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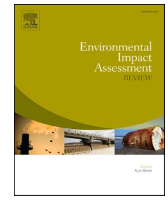

Do dependence on fossil fuels and corruption spur ecological footprint?

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ABSTRACT

Corruption, a benchmark for institutional quality plays a critical role in achieving sustainable development, especially in developing countries. The nexus between corruption and economics is widely discussed in economic literature, however, the nexus between corruption and environmental degradation has received less attention. Here, we investigate the relationship between corruption and environmental degradation by accounting for income, urbanization, and disaggregate energy consumption in Newly Industrialized Countries from 1984 to 2016. Utilizing panel data methods, the empirical results reveal the existence of a long-run relationship between environmental degradation and regressors. Corruption, economic growth, and fossil fuel utilization have positive and statistically significant effect on environmental degradation, whereas renewable energy consumption has negative and statistically significant effect on environmental degradation. Besides, urbanization has positive but statistically insignificant effect on environmental degradation. The results reveal corruption poses a risk to the achievement of environmental aims of Sustainable Development Goals in Newly Industrialized Countries.

1. Introduction

The Stockholm Conference (1972) is of great importance—as it was the first initiative on environmental problems on a global scale—hereupon, interest and awareness of environmental problems have increased worldwide. It was outlined in the conference that protection and development of the environment is the duty of all governments, and international cooperation to address environmental issues (United Nations, 1972, 3–5). Afterward, to effectively mitigate environmental problems, many initiatives such as Habitat I (1976), United Nations Conference on Environment and Development, Rio Conference (1992), United Nations Population and Development Conference (1994), Kyoto Protocol (1997), Millennium Summit (2000), United Nations Conference on Environment and Development, Rio + 20 Conference (2012), and among others were carried out by international organizations, and common environmental targets were set by governments to improve environmental protection. In this regard, each country made legislation to achieve common goals, albeit at different levels, and significant success was observed to some extent. For instance, by 2015, the rate of deforestation decreased, ozone-depleting substances were largely eliminated, global availability of safe drinking water increased from 76% to 91% (United Nations Development Programme, 2015: 50–54). However, other environmental targets are yet to be achieved. For instance, air pollution which causes majority of deaths from environmental factors has unfortunately increased in less developed regions (United Nations Development Programme, 2015: 49–50). A report published in 2016 by the World Health Organization (WHO) reveals 1 in every 4 deaths worldwide is caused by environmental factors. It is projected that 12.6 million persons die yearly from living and working in unhealthy environment. The vast majority of these deaths (8.2 million) are caused by non-communicable diseases associated with air pollution (WHO, 2016).

The weakening or failure to implement environmental regulations because of corruption is one of the main reasons for missing environmental targets (Lopez and Mitra, 2000; Damania et al., 2003; Fredriksson et al., 2004; Leitão, 2010; Chang and Hao, 2017: 499; Balsalobre-Lorente et al., 2019). In this context, previous studies consider corruption as a central factor affecting environmental quality (Lopez and Mitra, 2000; Walter and Luebke, 2013). The report of Transparency International (2017) underscores the importance of corruption in the design and implementation of Sustainable Development Goals (SDGs, 2021), including ecological aims.

Corruption can affect environmental quality directly and indirectly. Within this scope, corruption causes an expansion of the informal sector,

