as uncorrelated random draws and is more efficient than FE when the orthogonality assumption holds (Hsiao, 2014). The Hausman (1978) test is used to discriminate between FE and RE: failure to reject the null hypothesis indicates that RE is both consistent and efficient, while rejection favors FE.

Given the potential presence of heteroskedasticity and cross-sectional dependence arising from shared regional shocks among Central Asian economies, cluster-robust standard errors are employed throughout the estimation. To further ensure the reliability of the findings, robustness is assessed using:

(i) alternative standard error specifications (Driscoll–Kraay and bootstrap with 1,000 replications);

(ii) alternative model specifications (baseline without controls, specification with country-specific time trends, and feasible generalized least squares);

(iii) subsample analysis for the periods 2000–2010 and 2011–2020; and

(iv) outlier analysis excluding observations with standardized residuals exceeding ±2.5 in absolute value.

All estimations are performed in Stata 17. The four hypotheses (*H1–H4*) are empirically tested using the coefficients of Equation (1) and the country-specific fixed effects obtained from the FE estimation.

3. RESULTS

Prior to the econometric estimation, pairwise correlations among the variables were examined to obtain preliminary insights into their relationships. Table 2 presents the correlation matrix for all variables included in the analysis.

The correlation analysis reveals that CO_2 emissions exhibit a positive and statistically significant correlation with PM2.5 concentrations ($r = 0.412$, $p < 0.01$). GDP per capita shows a negative correlation with PM2.5 ($r = -0.287$, $p < 0.05$). Energy intensity is positively correlated with both CO_2 emissions ($r = 0.478$, $p < 0.01$) and PM2.5 concentrations ($r = 0.345$, $p < 0.01$). The correlation coefficients among explanatory variables remain below 0.70, indicating that multicollinearity is unlikely to pose a severe problem in the regression analysis (Xolmuratov et al., 2025).

To ensure the validity of panel regression analysis and avoid spurious regression, the Pesaran (2007) cross-sectionally augmented IPS (CIPS) panel unit root test was conducted. Table 3 reports the test results for all variables at levels and first differences.

Table 2. Correlation matrix

Variable	PM2.5	CO_2	GDPpc	Urban	EnergyInt
PM2.5	1.000				
CO_2	0.412***	1.000			
GDPpc	−0.287**	0.534***	1.000		
Urban	−0.156	0.389***	0.612***	1.000	
EnergyInt	0.345***	0.478***	−0.223**	−0.145	1.000

Note: ***, **, * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Table 3. Panel unit root test results (CIPS test)

Variable	Level	First Difference	Order of Integration
PM2.5	−2.847***	–	I(0)
CO_2	−2.634**	–	I(0)
GDPpc	−1.845	−3.912***	I(1)
ln(GDPpc)	−2.578**	–	I(0)
Urban	−2.412**	–	I(0)
EnergyInt	−2.756***	–	I(0)

Note: Critical values at 1%, 5%, and 10% significance levels are −2.57, −2.33, and −2.21, respectively. ***, **, * denote rejection of the null hypothesis of unit root at 1%, 5%, and 10% levels.

The CIPS test results indicate that PM2.5, CO_2, Urban, and EnergyInt are stationary at levels, i.e., integrated of order zero, I(0). While GDPpc in levels appears to contain a unit root, its natural logarithm transformation is stationary. Consequently, the logarithmic transformation of GDP per capita (ln(GDPpc)) was employed in the regression models.

Given the geographic proximity and shared economic characteristics of Central Asian countries, cross-sectional dependence may arise from common regional shocks. Table 4 presents the results of the Pesaran (2004) CD test.

Table 4. Cross-sectional dependence test results

Test	Statistic	p-value	Decision
Pesaran CD	1.847	0.065	Fail to reject H_0
Breusch-Pagan LM	18.234	0.052	Fail to reject H_0
Pesaran Scaled LM	1.923	0.054	Fail to reject H_0

Note: H0: No cross-sectional dependence.

The test results indicate failure to reject the null hypothesis of cross-sectional independence at the conventional 5% significance level across all three tests. The Pesaran CD statistic of 1.847 (p = 0.065) suggests weak evidence of cross-sectional dependence.

Groupwise heteroskedasticity was tested using the modified Wald test in the fixed effects model. Table 5 presents the results.

Table 5. Heteroskedasticity test results

Test	χ^2 Statistic	df	p-value	Decision
Modified Wald	24.67	5	0.000	Reject H_0

Note: H0: $\sigma_i 2 = \sigma 2$ for all i (homoskedasticity).

The modified Wald test strongly rejects the null hypothesis of homoskedasticity ($\chi^2 = 24.67$, $p < 0.001$), indicating the presence of groupwise heteroskedasticity across countries. The Wooldridge (2010) test for first-order autocorrelation in the panel data was also employed. Table 6 reports the test results.

The Wooldridge test fails to reject the null hypothesis of no first-order autocorrelation ($F = 3.412$, p = 0.138). Table 7 presents the variance inflation factor (VIF) values for all explanatory variables.

Table 7. Multicollinearity diagnostics (VIF)

Variable	VIF	1/VIF (Tolerance)
CO_2	1.82	0.549
ln(GDPpc)	2.14	0.467
Urban	1.67	0.599
EnergyInt	1.53	0.654
Mean VIF	1.79	–

Note: VIF > 10 indicates severe multicollinearity.

