

Corruption and Environmental Degradation: Evidence from the EECCA Region

Abdulmecit Yıldırım^{1*}, Hüseyin İşlek², İlyas Okumuş³

^{1,2}Muş Alparslan University, Türkiye

³Kahramanmaraş Sütçü İmam University, Türkiye

E-mail: ¹a.yildirim@alparslan.edu.tr, ²h.islek@alparslan.edu.tr, ³ilyas.okumus@hotmail.com

*Corresponding Author

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Abstract

Research Originality: This research introduces a novel analytical approach to examine the interactions among corruption, per capita income, and the environment across the member countries of the GREEN Action Task Force platform. The study finds that lower-income countries experience a larger reduction in environmental degradation when corruption declines.

Research Objective: The study aims to determine the effect of corruption on CO₂ emissions and to examine how this relationship changes with economic development. Moreover, the research tests the validity of the Environmental Kuznets Curve hypothesis within this specific context.

Research Method: The study used the Driscoll-Kraay and FGLS methods to address potential cross-section dependence, heteroskedasticity, and autocorrelation issues that commonly arise in panel data analysis.

Empirical Results: Corruption has a significant negative effect on CO₂ emissions. The interaction between corruption and per capita income reveals that the impact of reduced corruption on CO₂ emissions is more apparent in countries with lower per capita income. The study also confirms the validity of the Environmental Kuznets Curve hypothesis.

Implications: Policymakers, particularly in lower-income countries, should prioritize anti-corruption policies to protect the environment during economic development.

Keywords:

Corruption; CO₂ emissions; environmental degradation; renewable energy; environmental Kuznets curve

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INTRODUCTION

The relationship between economic growth and the environment has been a central academic focus for decades. As countries pursue economic development, they also need to mitigate environmental impacts to support sustainable development. In this context, governments have implemented many innovative policies, practices, and technologies to ensure ecological sustainability. However, transitioning to an environmentally friendly development model may be difficult, particularly for emerging economies. Overcoming these challenges requires a multifaceted strategy that includes government incentives, private-sector innovations, and public support. In addition, knowledge exchange and international cooperation are critical to developing effective solutions to mitigate the negative environmental externality of the development process.

A notable initiative is the GREEN Action Task Force platform, established in 1993 by the OECD to develop environmental policies and integrate environmental considerations into economic, social, and political reforms. The transition economies of Eastern Europe, the Caucasus, and Central Asia (EECCA) have joined this platform, aiming for ecologically friendly economic development. According to the OECD (2020) report, corruption remains widespread and continues to have a significant impact in these countries. Lopez and Mitra (2000) stated that corruption is more prevalent in developing countries and that lobbying activities in these countries have a significant impact on environmental degradation. Given that environmental awareness and policy effectiveness are influenced by economic, political, and sociocultural dynamics, corruption is a key factor that has both direct and indirect effects on economic development and environmental outcomes. This often leads to the inefficient use or misallocation of resources intended for environmental protection and sustainable development projects. Varvarigos (2023) notes that corruption committed by public officials in developing countries reduces the effectiveness of environmental policies. This situation can hinder the effective implementation of environmental policies and regulations, undermining the country's economic and ecological objectives. Consequently, corruption weakens transparency and accountability in decision-making processes, prioritizing short-term economic interests over long-term ones.

Despite extensive research on economic growth, corruption, and environmental degradation, no consensus has emerged. Specifically, we observed that studies examining the relationship between economic development, corruption, and the environment, particularly in GREEN Action Task Force member countries, are not adequately discussed in the relevant literature. These countries, with their distinct transitional profiles and institutional development, provide a unique context. Therefore, this gap provides an opportunity to examine in detail how economic growth, corruption, and environmental degradation are interrelated in these countries. This study aims to address this gap by analyzing these relationships in the member countries of the GREEN Action Task Force platform. It is anticipated that the findings may provide valuable insights for the Task Force administration and policymakers in member countries regarding sustainable development policies.

Classifying research that examines the relationship between economic development, governance, and the environment is challenging. To provide a clear overview of the study's

objectives, we primarily focus on literature examining the role of governance, especially corruption, in the relationship between economic development and the environment. The current literature demonstrates that corruption significantly affects the nexus between the environment and economic development. Research in this area has expanded by recognizing the quality of governance, particularly corruption control, as a significant factor influencing the environment.

Many studies have found a significant positive relationship between corruption and environmental degradation, suggesting that higher corruption levels are associated with poorer environmental quality. For example, Lisciandra and Migliardo (2017) found that increased corruption reduces environmental performance and increases CO₂ emissions. Similarly, Ikhsan and Amri (2024) determined that controlling corruption significantly reduces CO₂ emissions, indicating that good governance can benefit the environment. Cole (2007) confirmed the positive impact of corruption on per capita emissions of SO₂ (sulfur dioxide) and CO₂. Yahaya et al. (2020) demonstrated, through empirical analyses, that the interaction between financial development and corruption in Sub-Saharan African countries negatively affects environmental degradation. Haseeb and Azam (2021) found evidence of bidirectional causality between corruption and environmental degradation. They stated that the impact of corruption on environmental degradation is greater in developing countries. These findings indicate that corruption can exacerbate environmental degradation, especially in developing countries.