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which does not have to comply with regulations, as well as, to increase production that is contrary to regulations in the formal sector (Desai, 1998: 172; Choi and Thum, 2005; Biswas et al., 2012: 151; Sekrafi and Sghaier, 2018: 967). These two effects will undoubtedly affect the ability of governments to control environmental quality (Sahli and Rejeb, 2015:1655). Besides, the existence of corruption has limiting effects on equity, effectiveness, and efficiency expected from regulatory measures on energy research development and demonstration (Balsalobre-Lorente et al., 2019: 272). Corruption can also lead to over-exploitation of natural resources during the extraction process, distribution, and management. Ecosystem and wildlife degradation stimulated by corruption facilitates illegal trading of endangered species, species on extinction and diverts environmental policy allocated funds for personal gains (Lisciandra and Migliardo, 2017: 298; Sekrafi and Sghaier, 2018: 966). In this context, Harring (2013) asserted that corruption dampens patriotism, hence, declines economic efforts toward environmental protection (Harring, 2013). The environmental effects of corruption may be assessed in the theoretical account of the pollution haven hypothesis (PHH). In countries with high corruption, improper use of the environment, and natural resources for private interests will increase, hence, affecting environmental standards. Thus, corruption encourages the entry of polluting firms in the form of Foreign Direct Investment (FDI) due to weak environmental regulations (Akhbari and Nejati, 2019:3). It is reported that the severity of corruption determines the nature and magnitude (i.e. haven or halo — clean or dirty) of FDI that hampers environmental sustainability (Cole et al., 2006).

Corruption affects environmental quality indirectly through its impact on income. In literature, there are three different approaches to the effect of corruption on economic growth. The first opinion ('grease the wheels' (GTW) hypothesis) asserts that corruption increases economic growth [Leff, 1964; Lui, 1985; Acemoglu and Verdier, 1998; Summers and Heston, 1988; Rock and Bonnett, 2004; Huntington, 2006]. According to the GTW hypothesis, corruption could help entrepreneurs to avoid inefficient administrative arrangements and long-bureaucratic processes that hinder investments, which in turn increases economic efficiency (Chang and Hao, 2017:501; Sharma and Mitra, 2019: 693–694). The second opinion ('sand in the wheels' (STW) hypothesis) asserts that an increase in corruption reduces economic growth [Mauro, 1995; Poirson, 1998; Rose-Ackerman, 1999; Mo, 2001; Glaeser and Saks, 2006]. In this regard, corruption reduces economic growth by leading public spending from productive areas to unproductive areas, misguiding market incentives, and increasing inequality of opportunity, transaction costs, and uncertainty in decision-making processes (Mo, 2001: 67; Huang, 2016:248). The third opinion developed recently supports an inverted U-shaped nexus between corruption and economic growth (Méndez and Sepúlveda, 2006; Aidt, 2009; Méon and Weill, 2010; Swaleheen, 2011; Zhou and Peng, 2012). According to this approach, corruption has a positive effect on economic growth in countries with less effective institutions, otherwise, corruption is detrimental to economic growth. Therefore, the effect of corruption on economic growth deduced from existing studies lacks theoretical consensus, hence, cannot ascertain the indirect effect of corruption on environmental degradation.

Based on the reasons outlined, this research aims to assess the effect of corruption on environmental quality in Newly Industrialized Countries (NICs) from 1984 to 2016. There are several reasons for choosing NICs as the focused group. First, NICs[1] represent a subset of developing countries that have demonstrated upward mobility in the global economy by rapid economic growth, dynamic export potential, and rapid industrialization (Moon, 1990; 153). Second, NICs have a high level of environmental degradation and corruption. On the one hand, NICs accounted for approximately 42% of the total world ecological footprint in 2016 (Global Footprint Network (GFN), 2020). On the other hand, the Corruption Perception Index (CPI) of these countries vary between 28 and 47, with an average CPI score of 36 while the 2019 corruption perception index (CPI)[2] of European Union countries is between 43 and 87, with an average CPI score of 62 (Transparency International, 2020). Thus, these scores are quite high, inferring NICs show poor performance in environmental sustainability and weak institutions aimed at achieving the SDGs (SDG 13, and 16). Considering the importance of corruption in the success of all SDGs (Transparency International, 2017), insight into the effect of corruption on environmental performance is crucial to establish efficient environmental policies. However, there is a paucity of research and little knowledge about how corruption and environment interact in NICs. To the best of our knowledge, this is the first study that investigates the nexus between corruption and ecological footprint in NICs. Unveiling the interaction between corruption and environmental pollution is significant for harmonizing environmental and institutional aims of the SDGs. This study may provide key inferences for policymakers to have insights on developing and implementing efficient environmental policies and synergy among the two SDGs (i.e., SDG 13 and 16). In other words, this paper may provide empirical findings on whether corruption deteriorates environmental quality in NICs. Besides, NICs are responsible for almost 42% of the total ecological footprint, establishing efficient policies to combat climate change will not only contribute to improving environmental quality in NICs but will also contribute to reducing the global environmental burden.