All VIF values are substantially below the conventional threshold of 10, with the mean VIF of 1.79.

Table 6. Serial correlation test results

Test	F-Statistic	df	p-value	Decision
Wooldridge	3.412	(1, 4)	0.138	Fail to reject H_0

Note: H0: No first-order autocorrelation.

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Table 8. Summary of diagnostic tests

Issue	Test	Result	Implication
Unit Root	CIPS	Variables are I(0)	Standard panel methods valid
Cross-sectional Dependence	Pesaran CD	Not significant	Standard errors valid
Heteroskedasticity	Modified Wald	Present	Use robust standard errors
Autocorrelation	Wooldridge	Not significant	No correction needed
Multicollinearity	VIF	Mean = 1.79	No concern

The tolerance values (1/VIF) all exceed 0.40. Table 8 summarizes the diagnostic test results and their implications for model specification.

Based on the diagnostic test results, panel regression estimation was conducted using heteroskedasticity-robust (clustered) standard errors. Table 9 presents the estimation results from three panel regression models: pooled OLS, fixed effects (FE), and random effects (RE). All models include the full set of control variables and employ cluster-robust standard errors.

Table 9. Panel regression results: CO_2 emissions and PM2.5 concentration

Variable	Pooled OLS	Fixed Effects	Random Effects
	(1)	(2)	(3)
CO_2	–0.372	0.891***	0.867***
	(0.245)	(0.157)	(0.162)
ln(GDPpc)	–2.145**	–1.876**	–1.923**
	(0.867)	(0.745)	(0.756)
Urban	0.089	–0.124	–0.098
	(0.078)	(0.095)	(0.087)
EnergyInt	0.015**	0.012*	0.013**
	(0.006)	(0.007)	(0.006)
Constant	35.672***	42.345***	40.128***
	(8.234)	(7.456)	(7.689)
Country FE	No	Yes	–
Time FE	No	Yes	Yes
Observations	105	105	105
R^2	0.234	0.918	0.412
R^2 (within)	–	0.456	0.448
R^2 (between)	–	0.934	0.926
F-statistic	7.89***	28.45***	–
Wald χ^2	–	–	89.67***

Note: Cluster-robust standard errors in parentheses. ***, **, * denote statistical significance at 1%, 5%, and 10% levels, respectively.

The pooled OLS model yields a negative and statistically insignificant coefficient for CO_2 (–0.372, $p > 0.10$). In contrast, both the FE and RE models produce positive and highly significant coefficients for CO_2 emissions (0.891 and 0.867, respectively, both $p < 0.01$). The explanatory power improved substantially from Pooled OLS ($R^2 = 0.234$) to FE ($R^2 = 0.918$). The within-R^2 of 0.456 in the FE model indicates that CO_2 emissions and control variables explain approximately 46% of the within-country variation in PM2.5 concentrations over time. To formally select between the FE and RE models, the Hausman (1978) specification test was conducted. Table 10 presents the test results.

Table 10. Hausman specification test results

Variable	Coefficients		Difference	S.E.
	(FE) β_FE	(RE) β_RE	(β_FE – β_RE)	
CO_2	0.891	0.867	0.024	0.038
ln(GDPpc)	–1.876	–1.923	0.047	0.089
Urban	–0.124	–0.098	–0.026	0.041
EnergyInt	0.012	0.013	–0.001	0.003

Test Statistic	Value
$\chi^2(4)$	0.412
p-value	0.521
Decision	Fail to reject H_0

Note: H0: Difference in coefficients is not systematic (RE is consistent and efficient).

The Hausman test yields a chi-squared statistic of 0.412 with a p-value of 0.521, indicating failure to reject the null hypothesis at conventional significance levels. Consequently, the random effects model is preferred as it is both consistent and efficient under these conditions.

Table 11 reports the estimated country-specific fixed effects from the FE model, revealing substantial heterogeneity in baseline PM2.5 levels across Central Asian countries.

Tajikistan exhibits the highest fixed effect (26.246), while Turkmenistan displays the lowest fixed effect (7.486). Next, Table 12 presents the RE model estimates with alternative standard error specifications.

Table 11. Country-specific fixed effects

Country	Fixed Effect (α_i)	Std. Error	Interpretation
Kazakhstan (ref.)	0.000	–	Reference category
Kyrgyzstan	13.764***	1.632	+13.76 μg/m³ above Kazakhstan
Tajikistan	26.246***	1.561	+26.25 μg/m³ above Kazakhstan
Turkmenistan	7.486***	1.487	+7.49 μg/m³ above Kazakhstan
Uzbekistan	16.123***	1.055	+16.12 μg/m³ above Kazakhstan

Note: *** denotes statistical significance at 1% level. Kazakhstan serves as the reference category.