The direct and indirect effects of corruption are also examined. For instance, Hwang et al. (2024) found that corruption has a positive direct effect on CO₂ emissions, while it has a negative indirect effect by hindering economic growth. Consequently, the overall net effect of corruption on environmental quality is negative. Usman et al. (2022) found that in African countries, control of corruption and income level increase CO₂ emissions, but their interaction reduces CO₂ emissions, indicating a mitigating effect. Leitão (2021) observed that higher corruption levels are associated with higher emissions across several European countries (Portugal, Spain, Italy, Ireland, and Greece). Similarly, Ridzuan et al. (2019) reported that in three ASEAN countries (Malaysia, Indonesia, and the Philippines), higher corruption worsens environmental degradation by increasing CO₂ emissions. Sekrafi and Sghaier (2018), using the ICRG corruption index, identified a significant negative relationship between corruption control and CO₂ emissions in Tunisia, suggesting that stronger corruption control is associated with lower CO₂ emissions.

However, some studies have found a non-significant relationship between corruption and environmental indicators, suggesting that this nexus is not universal. Wawrzyniak and Doryń (2020) explore the role of institutional quality, specifically government effectiveness and control of corruption, to examine the impact of economic growth on carbon dioxide emissions. They found no evidence that controlling corruption affects the nexus between economic growth and CO₂ emissions. However, their results show that government effectiveness influences the relationship between economic growth and CO₂ emissions. Similarly, Akhbari and Nejati (2019) and Arminen and Menegaki (2019) found that corruption does not significantly affect carbon emissions in developed countries and

high and upper-middle-income countries, respectively. These divergent findings indicate that the environmental impact of corruption may depend on the level of development, institutional context, or specific environmental indicators assessed.

The Environmental Kuznets Curve (EKC) hypothesis is supported by some studies that consider corruption. For example, Rehman et al. (2012) found that the EKC hypothesis holds for South Asian countries. However, the positive effect of economic development on the environment occurs at a higher income level. In other words, corruption delays the turning point of the EKC. Sadiq et al. (2024) similarly found that the EKC hypothesis is valid for BRICS-1 countries. Likewise, Zhang et al. (2016) and Wawrzyniak and Doryń (2020) found an inverted U-shaped relationship between economic growth and CO₂ emissions for 19 APEC countries and 93 emerging and developing countries, respectively. The results confirm the EKC hypothesis for these countries when corruption is taken into account.

On the other hand, several findings are inconsistent with the traditional EKC hypothesis when corruption is taken into account. Khalfaoui et al. (2023) examined corruption and environmental degradation using four different indicators (ecological footprint, CO₂ emissions, GHG emissions, and carbon emission intensity). The results indicated that corruption worsens environmental quality based on three indicators (ecological footprint, GHG emissions, and CO₂ emission intensity). They also found a U-shaped relationship between income level and CO₂ emissions, which contradicts the EKC hypothesis. In addition, Liu et al. (2020) found an N-shaped trajectory and a U-shaped EKC hypothesis between economic growth and CO₂ emission. A similar result was obtained by Hwang et al. (2024) for nine CIS countries.

The relationship between economic development, environment, and corruption is multidimensional. Previous research on this nexus presents conflicting evidence regarding the validity of the EKC hypothesis, particularly in the context of corruption. Generally, corruption acts as a barrier to sustainable policies and practices, worsening the environment. However, the specific effects and transmission mechanisms of corruption can vary by region and income levels. The inconsistencies in existing research highlight the need for further investigation into this subject. This is particularly relevant for the member countries of the GREEN Action Task Force platform, which are the focus of this study. These countries face distinct challenges in balancing their economic goals with environmental concerns.

This study makes several contributions to existing literature. First, it provides a detailed examination of the nexus among economic growth, corruption, and environmental degradation in the context of the GREEN Action Task Force member countries, thereby addressing a gap in the literature. Second, it tests the validity of the EKC hypothesis across selected countries, accounting for the impact of corruption. Third, this paper investigates the specific role of corruption in mediating the relationship between economic growth and environmental sustainability, focusing particularly on the EECCA countries that are members of the GREEN Action Task Force platform. Fourth, the findings are expected to provide policymakers with valuable insights for developing more effective sustainable development strategies in contexts where corruption is a significant issue.

This paper is structured as follows. The Method section outlines the dataset, describing the variables and their abbreviations, the dataset's sources, the methodological framework, and the empirical approach used in the analysis. The Results and Discussion section emphasizes the preliminary results, model selection, and diagnostic test outcomes, along with the empirical findings, highlighting their significance in relation to the study objectives. Finally, the Conclusion section summarizes the study, discusses the implications of the findings, and provides policy recommendations.

METHODS

We obtained the dataset for the 2012-2020 period from the World Development Indicator (WDI) of the World Bank, except for the Corruption Perception Index (CPI), which we obtained from Transparency International. We used carbon dioxide (CO₂) emissions, measured in kilotons (kt), as a proxy for environmental degradation. We used several other explanatory variables, including Renewable energy consumption (RWE), Foreign direct investment (FDI), Urban population (URBP), and Trade openness (TRA), to avoid omitted-variable bias in our empirical estimation. RWE is expressed as the percentage share of renewable energy in the total final energy consumption. FDI is measured as the net inflow of foreign direct investment as a percentage of GDP. URBP indicates the proportion of the total population residing in urban areas. TRA is measured as the percentage share of trade volume in GDP, reflecting the degree of economic openness. A comprehensive overview of the variables, including their abbreviations, descriptions, units of measurement, and data sources, is provided in Table 1. The list of countries included in the analysis is presented in Table A1 in the Appendix.