2. Literature review

The nexus between corruption and environment attracted less scientific attention from earlier researchers. However, the number of studies on this topic begun to increase with the rise of ecological concerns. Hence, corruption-environment nexus is one of the contemporary issues for researchers and policymakers in the 21st century. Although the effectiveness of environmental policies under the existence of corruption was examined in limited studies for high-income countries, the effect of corrupt practices on environmental quality in developing economies has attracted special attention. The prominent studies on corruption-environment nexus are reported in Table 1.

The existing literature outlined in Table 1 shows the number of studies that investigate the empirical relationship between corruption and environmental degradation is quite limited. Second, although most of the studies find corruption increases environmental pollution, however, no dominant consensus on the effect of corrupt practices on environmental pollution exist. Third, even though corruption-environmental quality is examined in various samples, no study investigates the effect of corruption on environmental quality in the case of NICs. NICs have a high corruption and ecological footprint level and clarifying this relationship will not only contribute to improving environmental quality in NICs but will also contribute to reducing the global environmental burden. From this point of view, this study is conducted to unveil the effect of corrupt practices in NICs by utilizing a panel data estimation method that contributes to the existing literature. Having insights on corruption-environment interactions allow proper inferences to develop effective policy proposals.

3. Theoretical background, model, and data

The supply and demand side of nature determines environmental quality. The Ecological Footprint (EF) focuses on demand side of environmental quality and measures the ecologically productive lands and water areas required to provide natural resources consumed by either an

[1] Brazil, China, India, Malaysia, Mexico, Philippines, South Africa, Thailand and Turkey

[2] CPI is scored between 0 and 100, and 0 shows the highest level of corruption, while 100 shows the lowest level of corruption

Table 1
Effects of Corruption on Environmental Degradation.

Author(s)	Sample-Period	Methodology	Results
Fredriksson et al. (2004)	12 OECD Countries 1982–1996	Generalized Least Square (GLS)	+
Welsch (2004)	122 Countries	Regression Analysis	M
Pellegrini and Gerlagh (2006)	13 Countries	Ordinary Least Squares (OLS)	–
Cole (2007)	94 Countries, 1987–2000	Random Effects (RE)	Direct Effect (+) Indirect Effect (−) Total Effect in high-income countries (−)
Faiz-Ur-Rehman Ali and Nasir (2007)	4 South Asian Countries, 1984–2003	Pooled OLS (POLS)	+
Leitão (2010)	94 Countries, 1981–2000	Fixed Effects (FE), RE	Indirect impact on emissions through per capita income
Biswas et al. (2012)	More than 100 countries, 1999–2005	POLS	Positive effect on environmental pollution through the shadow economy
Gani (2012)	99 Countries 1998–2007	OLS	+
Goel et al. (2013)	More than 100 countries, 2004–2007	2 Stage Least Squares	Higher levels of corruption show as lower recorded emissions
Rehman et al. (2012)	4 South Asian Countries, 1984–2008	FE	+
Sahli and Rejeb (2015)	21 MENA Countries, 1996–2013	FE, 2 Stage Least Squares	+
Lisciandra and Migliardo (2017)	153 Countries, 2002–2012	Between Estimator, POLS, FE	+
Azam and Khan (2017)	ASEAN Countries, 1994–2014	OLS	Malaysia (+) Thailand (*) Indonesia (*)
Wang et al. (2018)	BRICS Countries, 1996–2015	Partial Least Squares	M
Sekrafi and Sghaier (2018)	13 MENA Countries, 1984–2012	Generalized Method of Moment (GMM)	+
Masron and Subramaniam (2018)	64 Developing Countries, 2005–2013	GMM	+
Balsalobre-Lorente et al. (2019)	16 OECD Countries, 1995–2016	FE	Negative effect on environmental quality through energy innovations
Akhbari and Nejati (2019)	61 Countries, 2003–2016	Panel Threshold Model	(+) Developed Countries (*) Developing Countries
Sinha et al. (2019a)	BRICS and N11 Countries, 1990–2017	Several Estimation Techniques	+
Arminen and Menegaki (2019)	High-Income and Upper-Middle-Income Countries, 1985–2011	Difference and System GMM	*
Zandi et al. (2019)	6 ASEAN Countries	Fully Modified OLS (FMOLS)-Dynamic OLS (DOLS)	+
Haseeb and Azam (2020)	Low, Lower-Middle, Upper-Middle-and High-İncome Countries, 1995–2015	FMOLS	+