Table 12. Robustness check: Alternative standard error specifications

Variable	Cluster–Robust	Driscoll–Kraay	Bootstrap
	(1)	(2)	(3)
CO_2	0.867***	0.867***	0.867***
	(0.162)	(0.178)	(0.155)
ln(GDPpc)	–1.923**	–1.923**	–1.923**
	(0.756)	(0.812)	(0.734)
Urban	–0.098	–0.098	–0.098
	(0.087)	(0.095)	(0.082)
EnergyInt	0.013**	0.013*	0.013**
	(0.006)	(0.007)	(0.006)

Note: ***, **, * denote statistical significance at 1%, 5%, and 10% levels. Bootstrap standard errors based on 1,000 replications.

Table 13 examines the sensitivity of results to alternative model specifications (Driscoll & Kraay, 1998). The CO_2 coefficient remains positive, statistically significant at the 1% level, and stable across all specifications, ranging from 0.834 to 0.923.

Table 13. Robustness check: Alternative model specifications

Variable	Baseline RE	Without Controls	With Time Trends	FGLS
	(1)	(2)	(3)	(4)
CO_2	0.867***	0.923***	0.834***	0.878***
	(0.162)	(0.187)	(0.168)	(0.145)
ln(GDPpc)	–1.923**	–	–1.756**	–1.867**
	(0.756)		(0.789)	(0.698)
Urban	–0.098	–	–0.112	–0.089
	(0.087)		(0.092)	(0.078)
EnergyInt	0.013**	–	0.011*	0.014**
	(0.006)		(0.007)	(0.005)
Country Trends	No	No	Yes	No
Observations	105	105	105	105
R^2 / Wald χ^2	0.412	0.298	0.445	156.78***

Note: ***, **, * denote statistical significance at 1%, 5%, and 10% levels.

Table 14 presents the results for two subperiods to examine temporal stability. The coefficient remains statistically significant at the 1% level in both subperiods.

Table 14. Robustness check: Subsample analysis

Variable	Full Sample	2000–2010	2011–2020
	(2000–2020)		
CO_2	0.867***	0.912***	0.823***
	(0.162)	(0.198)	(0.187)
ln(GDPpc)	–1.923**	–2.145**	–1.678*
	(0.756)	(0.912)	(0.867)
Observations	105	55	50
R^2 (within)	0.448	0.467	0.423

Note: ***, **, * denote statistical significance at 1%, 5%, and 10% levels. Random effects model with cluster-robust standard errors.

Table 15 presents results after excluding observations with standardized residuals exceeding ±2.5. The exclusion of four outlying observations yields a coefficient estimate of 0.845, differing from the full-sample estimate by only 2.5%.

Table 15. Robustness check: Outlier analysis

Variable	Full Sample	Excluding Outliers
CO_2 Coefficient	0.867***	0.845***
Standard Error	(0.162)	(0.154)
Observations	105	101
Outliers Excluded	–	4
R^2 (within)	0.448	0.462

Note: *** denotes statistical significance at 1% level. Four observations with |standardized residual| > 2.5 were excluded.

Table 16 summarizes the CO_2 coefficient estimates across all robustness specifications. Across all ten specifications examined, the CO_2 coefficient ranges from 0.823 to 0.923, with a mean of 0.866 and a standard deviation of only 0.032. All coefficients are statistically significant at the 1% level, and the 95% confidence intervals consistently exclude zero.

Based on the estimation results presented above, all four hypotheses formulated in this study are empirically tested. Table 17 summarizes the outcomes.

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Table 16. Summary of CO_2 coefficient estimates across specifications

Specification	CO_2 Coefficient	95% CI	Significant
Baseline RE	0.867	[0.550, 1.184]	***
Fixed Effects	0.891	[0.583, 1.199]	***
Driscoll-Kraay SE	0.867	[0.518, 1.216]	***
Bootstrap SE	0.867	[0.563, 1.171]	***
Without Controls	0.923	[0.556, 1.290]	***
With Time Trends	0.834	[0.505, 1.163]	***
FGLS	0.878	[0.594, 1.162]	***
Subperiod 2000–2010	0.912	[0.524, 1.300]	***
Subperiod 2011–2020	0.823	[0.456, 1.190]	***
Excluding Outliers	0.845	[0.543, 1.147]	***

Note: *** denotes statistical significance at 1% level. CI = Confidence Interval.

Table 17. Summary of hypotheses testing results

Hypothesis	Statement	Key Evidence	Result
H1	CO2 emissions → positive effect on PM2.5	β = 0.867, p < 0.01; stable across 10 specifications (0.823–0.923)	Confirmed
H2	GDP per capita → negative effect on PM2.5 (EKC)	β = –1.923, p < 0.05	Confirmed
H3	Energy intensity → positive effect on PM2.5	β = 0.013, p < 0.05	Confirmed
H4	Significant cross-country heterogeneity in baseline PM2.5	Fixed effects from +7.49 to +26.25 μg/m³, all p < 0.01	Confirmed

Note: All coefficients are from the random effects model with cluster-robust standard errors, except H4, which is based on country-specific fixed effects from the FE estimation.

H1 is confirmed. The coefficient on CO_2 emissions in the preferred random effects model is 0.867 ($p < 0.01$), indicating that a one million metric ton increase in industrial CO_2 emissions is associated with a 0.87 μg/m³ rise in mean annual PM2.5 concentration. The estimate remains positive and significant at the 1% level across all ten robustness specifications (range: 0.823–0.923), providing strong support for the co-pollutant hypothesis.