Table 1. Description of Variables and Data

Variable	Description	Unit of measurement	Source
CO ₂	CO ₂ emissions	Kilotons (kt)	WDI
CC	Control of corruption: estimate	index ranges -2.5 (high corruption) to 2.5 (low corruption)	WDI
CPI	Corruption Perception Index	index ranges 0 (high corruption) to 100 (low corruption)	Transparency International
GDPPC	GDP per capita	constant 2015 US \$	WDI
RWE	Renewable energy consumption	% of total final energy consumption	WDI
FDI	Foreign direct investment, net inflows	% of GDP	WDI
URBP	Urban population	% of the total population	WDI
TRA	Trade	% of GDP	WDI

We employed a slightly modified version of the widely used Environmental Kuznets Curve (EKC) model to examine the effect of corruption on environmental degradation. Specifically, we included corruption and its interaction with economic development as additional explanatory variables in the EKC model. Our empirical strategy is based on Usman et al. (2022). The panel version of the empirical model is presented in Equation (1).

$$\ln CO_{2it} = \beta_i + \beta_1 CC_{it} + \beta_2 \ln GDPPC_{it} + \beta_3 \ln GDPPC_{it}^2 + \beta_4 RWE_{it} + \beta_5 FDI_{it} + \beta_6 URBP_{it} + \beta_7 TRA_{it} + \beta_8 CC_{it} \times \ln GDPPC_{it} + u_{it} \tag{1}$$

Where i , t , and u_{it} indicate country, period, and residual term, respectively. The definitions of the model's variables are provided in Table 1. The prefix \ln denotes the natural logarithmic transformation of the variables.

The square of per capita income was added to the model to test whether the EKC hypothesis is valid for the member countries of the GREEN Actions Task Force Platform. The impact of corruption on environmental degradation may vary by income level. To account for this effect, the interaction term $CC \times \ln GDPPC$ is included in the empirical model. Other variables were included as control variables to provide a more comprehensive analysis.

Ignoring cross-sectional dependence in panel data can lead to spurious relationships due to common shocks affecting multiple countries. Hence, we first investigate the presence of cross-sectional dependence using Pesaran's (2004) cross-sectional dependence test (hereafter, the CD test), which is more appropriate when $T < N$. The CD test for cross-sectional dependence is constructed as follows:

$$CD = \sqrt{\frac{2T}{N(N-1)}} (\sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij}^2) \tag{2}$$

Where N is the cross-sections unit, and T is the time period. $\hat{\rho}_{ij}$ is the pairwise correlation coefficient between units i and j .

In the presence of heteroskedasticity and autocorrelation, Ordinary Least Squares (OLS) remains unbiased but loses efficiency, leading to incorrect t-statistics and p-values and potentially misleading hypothesis tests. We investigate the existence of heteroskedasticity and autocorrelation using the Brown and Forsythe (1974)¹ test, and the Baltagi-Wu (1999) LBI test, respectively. The heteroskedasticity test statistics are constructed as in Equation (3).

$$W_0 = \frac{\sum_i n_i (\bar{X}_i - \bar{X})^2 / (g-1)}{\sum_i \sum_j (X_{ij} - \bar{X})^2 / \sum_i (n_i - 1)} \tag{3}$$

Where n_i is the number of observations in each cross-section unit, and g is the number of cross-section units. The Baltagi-Wu LBI test statistic is defined as in Equation 4

$$d_* = d_1 + d_2 + d_3 + d_4 \tag{4}$$

Where $d_1 = \frac{\sum_{i=1}^N \sum_{j=1}^{n_i} \{ \bar{z}_{it_{ij}} - \bar{z}_{it_{i,j-1}} I(t_{ij} - t_{i,j-1} = 1) \}^2}{\sum_{i=1}^N \sum_{j=1}^{n_i} \bar{z}_{it_{ij}}^2}$, $d_2 = \frac{\sum_{i=1}^N \sum_{j=1}^{n_i-1} \bar{z}_{it_{ij}}^2 \{ 1 - I(t_{i,j+1} - t_{ij} = 1) \}}{\sum_{i=1}^N \sum_{j=1}^{n_i} \bar{z}_{it_{ij}}^2}$

$d_3 = \frac{\sum_{i=1}^N \bar{z}_{it_{i1}}^2}{\sum_{i=1}^N \sum_{j=1}^{n_i} \bar{z}_{it_{ij}}^2}$, and $d_4 = \frac{\sum_{i=1}^N \bar{z}_{it_{in_i}}^2}{\sum_{i=1}^N \sum_{j=1}^{n_i} \bar{z}_{it_{ij}}^2}$

¹ This test is an alternative test of heteroskedasticity based on the trimmed mean and median. Equation 3 presents the test statistic for the mean. For detailed information, see Brown, and Forsythe (1974).

I(.) is the indicator function that equals 1 when the condition is true and 0 when it is false. $\tilde{Z}_{it,i,j-1}$ represents the residuals from the within estimator. In the presence of heteroskedasticity, cross-sectional dependence, or autocorrelation in the empirical model, it is necessary to use a robust estimator.

Based on the diagnostic test results indicated in Table A4, the model exhibits autocorrelation and heteroskedasticity. Therefore, to examine the impact of corruption on environmental degradation and to assess the validity of the EKC hypothesis for the member countries of the GREEN Action Task Force Platform, we used the Driscoll-Kraay methodology, a robust estimator that addresses the issues mentioned above. The Driscoll-Kraay (1998) methodology is described as follows.

Consider the following panel model:

$$y_{it} = x'_{it}\beta + u_{it} \tag{5}$$

The Driscoll-Kraay method is used in a two-step process to estimate the fixed effects regression.