Notes: +: positive effect, −: negative effect, *: statistically insignificant effect, M: mixed results.

individual or country and eliminate the waste it creates with the current technology and resource management (GFN, 2020). In this respect, EF consists of six components, including carbon footprint (necessary ocean and forest field to absorb CO_2 emissions), cropland footprint (necessary field for food), forest footprint (necessary forest field for paper and wood production), grazing land footprint (necessary field for farming), built-up land footprint (necessary field for residential, transportation, industrial structures, and power plants), and fishing grounds footprint (necessary field for seafood production). Thus, a higher ecological footprint means higher environmental degradation (GFN, 2020; Akalin and Erdogan, 2021; Erdogan and Okumus, 2021). In this manner, the EF considers various aspects of the environmental burden caused by anthropogenic activities (Erdogan and Okumus, 2021), thus, considered more holistic and comprehensive indicator than other environmental indicators (Solarin, 2019; Ulucak and Lin, 2017). Therefore, we utilized *EF* as indicator of environmental degradation. The theoretical background of the corruption-environmental degradation nexus can be explained by two approaches namely GTW and STW hypotheses. The GTW hypothesis points out the positive effect of corruption on environmental pollution. Hence, corruption eases the business in countries that have long-bureaucratic process by bribing officials and promoting capital formation, which in turn, increases resource use and economic growth — thereby increasing environmental pollution (Chang and Hao, 2017; Sharma and Mitra, 2019). In addition to the GTW hypothesis, corrupt officials may ignore the violation of environmental legislation for their interests. Furthermore, corruption makes it difficult to control the informal sector, thus, the informal production process may ignore environmental standards and legislation. The STW approach is based on the idea of reducing the effect of corruption on environmental pollution. Thus, corruption hinders economic growth by distorting market mechanisms and increasing transaction costs. Additionally, economic agents may prefer rent-seeking activities instead of productive ones, which in turn, decreases economic development and resource use (Huang, 2016; Mo, 2001). This process will result in a decrease in environmental pollution.