H2 is confirmed. The coefficient on ln(GDPpc) is –1.923 ($p < 0.05$) in the random effects model, implying that higher levels of economic development are associated with lower particulate pollution, ceteris paribus. The negative sign and statistical significance persist across the fixed effects model (–1.876, $p < 0.05$) and all alternative specifications, consistent with the declining segment of the Environmental Kuznets Curve.

H3 is confirmed. The coefficient on EnergyInt is 0.013 ($p < 0.05$) in the random effects model, indicating that a one-unit increase in energy use per USD 1,000 of GDP raises PM2.5 concentration by 0.013 μg/m³. The effect retains its positive sign and statistical significance (at least at the 10% level) in all robustness checks, confirming that energy-inefficient production structures contribute to particulate pollution.

H4 is confirmed. The country-specific fixed effects reported in Table 11 are all statistically significant at the 1% level and reveal substantial heterogeneity: relative to Kazakhstan (reference category), baseline PM2.5 is higher by 26.25 μg/m³ in Tajikistan, 16.12 μg/m³ in Uzbekistan, 13.76 μg/m³ in Kyrgyzstan, and 7.49 μg/m³ in Turkmenistan. This confirms that geographic, economic, and structural differences generate significantly different baseline pollution levels across the region.

4. DISCUSSION

The empirical results of this study offer several important insights into the relationship between industrial CO_2 emissions and PM2.5 air pollution in Central Asia.

The central finding – that a one million metric ton increase in industrial CO_2 emissions is associated with a 0.87–0.89 μg/m³ rise in mean annual PM2.5 concentration – confirms *H1* and provides strong empirical support for the co-pollutant hypothesis in the Central Asian context. The magnitude of this effect is economically meaningful: given that the regional average PM2.5 concentration (26.07 μg/m^3) already exceeds the WHO guideline of 5 μg/m^3 by more than fivefold, even modest increases driven by industrial emissions translate into substantial public health consequences. Importantly, the stability of the coefficient across ten alternative specifications (range: 0.823–0.923) lends exceptional robustness to this finding.

When compared with prior research, our estimated coefficient appears notably larger than those typically reported for developed economies but consistent in sign with most developing country studies. Yang et al. (2016), using Input–Output Analysis for China, identified significant correlations between CO_2 reduction policies and air quality outcomes but did not quantify the elasticity in directly comparable terms. Li et al. (2020), employing gridded data for Chinese urban agglomerations, found spatial co-location of CO_2 and PM2.5 hotspots but estimated weaker marginal effects, likely reflecting China's more advanced pollution control infrastructure. Our higher coefficient for Central Asia (0.87–0.89) plausibly reflects the limited penetration of abatement technologies, the legacy of Soviet-era heavy industry, and less stringent environmental regulation across the region. This interpretation aligns with Chung and Liu (2024), who demonstrated that the CO_2–PM2.5 relationship is strongly moderated by technological development and industrial structure.

A particularly interesting contrast emerges with the findings of Wu et al. (2025), who reported a negative global correlation between CO_2 and PM2.5 based on data from 186 countries. Our positive and highly significant coefficient for Central Asia directly contradicts this global pattern, but is fully consistent with their explanation. Wu et al. (2025) attributed the negative global correlation to the increasing share of oil and natural gas in the global energy mix, while noting that coal-dependent regions exhibit a reinforced positive relationship. Central Asia – particularly Kazakhstan and Kyrgyzstan, which rely heavily on coal – fits precisely into the latter category. Our results, therefore, do not refute Wu et al.'s (2025) findings but rather confirm that the CO_2–PM2.5 nexus is highly heterogeneous across regions and energy regimes, and that Central Asia represents a distinct subgroup requiring separate analytical treatment. A similar conclusion emerges from Kim et al. (2025), whose analysis of 13,189 urban areas worldwide showed that regions undergoing rapid economic growth record simultaneous increases in both pollutants – precisely the pattern we observe in Central Asia.

The negative and statistically significant coefficient on GDP per capita (–1.92, $p < 0.05$) confirms *H2* and provides evidence consistent with the Environmental Kuznets Curve framework in the Central Asian context. This finding resonates with the inverted U-shaped patterns documented by Hao and Liu (2016) in 73 Chinese cities, Ding et al. (2019) in the Beijing–Tianjin–Hebei region, and Chang et al. (2022) in 284 Chinese cities. However, unlike these Chinese studies, which observed the downward-sloping portion of the EKC, our results capture a region that appears to be transitioning from the rising to the declining phase of the curve – economic development is beginning to deliver air quality dividends, but the process remains incomplete. This interpretation is also in line with Dong et al. (2020), who found that urbanization initially increases PM2.5 but eventually contributes to its reduction as countries advance through development stages.

The positive and marginally significant effect of energy intensity (0.013, $p < 0.05$) confirms *H3* and reinforces the conclusion that energy-inefficient production structures are a key driver of particulate pollution. This result corroborates the findings of Sikder et al. (2022), who documented that in developing economies, a 1% increase in energy use elevates CO_2 emissions by 0.23%, and aligns with Zoundi (2017) and Alvarez-Herranz et al. (2017), who showed that energy-sector innovation and renewable energy adoption meaningfully improve air quality. The implication is that energy efficiency improvements can serve as a "double-dividend" policy instrument, delivering both economic savings and environmental benefits simultaneously.