First, to eliminate unobserved individual effects, the variables are transformed using the within (fixed effects) transformation. Thus, the transformed model is obtained as shown in Equation (6).

$$\tilde{y}_{it} = \tilde{x}'_{it}\beta + \tilde{u}_{it} \tag{6}$$

In the second step, the transformed model, as expressed in Equation 6, is estimated using pooled OLS estimation with Driscoll-Kraay standard errors. We assume that the panel model in Equation (5) satisfies the strong exogeneity condition. That is, $E(x_{it}u_{it}) = 0$. On the other hand, the disturbance term u_{it} may exhibit autocorrelation, heteroskedasticity, and cross-sectional dependence. Under these conditions, the parameters can be consistently estimated using the Pooled OLS method.

Driscoll and Kraay standard errors for the parameter estimates are obtained by taking the square roots of the diagonal elements of the asymptotic covariance matrix.

$$V(\hat{\beta}) = (X'X)^{-1}\hat{S}_T(X'X)^{-1}, \hat{S}_T = \hat{\Omega}_0 + \sum_{j=1}^{m(T)} w(j,m)[\hat{\Omega}_j + \hat{\Omega}'_j] \tag{7}$$

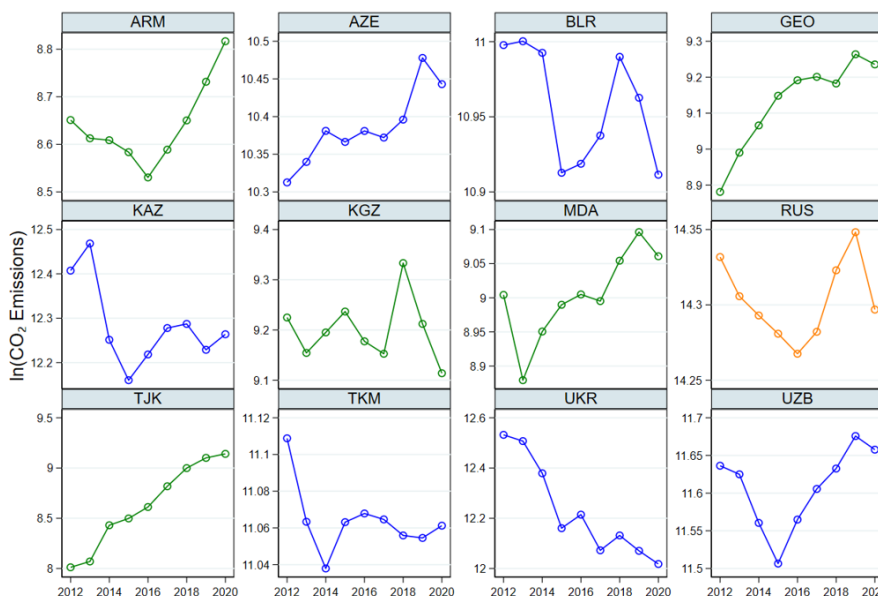
In Equation 7, $m(T)$ and $w(j,m)$ denote the lag length for autocorrelation and the modified Bartlett weights, respectively.

The Driscoll-Kraay covariance matrix estimator, calculated using Equation 7, is equivalent to the heteroskedasticity- and autocorrelation-consistent Newey-West covariance matrix estimator applied to cross-sectional means. Since this method relies on cross-sectional means, the standard error estimates are consistent regardless of the cross-sectional dimension N of the units. Driscoll and Kraay (1998) have shown that consistency is maintained even as N approaches infinity. Moreover, the standard errors estimated using this method are robust to cross-sectional dependence, heteroscedasticity, and autocorrelation.

RESULTS AND DISCUSSION

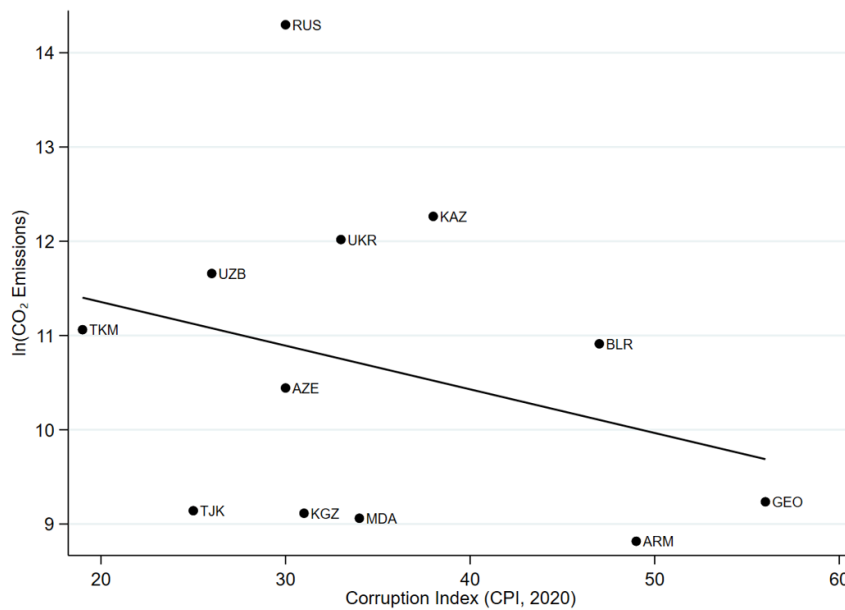
This section presents empirical findings regarding the relationship between economic indicators and environmental degradation. Figure 1 provides an initial overview of the environmental landscape, illustrating trends in carbon dioxide (CO₂) emissions across 12 EECCA countries from 2012 to 2020. As seen in Figure 1, countries are divided into three groups based on the magnitude of their CO₂ emissions. Armenia (ARM), Georgia (GEO), Kyrgyzstan (KGZ), and Tajikistan (TJK) have the lowest CO₂ emissions, with their logged values generally ranging from 8.0 to 9.4. Most countries in this group exhibit an overall upward trend in emissions from 2012 to 2020. Azerbaijan (AZE), Belarus (BLR), Kazakhstan (KAZ), Moldova (MDA), Turkmenistan (TKM), Ukraine (UKR), and Uzbekistan (UZB) comprise the second group, indicated in blue in Figure 1. These countries have logged emission values ranging from approximately 10.5 to 12.5, showing a mixed trend. Russia (RUS) is a clear outlier in terms of CO₂ emissions, with values consistently above 14. CO₂ emissions in Russia show significant variation from year to year but remain high compared to all countries under investigation.