Economic development has been an internal part of the empirical assessment of the environment since the inception and application of the EKC hypothesis (Grossman and Krueger, 1991). Later on, disaggregate energy namely renewable and non-renewable energy gained prominence in empirical analyses [*see* Cole et al., 1997; Richmond and Kaufmann, 2006]. The urbanization and environmental pollution nexus can be explained by using ecological modernization theory and compact city theory. On the one hand, it is emphasized in the ecological modernization theory that society will transform through the industrialization process—as long as industrialization accelerates, migration from rural areas to urban areas will accelerate—which in turn increases urbanization. This process may lead to more resource use, unplanned urbanization, and distortion of ecological balance. Moreover, urbanization may affect energy use by increasing the need for urban infrastructures such as lighting, and transportation systems. On the other hand, the compact city theory is based on the idea of the establishment of urban areas with high population density that requires improved urban infrastructure and technology use. In this manner, the environmental burden of urbanization will decrease with technology use and infrastructure improvements (Adams and Klobodu, 2017; Ahmed et al., 2020; Erdogan, 2020; Mol and Spaargaren, 2000; Spaargaren, 2000). Sinha et al. (2019b) and Sarkodie et al. (2020a) emphasized urbanization may be one of the significant determinants of environmental pollution in emerging, developing, and developed countries. Based on these theoretical discussions, we employed the linear-logarithmic model to investigate corruption and environmental degradation nexus in NICs for the period 1984–2016, expressed mathematically as:

$$lnEF_{it} = \beta_{0i} + \beta_1 lnY_{it} + \beta_2 lnCOR_{it} + \beta_3 lnNR_{it} + \beta_4 lnREN_{it} + \beta_5 lnUR_{it} + \varepsilon_{it} \quad (1)$$

Where *EF* is ecological footprint per capita, *Y* denotes gross domestic product (GDP) per capita (constant, 2010 US$), *COR* is Bayesian Corruption Index, *NR* represents non-renewable energy consumption per capita (Oil Consumption, Tones), *REN* is renewable energy consumption per capita (is defined in billions of kilowatt hours as net renewable electric power consumption.) and *UR* denotes urban population (% of the total population). Data on ecological footprint were obtained from the Global Footprint Network (GFN, 2019), whereas data for GDP per capita and urbanization were obtained from the World Bank (2020). The Oil Consumption data were obtained from World (2019), whereas data on renewable energy consumption were derived from the U.S. Energy Information Administration (2019). Per capita values of these variables were obtained by dividing by the population of each country in the related year. The Bayesian Corruption Index (2019) is based on the combined information of 17 different surveys and 110 different survey queries based on the perceived level of corruption. This is a widely used alternative to the other indicators such as the CPI published by Transparency International, and Worldwide Governance Indicators (WGI) published by the World Bank. The Bayesian Corruption Index could be considered an augmented version of WGI. This augmentation allows an increase in the BCI coverage: a 60% to 100% increase relative to both WGI and CPI, respectively. Besides, unlike the other corruption measures such as WGI, and CPI, the Bayesian Corruption Index employs underlying data with any ex-ante imputations or other manipulations (Standaert, 2015). The Bayesian Corruption Index data lie between 0 and 100, and high values of index refer to the high level of corruption, while low values of index refer to a low level of corruption.

4. Methodology and empirical results

We began our analysis by implementing Lagrange Multiplier (LM) (Breusch and Pagan, 1980), panel Cross-Section Dependence (CD) (Pesaran, 2004), and Bias-Adjusted LM (Pesaran et al., 2008) tests to examine potential correlation across countries. Breusch and Pagan (1980) suggest a cross-section dependence approach based on LM expressed as:

$$LM = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\left(\widehat{p}_{ij}^{2}\right) \sim X^2 N(N-1) \Big/ 2 \quad (2)$$

Where $\left(\widehat{p}_{ij}^{2}\right)$ is the correlation coefficient of residuals. LM approach is feasible when the time dimension of the data is higher than the number of cross-sections (Erdogan et al., 2020). The CD method can be implemented by the following procedure based on the average of pairwise correlation coefficients presented as:

$$CD = \sqrt{(2T/N(N-1))}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\widehat{p}_{ij} \quad (3)$$

Where $\widehat{\rho}_{ij}$is the pair-wise correlation of the residuals. The CD test has $N(0,1)$ distribution when $N \to \infty$ and $T \to \infty$, and has good small sample properties. The LM test is vulnerable to size distortions when $N > T$ (Pesaran et al., 2008). Therefore, the LM test is augmented by using mean and variance to solve size distortions when *(N)* is relatively larger than *(T)*. The bias-adjusted LM test is given as (Erdogan and Acaravci, 2019):

$$LM_{adj} = \sqrt{2/N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\left((T-k)\widehat{p}_{ij}^{2} - \mu_{Tij}\right) \Big/ \upsilon_{Tij} \quad (4)$$

Where k is the number of regressors and μ_{Tij} $\upsilon_{Tij}$are the mean and variance, respectively. The three approaches test the null hypothesis of "no cross-section dependence" against the alternative of "cross-section dependence".