The substantial variation in country-specific fixed effects confirms *H4* and reveals remarkable heterogeneity in baseline air quality across the five Central Asian republics. Tajikistan's exceptionally high fixed effect (+26.25 μg/m^3 above Kazakhstan) reflects a combination of mountainous topography that traps pollutants in populated valleys, widespread use of coal and biomass for residential heating during harsh winters, and limited financial ca-

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pacity to invest in pollution abatement. Conversely, Turkmenistan's comparatively lower fixed effect (+7.49 μg/m^3) may be attributed to its sparse population distribution, a natural-gas-dominated industrial structure that generates fewer particulate emissions than coal-intensive economies, and atmospheric conditions favorable for pollutant dispersion. Kazakhstan, despite its larger industrial base, serves as the reference country with the lowest baseline pollution due to its more diversified economy, greater investment in environmental infrastructure, and lower population density in industrial regions. Uzbekistan occupies an intermediate position (+16.12 μg/m^3), consistent with its mixed industrial base and moderate urbanization. These country-specific patterns underscore that uniform regional environmental policies would be ineffective – differentiated strategies reflecting each country's structural conditions are essential.

The sharp improvement in explanatory power from pooled OLS (R^2 = 0.234) to the fixed effects model (R^2 = 0.918) deserves particular methodological emphasis. The negative and insignificant CO_2 coefficient in the pooled OLS specification (–0.372) most likely reflects severe omitted variable bias, as unobserved country characteristics – geography, industrial composition, regulatory frameworks, and institutional capacity – are simultaneously correlated with both CO_2 emissions and PM2.5 concentrations. This finding carries an important methodological lesson for future environmental economics research in Central Asia and comparable regions: ignoring country-specific heterogeneity can produce not merely biased but qualitatively misleading results, including reversed signs. Our finding echoes the cautionary evidence of Musa et al. (2024) for SAARC economies, where failure to account for unobserved heterogeneity substantially distorted the estimated pollution–income relationship.

From a theoretical standpoint, our results validate the applicability of both the co-pollutant hypothesis and the Environmental Kuznets Curve framework to Central Asia, while highlighting important regional specificities. The co-existence of a strong positive CO_2–PM2.5 link and a negative GDP–PM2.5 relationship suggests that Central Asian countries are positioned at a critical juncture – the ascending portion of the EKC, where industrial expansion continues to drive emissions upward, but with growing potential for environmental improvement as development deepens and policy frameworks mature. This interpretation implies that proactive policy interventions can accelerate the region's transition to the descending phase of the curve, avoiding the prolonged high-pollution trajectories observed historically in East Asia.

Several limitations of this study should be acknowledged. First, the use of country-level aggregate data may mask substantial within-country variation, and future research employing city- or province-level data could provide finer-grained insights into the spatial dynamics of the CO_2–PM2.5 nexus. Second, while the panel approach effectively controls for time-invariant unobserved heterogeneity, it cannot fully address potential endogeneity arising from reverse causality or time-varying omitted confounders; instrumental variable strategies or natural experiments would strengthen causal identification. Third, the analysis focuses exclusively on industrial CO_2 emissions, whereas PM2.5 concentrations are also shaped by transportation, residential heating, agriculture, and natural dust sources – incorporating these additional drivers would enrich the understanding of air quality determinants in Central Asia. Despite these limitations, the consistency of the results across multiple specifications and robustness checks provides considerable confidence in the validity of the main findings.

CONCLUSION

The purpose of this study was to assess the impact of industrial CO_2 emissions on PM2.5 air pollution in five Central Asian countries – Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan – using panel data covering the period 2000–2020. Employing pooled OLS, fixed effects, and random effects estimators together with a comprehensive set of diagnostic and robustness procedures, the analysis addressed a significant empirical gap in the environmental economics literature concerning an underrepresented region that nonetheless faces some of the most acute air quality challenges in the world.

The findings confirm all four hypotheses formulated in the study. Industrial CO_2 emissions exert a statistically significant positive effect on PM2.5 concentrations. GDP per capita has a significant negative effect consistent with the Environmental Kuznets Curve framework. Energy intensity positively influences particulate pollution. Finally, baseline PM2.5 levels vary substantially across Central Asian countries. These results remained stable across ten alternative specifications, lending strong confidence to the underlying co-pollutant relationship.

Several overarching conclusions emerge from these findings. First, the strong co-pollutant link between industrial CO_2 and PM2.5 in Central Asia indicates that climate change mitigation and air quality management are not competing policy objectives, but mutually reinforcing ones – integrated policy frameworks can therefore deliver simultaneous gains in both domains. Second, the estimated effect for Central Asia exceeds values typically reported for advanced economies, underscoring the heightened vulnerability of developing regions where carbon-intensive industries coexist with limited pollution abatement capacity. Third, the pronounced country-level heterogeneity revealed through the fixed effects analysis demonstrates that uniform regional policies would be ineffective and that differentiated strategies tailored to each country's geographic, industrial, and institutional context are essential for meaningful progress. Fourth, the methodological comparison between pooled OLS and fixed effects estimation highlights the critical importance of accounting for unobserved heterogeneity in environmental economics research on developing regions.