Figure 1. CO₂ Emission in EECCA Countries



To capture the corruption levels of countries, this study uses two distinct indicators: the Control of Corruption (CC) index and the Corruption Perceptions Index (CPI). The Control of Corruption index, obtained from the World Governance Indicators, ranges from -2.5 (indicating high corruption) to 2.5 (indicating low corruption). The CPI, provided by Transparency International, ranges from 0 (indicating high corruption) to 100 (indicating low corruption), providing a comparative assessment of corruption levels across countries. GDP per capita (GDPPC), measured in constant 2015 US dollars, is used as a proxy for income level. These variables are the key components of the study, which consists of dependent and independent variables.

Figure 2. The Nexus Between Corruption and CO₂ Emissions



As illustrated in Figure 2, the average CPI index in 2020 is nearly 35, indicating that corruption is a serious problem in EECCA countries. Russia has the highest CO₂ emissions and the lowest CPI score. In contrast, Georgia and Armenia have relatively higher CPI scores and lower CO₂ emissions compared to other countries. The negative regression line indicates an inverse relationship between CO₂ emissions and CPI, suggesting that as corruption decreases, CO₂ emissions tend to decline.

Table 2. Summary Statistics

Variables	N	Mean	Median	SD	Min	Max	Skewness	Kurtosis
CO ₂	108	196497.18	45161.25	440411.72	3015.2	1703588.8	2.873	9.57
CC	108	-.771	-.92	.548	-1.434	.829	1.429	4.517
CPI	108	30.861	29	9.59	17	58	1.134	4.038
GDPPC	108	4699.834	4036.27	2972.015	855.68	11402.759	.693	2.47
RWE	108	12.806	6.75	14.115	0	55.8	1.177	3.485
FDI	108	3.827	3.066	3.228	-4.855	17.131	1.266	5.648
URBP	108	55.115	56.35	14.517	26.545	79.483	-.268	2.349
TRA	108	81.091	80.283	26.891	29.192	153.085	.267	2.526
lnCO ₂	108	10.62	10.695	1.721	8.011	14.348	.546	2.43
lnGDPPC	108	8.227	8.303	.723	6.752	9.342	-.41	2.273

Tables 2 and 3 provide the summary statistics and correlation matrix of the variables, respectively. As shown in Table 2, the summary statistics indicate that CO₂ emissions have a high mean and a wide standard deviation, suggesting considerable variability across observations. The high skewness and kurtosis suggest a highly skewed distribution. The relatively lower standard deviations of the control of corruption and corruption perception

index indicate lower variability in the data. Additionally, the skewness and kurtosis values for the variables suggest a slightly skewed distribution. The mean and standard deviation of GDP per capita show a wide income disparity among the countries under investigation. Similarly, renewable energy consumption has a high standard deviation relative to its mean, reflecting high disparity across countries. Foreign direct investment inflows, urban population, and trade volume exhibit moderate variability. Furthermore, the logarithmic transformations of CO₂ emissions and GDP per capita are less skewed than their untransformed counterparts, indicating that logarithmic transformations reduce the impact of extreme values on the distribution.

Table 3 presents the correlation matrix, which shows the relationships among the variables. The logarithmic transformation of CO₂ emissions (lnCO₂) positively correlates with lnGDPPC, indicating that higher GDP per capita is associated with higher CO₂ emissions. In contrast, lnCO₂ shows a negative correlation with RWE, indicating that higher renewable energy consumption is associated with lower CO₂ emissions. Both corruption indices are negatively correlated with carbon dioxide emissions. Urban population (URBP) is positively correlated with lnCO₂, implying that urbanization is associated with higher emissions. Similarly, foreign direct investment and international trade volume show a negative correlation with CO₂ emissions. These preliminary findings indicate that per capita income and renewable energy use are significant factors in CO₂ emissions. The levels of corruption, degree of urbanization, foreign direct investment, and international trade clarify this relationship.

Table 3. Matrix of Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) lnCO ₂	1.000							
(2) CC	-0.221	1.000						
(3) CPI	-0.296	0.947	1.000					
(4) lnGDPPC	0.607	0.273	0.170	1.000				
(5) RWE	-0.699	0.140	0.231	-0.712	1.000			
(6) FDI	-0.197	0.231	0.183	0.041	0.081	1.000		
(7) URBP	0.611	0.399	0.327	0.696	-0.666	-0.146	1.000	
(8) TRA	-0.337	0.428	0.432	-0.187	0.151	0.235	0.164	1.000

Model selection and diagnostic tests provide important information on the appropriateness and robustness of empirical models. The results of the unit and time-fixed effects detection tests are provided in Table A2 in the appendix. The findings indicate that Models 1 and 2 include unit fixed effects but not time fixed effects. Therefore, country-specific heterogeneity should be taken into account in empirical estimations. The insignificant time-fixed effects suggest that temporal variation does not substantially influence the dependent variables. Additionally, the results of the Hausman test are presented in Table A3. According to the Hausman test, the null hypothesis that the random effects are consistent and efficient cannot be rejected. This finding indicates

that the random-effects model is appropriate for capturing unobserved heterogeneity in the data.