Therefore, several policy directions warrant priority attention. Central Asian governments should design integrated climate–air quality strategies that leverage the co-benefits of industrial decarbonization. Tajikistan requires targeted interventions addressing residential heating and clean cooking, while Kazakhstan and Uzbekistan should prioritize industrial emission controls and modernization of energy infrastructure. The entire region would benefit from coordinated monitoring networks, harmonized emission standards, and accelerated adoption of renewable energy and energy-efficiency measures.

Future research can build on this paper in several productive directions. First, extending the analysis with city- or province-level data would reveal spatial dynamics that country-level aggregates inevitably mask. Second, incorporating post-pandemic observations as validated statistics become available will allow scholars to test whether the CO_2–PM2.5 relationship has fundamentally changed in the aftermath of COVID-19. Third, employing instrumental variable approaches or natural experiments could strengthen causal identification beyond what panel estimators alone can provide. Fourth, broadening the set of explanatory variables to include transportation, residential heating, agricultural activities, and natural dust sources would yield a more comprehensive account of air quality determinants in the region. Finally, comparative studies linking Central Asia with other post-Soviet or resource-dependent economies could help identify whether the patterns documented here reflect region-specific conditions or more general features of transition economies.

AUTHOR CONTRIBUTIONS

Conceptualization: Sokhibmalik Khomidov, Shaxnoz B. Boltayeva, Fozil Xolmurotov.
Data curation: Hulkar R. Turobova, Dilnoza Djuraeva.
Formal analysis: Fozil Xolmurotov.
Funding acquisition: Sobirjon S. Ruziyev, Sokhibmalik Khomidov, Dilnoza Djuraeva.
Investigation: Sobirjon S. Ruziyev, Hulkar R. Turobova, Shaxnoz B. Boltayeva.
Methodology: Sokhibmalik Khomidov, Dilnoza Djuraeva.
Project administration: Fozil Xolmurotov.
Resources: Sobirjon S. Ruziyev, Dilnoza Djuraeva, Shaxnoz B. Boltayeva.
Software: Fozil Xolmurotov.
Supervision: Sobirjon S. Ruziyev.

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Validation: Hulkar R. Turobova, Dilnoza Djuraeva.
Visualization: Sokhibmalik Khomidov, Dilnoza Djuraeva, Fozil Xolmurotov.
Writing – original draft: Sobirjon S. Ruziyev, Sokhibmalik Khomidov, Dilnoza Djuraeva, Shaxnoz B. Boltayeva, Fozil Xolmurotov.
Writing – review & editing: Hulkar R. Turobova, Fozil Xolmurotov.

DECLARATION OF GENERATIVE AI IN SCIENTIFIC WRITING

The authors used generative AI tools only for language editing and grammar improvement. The scientific content, analysis, and conclusions are the sole responsibility of the authors.

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REFERENCES

1. Alvarez-Herranz, A., Balsalobre-Lorente, D., Shahbaz, M., & Cantos, J. M. (2017). Energy innovation and renewable energy consumption in the correction of air pollution levels. *Energy Policy,* 105, 386-397. https://doi.org/10.1016/j.enpol.2017.03.009
2. Baltagi, B. H. (2021). *Econometric analysis of panel data* (6th ed.). Springer.
3. Cai, X., Zheng, S., Zhang, X., Ye, Z., Liu, C., & Tan, Z. (2024). The impact of CO_2 emission synergy on $PM_{2.5}$ emissions and a dynamic analysis of health and economic benefits: A case study of China's transportation industry. *Journal of Cleaner Production*, *471,* Article 143271. https://doi.org/10.1016/j.jclepro.2024.143405
4. Chang, H.-Y., Wang, W., & Yu, J. (2022). Revisiting the environmental Kuznets curve in China: A spatial dynamic panel data approach. *Energy Economics, 104,* Article 105680. https://doi.org/10.1016/j.eneco.2021.105600
5. Chen, Y., Zhao, J., Lai, Z., Wang, Z., & Xia, H. (2019). Exploring the effects of economic growth, and renewable and non-renewable energy consumption on China's CO_2 emissions: Evidence from a regional panel analysis. *Renewable Energy*, *140*, 341-353. https://doi.org/10.1016/j.renene.2019.03.058
6. Chung, W., & Liu, C. (2024). Study of the coupling effect of CO_2 and $PM_{2.5}$ emissions: A case study of Yangtze River Delta, China. *Heliyon*, *11*(2), Article e41059. https://doi.org/10.1016/j.heliyon.2024.e41616
7. Clayton, C. J., Marsh, D. R., Turnock, S. T., Graham, A. M., Pringle, K. J., Reddington, C. L., Kumar, R., & McQuaid, J. B. (2024). The co-benefits of a low-carbon future for $PM_{2.5}$ and O_3 air pollution in Europe. *Atmospheric Chemistry and Physics, 24*(18), 10717-10740. https://doi.org/10.5194/acp-24-10717-2024
8. Ding, Y., Zhang, M., Chen, S., Wang, W., & Nie, R. (2019). The environmental Kuznets curve for PM2.5 pollution in Beijing-Tianjin-Hebei region of China: A spatial panel data approach. *Journal of Cleaner Production, 220,* 984-994.
9. Dong, Q., Lin, Y., Huang, J., & Chen, Z. (2020). Has urbanization accelerated PM2.5 emissions? An empirical analysis with cross-country data. *China Economic Review*, *59*, Article 101381. https://doi.org/10.1016/j.chieco.2019.101381
10. Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics, 80*(4), 549-560. https://doi.org/10.1162/003465398557825
11. Forster, P.M., Forster, H. I., Evans, M. J., Gidden, M. J., Jones, C. D., Keller, C. A., Lamboll, R. D., Le Quéré, C., Rogelj, J., Rosen, D., Schleussner, C.-F., Richardson, T. B., Smith, C. J., & Turnock, S. T. (2020). Current and future global climate impacts resulting from COVID-19. *Nature Climate Change, 10,* 913-919. https://doi.org/10.1038/s41558-020-0883-0
12. Grossman, G. M., & Krueger, A. B. (1991). *Environmental impacts of a North American Free Trade Agreement* (NBER Working Paper No. 3914). National Bureau of Economic Research. https://doi.org/10.3386/w3914
13. Grossman, G. M., & Krueger, A. B. (1995). Economic growth and the environment. *Quarterly Journal of Economics, 110*(2), 353-377. https://doi.org/10.2307/2118443
14. Halmuratov, G., Madraximov, Q., Zakirova, G., Xolmuratov, X., Djumabayeva, S., Yaqubova, Y., & Xolmurotov, F. (2025a). The impact of energy consumption and trade openness on economic growth in Uzbekistan: A Vecm approach. *International Journal of Energy Economics and Policy, 15*(2), 23-31. https://doi.org/10.32479/ijeep.17550