Table A4 lists diagnostic tests that highlight several important considerations for the model's validity. First, the RESET test confirms that the functional form of both models is correctly specified, with no evidence of omitted variables or misspecification. Moreover, the residuals are normally distributed, whereas the unit effects are not. Hence, the composite error term is non-normally distributed, which may influence the efficiency of the estimators. Evidence of heteroskedasticity, autocorrelation, and cross-sectional dependence in both models suggests that the standard errors may be biased, affecting the reliability of the hypothesis tests. Addressing econometric issues, such as applying heteroskedasticity- and autocorrelation-consistent standard errors or using alternative estimation techniques, is essential for ensuring reliable inference.

The relationship between corruption, economic development, and carbon dioxide emissions is estimated using Equation 1. The effect of corruption on environmental degradation is examined while controlling several economic factors, as summarized in Table 1. We used Ordinary Least Squares (OLS) and the Driscoll-Kraay standard error estimators, as well as Feasible Generalized Least Squares (FGLS), to assess the robustness of the findings. Additionally, we utilized the Control of Corruption (CC) index and the Corruption Perception Index (CPI) as two distinct sources of corruption in our estimations. The results are consistent across various specifications and estimation methods, confirming the significant role of corruption in environmental degradation. The results are summarized in Table 4.

Our findings show that the Control of Corruption (CC) index has a statistically significant negative effect on CO₂ emissions, indicating that greater control of corruption (a higher CC index) is associated with lower emissions. This result is consistent with the findings obtained by Lisciandra and Migliardo (2017), Ikhsan and Amri (2024), Hwang et al. (2024), Leitão (2021), and Ridzuan et al. (2019), which emphasize the detrimental effect of corruption on environmental degradation. Specifically, in Models 1 and 3, the coefficient of the corruption index is negative and significant at the 1% level. This finding indicates that countries with better control of corruption tend to have lower CO₂ emissions. Hence, it can be argued that corruption undermines transparency and accountability in the decision-making processes of the transition economies in the EECCA region, leading to a prioritization of short-term economic interests over long-term sustainability goals. This result is consistent with the claim by Hwang et al. (2024) that corruption leads to the misallocation of resources by undermining the effectiveness of environmental regulations. However, our findings do not align with those of Wawrzyniak and Doryń (2020), Akhbari and Nejati (2019), and Arminen and Menegaki (2019), who found no significant relationship between corruption and environmental degradation. One possible explanation for this inconsistency could be regional differences, estimation techniques, control variables, and the range of periods in the datasets used in the studies. Therefore, region-specific policies may be more effective than uniform policies.

The interaction term ($CC \times \ln GDPPC$) is positive and significant, indicating that the effect of corruption on CO_2 emissions varies with income levels. The significance of this term is that, as per capita income increases, the effect of reduced corruption on CO_2 emissions decreases. In other words, in countries with a lower per capita income, a reduction in corruption has a stronger effect on environmental quality. This is likely because countries with higher per capita incomes already have more efficient production systems and technologies than those with lower per capita incomes. Therefore, the effect of corruption on CO_2 emissions may be relatively lower in wealthier countries. This result may explain why Akhbari and Nejati (2019), who focused on developed economies, and Arminen and Menegaki (2019), who focused on high- and upper-middle-income economies, found a non-significant relationship between corruption and environmental degradation.

Moreover, the models based on the Corruption Perceptions Index (CPI) indicate that corruption is not statistically significant for CO_2 emissions. The CPI coefficient is negative but only marginally significant in Model 4, suggesting weaker explanatory power than the CC index. Moreover, the interaction term ($CPI \times \ln GDPPC$) is statistically significant only in Model 4. In other words, the role of income in mitigating the effect of corruption on environmental degradation is clearer when the CC index is used in empirical models. This result highlights the importance of the measurement approach in empirical estimations, which can explain the divergent results of studies on the corruption-environment nexus.

The results of the study indicate a non-linear relationship between economic development and environmental degradation. In all models, the coefficients of $\ln GDPPC$ are positive and significant, while the coefficients of $\ln GDPPC^2$ are negative and significant. This confirms the inverted U-shaped relationship between economic development and environmental degradation. In other words, environmental degradation initially increases with economic development but eventually declines after a certain income level is reached. This finding is consistent with several studies that provide evidence for the EKC hypothesis. For instance, Bilgili et al. (2016), Ahmed et al. (2016), Dogan and Inglesi-Lotz (2017), and Danish et al. (2020) all confirmed the EKC hypothesis in their research. Moreover, Rehman et al. (2012), Zhang et al. (2016), Wawrzyniak and Doryń (2020), and Sadiq et al. (2024) also support the EKC hypothesis while also controlling for corruption. The confirmation of the EKC hypothesis in our study contributes to the growing body of evidence supporting this relationship in emerging economies, similar to the findings by Rehman et al. (2012) for South Asian countries and Sadiq et al. (2024) for BRICS-1 countries.

On the other hand, some studies could not support the EKC hypothesis (see, for example, Destek et al. (2018), Destek and Sinha (2020), Dogan et al. (2020), and Mehmood (2021)), while others indicate a more complex relationship (see, for example, Khalfaoui et al. (2023), Liu et al. (2020), Hwang et al. (2024), Shahbaz et al. (2017), Danish and Wang (2019), and Shah et al. (2020)). The reason for this divergent result may be regional heterogeneity and model specification, particularly the inclusion of corruption as an explanatory variable. As Rehman et al. (2012) stated, corruption not only affects emissions but also delays the EKC threshold. While the EKC hypothesis suggests that economic growth can provide environmental benefits for countries in the

region, high levels of corruption delay the onset of these improvements. In other words, poor institutional quality leads to a slower, more costly transition to a stage in which economic development positively influences the environment.

Table 4. Main Results

Dependent Variable: $\ln\text{CO}_2$	OLS		Driscoll-Kraay	
	Source of Corruption: CC	Source of Corruption: CPI	Source of Corruption: CC	Source of Corruption: CPI
	Model 1	Model 2	Model 3	Model 4
CC	-1.337** (.583)		-1.337*** (.23)	
CPI		-.048 (.032)		-.048* (.022)
$\ln\text{GDPPC}$	7.774*** (1.151)	8.223*** (1.209)	7.774*** (.662)	8.223*** (.5)
$\ln\text{GDPPC}^2$	-.438*** (.071)	-.481*** (.077)	-.438*** (.04)	-.481*** (.028)
RWE	-.034*** (.003)	-.035*** (.003)	-.034*** (.004)	-.035*** (.004)
FDI	-.003 (.003)	-.003 (.003)	-.003 (.002)	-.003 (.003)
URBP	.004 (.013)	.013 (.015)	.004 (.008)	.013 (.013)
TRA	.001 (.001)	.001 (.001)	.001* (0)	.001* (0)
$\text{CC}*\ln\text{GDPPC}$.147** (.069)		.147*** (.024)	
$\text{CPI}*\ln\text{GDPPC}$.005 (.004)		.005* (.002)
Constant	-25.79*** (4.945)	-26.814*** (5.069)	-25.79*** (2.391)	-26.814*** (2.25)
<i>Model Statistics</i>				
Observations	108	108	108	108
R2	.824	.82	0.99	0.99
Wald Test	75510.00	73949.49	5.74e+11	402051.84
Prob.> χ^2	0.000	0.000	0.000	0.000

Standard errors are in parentheses; *** p<.01, ** p<.05, * p<.1

The results for the other control variables are generally consistent across the models. Among the control variables, renewable energy consumption (RWE) has a negative, statistically significant effect on CO_2 emissions across all models. This result is consistent with several studies in the literature, including Magazzino (2021), Dogan and Inglesi-Lotz (2017), Shahbaz et al. (2019), Danish and Ulucak (2020), and Sarkodie et al. (2019), which analyzed biomass energy as a renewable energy source. This result highlights the importance of transitioning to cleaner energy sources to mitigate environmental

degradation. However, using ecological footprint as an indicator of environmental degradation rather than CO₂ emissions, the findings of Destek et al. (2021), Wang et al. (2020), and Mehmood (2021) are inconsistent with ours. The primary reason for these differences may be the use of different variables as indicators of environmental degradation. Additionally, variations in renewable energy production technology and efficiency could contribute to these varying results.

Regarding other control variables, foreign direct investment (FDI) and urbanization (URBP) do not have a statistically significant relationship with carbon dioxide emissions. This result contradicts the findings of Danish et al. (2020), who showed that urbanization positively contributes to environmental quality in BRICS countries. Trade openness (TRA) has a marginally significant positive effect in some specifications, suggesting that trade expansion may lead to increased environmental damage. The structure of trade, regulations, and the development stage of economies can affect the relationship between trade openness and environmental degradation. The fact that foreign direct investment, trade, and urbanization do not have a statistically significant effect on emissions suggests that the current structures of foreign investment, trade, and urbanization patterns in the EECCA region have not yet reached a level that can trigger an environmentally friendly transformation. This situation may indicate that foreign direct investments in the region are focused on existing carbon-intensive sectors rather than on technology transfer.

The models are re-estimated using feasible generalized least squares (FGLS) to ensure the robustness of our findings. The results of this analysis are reported in Table A5. The findings are generally consistent with those obtained from OLS and Driscoll-Kraay estimations. The coefficients of both corruption indices (CC and CPI) are negative and statistically significant. The interaction term aligns with previous findings, supporting the moderating effect of income level on the relationship between corruption and carbon dioxide emissions. In summary, the FGLS results confirm the validity of our main conclusions.

CONCLUSION

This study aims to investigate the relationship between corruption, economic development, and environmental degradation from 2012 to 2020 for the members of the GREEN Action Task Force Platform: Armenia, Azerbaijan, Belarus, Georgia, Kazakhstan, Kyrgyzstan, Moldova, Russia, Tajikistan, Turkmenistan, Ukraine, and Uzbekistan. We employ the Driscoll-Kraay procedure and FGLS for robustness to examine the aforementioned relationship. Both methods are robust to cross-sectional dependence, heteroscedasticity, and autocorrelation. We also consider country-specific heterogeneity in the analysis. Based on the Hausman test, we used a random-effects (RE) model because the error term is uncorrelated with the explanatory variables.