15. Halmuratov, G., Rustamov, K., Khankelov, T., Xolmuratov, X., Khudainazarov, S., Sabirjanov, T., & Xolmurotov, F. (2025b). The relationship between renewable energy production and economic growth: A short-term and long-term analysis in the case of Uzbekistan. *International Journal of Energy Economics and Policy, 15*(3), 567-575. https://doi.org/10.32479/ijeep.18609

16. Hao, Y., & Liu, Y.-M. (2016). The influential factors of urban PM2.5 concentrations in China: A spatial econometric analysis. *Journal of Cleaner Production, 112*(2), 1443-1453. https://doi.org/10.1016/j.jclepro.2015.05.005

17. Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica, 46*(6), 1251-1271. https://doi.org/10.2307/1913827

18. Helm, D. (2020). The environmental impacts of the coronavirus. *Environmental and Resource Economics, 76,* 21-38. https://doi.org/10.1007/s10640-020-00426-z

19. Hepburn, C., O'Callaghan, B., Stern, N., Stiglitz, J., & Zenghelis, D. (2020). Will COVID-19 fiscal recovery packages accelerate or retard progress on climate change? *Oxford Review of Economic Policy, 36*(Supplement_1), S359-S381. https://doi.org/10.1093/oxrep/graa015

20. Hsiao, C. (2014). *Analysis of panel data* (3rd ed.). Cambridge University Press. https://doi.org/10.1017/CBO9780511754203

21. Inglesi-Lotz, R., & Dogan, E. (2018). The role of renewable versus non-renewable energy to the level of CO_2 emissions: A panel analysis of sub-Saharan Africa's big 10 electricity generators. *Renewable Energy, 123*, 36-43. https://doi.org/10.1016/j.renene.2018.02.041

22. Ji, X., Yao, Y., & Long, X. (2018). What causes PM2.5 pollution? Cross-economy empirical analysis from socioeconomic perspective. *Energy Policy*, *119*, 458-472. https://doi.org/10.1016/j.enpol.2018.04.040

23. Kim, S.-Y., Kerr, G. H., van Donkelaar, A., Martin, R. V., West, J. J., & Anenberg, S. C. (2025). Tracking air pollution and CO_2 emissions in 13,189 urban areas worldwide using large geospatial datasets. *Communications Earth & Environment*, *6*(1), Article 311. https://doi.org/10.1038/s43247-025-02270-9

24. Li, Y., Cui, Y., Cai, B., Guo, J., Cheng, T., & Zheng, F. (2020). Spatial characteristics of CO_2 emissions and $PM_{2.5}$ concentrations in China based on gridded data. *Applied Energy*, *266,* Article 114852. https://doi.org/10.1016/j.apenergy.2020.114852

25. Musa, M., Rahman, P., Saha, S. K., Chen, Z., Ali, M. A. S., & Gao, Y. (2024). Cross-sectional analysis of socioeconomic drivers of PM2.5 pollution in emerging SAARC economies. *Scientific Reports*, *14*(1), Article 16357. https://doi.org/10.1038/s41598-024-67199-z

26. Nurjanov, A., Xolmurotov, F., Ibadullaev, E., Ataniyazov, J., Masharipova, M., Yusupova, F., & Xolmuratov, X. (2025). The impact of renewable energy consumption on export performance in Uzbekistan: A vector autoregression approach. *Environmental Economics, 16*(2), 186-198. http://dx.doi.org/10.21511/ee.16(2).2025.14

27. Panayotou, T. (1997). Demystifying the environmental Kuznets curve: Turning a black box into a policy tool. *Environment and Development Economics, 2*(4), 465-484. Retrieved from https://www.jstor.org/stable/44379189

28. Pesaran, M. H. (2004). *General diagnostic tests for cross section dependence in panels* (IZA Discussion Paper No. 1240). University of Cambridge. Retrieved from https://docs.iza.org/dp1240.pdf

29. Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics, 22*(2), 265-312. https://doi.org/10.1002/jae.951

30. Qodirov, A., Urakova, D., Amonov, M., Masharipova, M., Ibadullaev, E., Xolmurotov, F., & Matkarimov, F. (2024). The dynamics of tourism, economic growth, and CO2 emissions in Uzbekistan: An ARDL approach. *International Journal of Energy Economics and Policy, 14*(6), 365-370. https://doi.org/10.32479/ijeep.16591

31. Sikder, M., Wang, C., Yao, X., Huai, X., Wu, L., Kwame Yeboah, F., Wood, J., Zhao, Y., & Dou, X. (2022). The integrated impact of GDP growth, industrialization, energy use, and urbanization on CO_2 emissions in developing countries: Evidence from the panel ARDL approach. *Science of the Total Environment, 837,* Article 155795. https://doi.org/10.1016/j.scitotenv.2022.155795

32. Stern, D. I. (2004). The rise and fall of the environmental Kuznets curve. *World Development, 32*(8), 1419-1439. https://doi.org/10.1016/j.worlddev.2004.03.004

33. Wang, Q., Kwan, M-P., Zhou, K., Fan, J., Wang, Y., & Zhan, D. (2019). The impacts of urbanization on fine particulate matter (PM2.5) concentrations: Empirical evidence from 135 countries worldwide. *Environmental Pollution, 247,* 989-998. https://doi.org/10.1016/j.envpol.2019.01.086

34. Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). MIT Press.

35. World Bank. (2024). *Improving air quality in Central Asia*. World Bank Group. Retrieved from https://www.worldbank.org/en/region/eca/publication/air-quality-management-in-central-asia

36. World Bank. (2025). *World Development Indicators*. Retrieved from https://databank.worldbank.org/source/world-development-indicators

37. World Health Organization (WHO). (2021). *WHO global air quality guidelines: particulate matter (PM2.5 and PM10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide.* Retrieved from https://www.who.int/publications/i/item/9789240034228

38. Wu, C., Zhou, D., Zha, D., & Hong, J. H. (2025). Can carbon

http://dx.doi.org/10.21511/ee.17(3).2026.04

emission reduction mitigate the $PM_{2.5}$ air pollution? Evidence of the co-benefits from mitigating climate change. *Environment, Development and Sustainability, 27*(9), 21053-21074. https://doi.org/10.1007/s10668-023-03896-5

39. Xolmuratov, X., Akimov, E., Saburov, K., Quoromboyev, S., & Xolmurotov, F. (2025). Quantile regression analysis of factors influencing greenhouse gas emissions in Uzbekistan. *AIP Conference Proceedings, 3331*(1), Article 030019. https://doi.org/10.1063/5.0306161

40. Xolmurotov, F., Gadoeva, M., Uraeva, D., Eshmuratova, D., Ishmuratov, X., Xolmuratov, X., & Matnazarov, A. (2025a). Mapping the evolution and intellectual structure of innovation marketing research: A comprehensive bibliometric analysis (1972–2025). *Innovative Marketing, 21*(4), 1-15. https://doi.org/10.21511/im.21(4).2025.01

41. Xolmurotov, F., Khamidov, O., Davlatov, S., Ibadullaev, E., Xolmuratov, X., Sherov, A., & Arabova, G. (2025b). The impact of renewable energy consumption on unemployment rates in Uzbekistan: An ARDL approach. *Environmental Economics, 16*(1), 78-88. https://doi.org/10.21511/ee.16(1).2025.06

42. Xu, H., Huang, J., Zhao, D., Zhang, Z., Huang, J., Wang, F., Liu, J., Jiang, S., Feng, Y., Song, S., & Shi, G. (2025). Co-benefits between $PM_{2.5}$ control and carbon reduction revealed by interpretable machine learning methods. *Geophysical Research Letters*, *52*(12). https://doi.org/10.1029/2024GL112794

43. Yang, S., Chen, B., & Ulgiati, S. (2016). Co-benefits of CO_2 and $PM_{2.5}$ emission reduction. *Energy Procedia*, *104*, 92-97. https://doi.org/10.1016/j.egypro.2016.12.017

44. Yulduz, Y., Xolilla, X., Fozil, X., Xosiyat, M., Gulnoza, Z., Zilola, A., & Komil, S. (2025). Impact of energy consumption on agricultural economics in Uzbekistan: An ARDL approach. *International Journal of Energy Economics and Policy, 15*(3), 138-145. https://doi.org/10.32479/ijeep.18120

45. Zoundi, Z. (2017). CO_2 emissions, renewable energy and the Environmental Kuznets Curve, a panel cointegration approach. *Renewable and Sustainable Energy Reviews*, *72*, 1067-1075. https://doi.org/10.1016/j.rser.2016.10.018