The empirical results show that corruption has a positive effect on carbon dioxide emissions for both corruption indexes. This result indicates that corruption significantly worsens environmental degradation. The interaction term between corruption and income level (CC×lnGDPPC and CPI×lnGDPPC) emphasizes that the impact of reduced

corruption on environmental degradation is stronger in countries with lower per capita income. As per capita income increases, the effect of reduced corruption on reducing CO₂ emissions becomes weaker. This result implies that the incremental benefit of reduced corruption may be lower, as wealthier countries already implement environmentally friendly policies and technologies. Hence, anti-corruption policies could significantly improve environmental outcomes in developing economies.

Furthermore, the results show an inverted U-shaped relationship between economic development and environmental degradation, which confirms the validity of the EKC hypothesis for the members of the GREEN Action Task Force Platform. In other words, environmental degradation initially rises with economic development but eventually declines after a certain income threshold is reached. The confirmation of the EKC hypothesis in our study contributes to the growing body of evidence supporting this relationship in emerging economies. However, the threshold level of the EKC curve may be influenced by corruption levels. These results indicate that reducing corruption should be a key component of environmental policies. In addition, renewable energy consumption has negative effects on carbon dioxide emissions. Therefore, investing in clean energy infrastructure should be a priority for policymakers to achieve sustainable development. Moreover, since the EKC hypothesis is valid, policymakers should integrate environmental protection into economic development policies.

In summary, our study provided region-specific evidence on the nexus of governance, development, and the environment, highlighting the need for targeted policy interventions. It emphasizes the significance of a comprehensive approach that addresses both governance issues and technical solutions, such as renewable energy, to promote sustainable development policies. Further research on the corruption-environmental degradation nexus may explore the transmission channels through which corruption affects environmental outcomes and examine the role of institutional quality in mitigating the diverse effects of corruption.

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APPENDIX

Table A1. List of countries

Armenia, Azerbaijan, Belarus, Georgia, Kazakhstan, Kyrgyzstan, Moldova, Russia, Tajikistan, Turkmenistan, Ukraine, Uzbekistan

Table A2. Unit and time-fixed effect detection tests

Models		Unit Effect	Time Effect	Both
Model 1 (CC)	LR Test	446.02 (0.000)	0.00 (1.000)	446.02 (0.000)
	F Test	1405.03 (0.000)	0.21 (0.988)	146.42 (0.000)
	LM Test	318.05 (0.000)	0.00 (1.000)	-
Model 2 (CPI)	LR Test	441.69 (0.000)	0.00 (1.000)	441.69 (0.000)
	F Test	1345.25 (0.000)	0.28 (0.972)	137.72 (0.000)
	LM Test	304.77 (0.000)	0.00 (1.000)	-

H₀: No unit and time fixed effect

Table A3. Hausman test

Models	χ^2 Statistic	Prob.
Model 1 (CC)	4.93	0.765
Model 2 (CPI)	13.14	0.069

H₀: Fixed effect and random effect are consistent, but the random effect is effective. H₁: Fixed effect is consistent, Random effect is inconsistent.

Table A4. Diagnostic Tests

Test	Source of Corruption	Test Statistic(s)	p-value(s)	Conclusion
Normality	CC	Joint test on e: $\chi^2(2) = 0.50$	0.7796	e: Normally distributed
		Joint test on u: $\chi^2(2) = 9.32$	0.0095	u: Not normally distributed
	CPI	Joint test on e: $\chi^2(2) = 0.29$	0.8660	e: Normally distributed
		Joint test on u: $\chi^2(2) = 8.85$	0.0120	u: Not normally distributed
Heteroskedasticity	CC	W ₀ = 3.70	0.0002	Evidence of heteroskedasticity
		W ₅₀ = 1.80	0.0636	
		W ₁₀ = 3.70	0.0002	
	CPI	W ₀ = 2.93	0.0022	Evidence of heteroskedasticity
W ₅₀ = 1.93	0.0445			
W ₁₀ = 2.93	0.0022			
Cross-sectional Dependence	CC	Pesaran's test = 0.125	0.9006	No cross-sectional dependence
	CPI	Pesaran's test = -0.022	0.9828	No cross-sectional dependence
Autocorrelation	CC	Baltagi-Wu LBI = 1.412	< 2	Evidence of autocorrelation
	CPI	Baltagi-Wu LBI = 1.451	< 2	Evidence of autocorrelation
Functional Form (RESET Test)	CC	ResetS1 = 0.163	0.8499	No specification error (correct form)
		ResetS2 = 1.435	0.2296	
		ResetS3 = 1.641	0.1464	
	CPI	ResetS1 = 0.837	0.4364	No specification error (correct form)
		ResetS2 = 1.906	0.1170	
		ResetS3 = 1.574	0.1651	

Table A5. FGLS Results (for robustness)

Dependent Variable: $\ln\text{CO}_2$	FGLS	
	Source of Corruption: CC	Source of Corruption: CPI
	Model 5	Model 5
CC	-1.316** (.584)	
CPI		-.02 (.03)
$\ln\text{GDPPC}$	6.628*** (1.029)	6.716*** (1.114)
$\ln\text{GDPPC}^2$	-.368*** (.062)	-.386*** (.067)
RWE	-.036*** (.003)	-.035*** (.004)
FDI	-.002 (.002)	-.002 (.002)
URBP	.009 (.009)	.013 (.01)
TRA	.001* (0)	.001** (0)
CCx $\ln\text{GDPPC}$.147** (.068)	
CPIx $\ln\text{GDPPC}$.002 (.003)
_Constant	-21.287*** (4.434)	-20.913*** (4.873)
Model Statistics		
Observations	108	108
Wald Test	103131	102071
Prob.> χ^2	0.000	0.000

Standard errors are in parentheses

*** p<.01, ** p<.05, * p<.1