We implemented a panel bootstrap unit root test proposed by Smith et al. (2004) to determine the integrational level of the variables. The panel bootstrap unit root method adopts the test strategies of Im et al. (2003) ($\overline{t}$), Leybourne (1995) ($\overline{Max}$), and Pantula et al. (1994)($\overline{WS}$); moreover, this method considers cross-section dependence by using a bootstrap methodology, and tests null of "unit root" hypothesis against the alternative of "stationarity". The test statistics ($\overline{t}$) for panel bootstrap unit root test can be estimated by using the following specification:

$$\overline{t}_s = \sqrt{N}\{\overline{t} - E(t_i)\} \Big/ \sqrt{Var(t_i)} \quad (5)$$

Where $\overline{t} = N^{-1}\sum_{i=1}^{N} t_i$. $\overline{Max}$ statics can be obtained by using the following specification:

$$\overline{Max}_s = \frac{\sqrt{N}\left\{\overline{Max} - E(Max_i)\right\}}{\sqrt{Var(Max_i)}} \quad (6)$$

Where $\overline{Max} = N^{-1}\sum_{i=1}^{N} Max_i$. The $\overline{WS}$ statistics can be obtained by following:

$$\overline{WS}_s = \frac{\sqrt{N}\left\{\overline{WS} - E(WS_i)\right\}}{\sqrt{Var(WS_i)}} \quad (7)$$

After examining the stationarity properties of variables, we investigated whether cointegration exists in the model through Pedroni (1999) approach. The Pedroni (1999) approach can be implemented by using Eq. 1 as:

$$\varepsilon_{it} = \psi_i \varepsilon_{it-1} + \sum_{k=1}^{K_i}\psi_{ik}\varepsilon_{it-k} + v_{it} \quad (8)$$

Pedroni (1999) employs "no cointegration" in the null while "cointegration" in the alternative. We employed the Panel Autoregressive Distributed Lag (ARDL) method proposed by Pesaran et al. (1999), Panel Fully Modified Ordinary Least Squares (FMOLS) method proposed by Pedroni (2000), and Panel Dynamic Ordinary Least Squares (DOLS) method proposed by Pedroni (2001) to estimate long-run coefficients, respectively. The data generating process of the Panel ARDL model is expressed as:

$$y_{it} = \sum_{j=1}^{p}\lambda_{ij}y_{i,t-j} + \sum_{j=0}^{q}\delta_{ij}^{'}x_{i,t-j} + \mu_i + \varepsilon_{it} \quad (9)$$

Where $x_{it}(kx1)$ is the vector of regressors for group i; μ_i is fixed effects; λ_{ij} are scalars, and δ_{ij} are $(kx1)$ coefficients vectors. The time dimension (T) of the data structure must be large enough to perform analysis for each group. Pesaran et al. (1999) reshaped Eq. (9) as:

$$\Delta y_{it} = \phi_i y_{i,t-1} + \beta_i^{'} x_{it} + \sum_{j=1}^{p-1}\lambda_{i,j}^{*}\Delta y_{i,t-j} + \sum_{j=0}^{q-1}\delta_{ij}^{*'}\Delta x_{i,t-j} + \mu_i + \varepsilon_{it} \quad (10)$$

$i = 1, 2, \ldots, N and t = 1, 2, \ldots, T. and \phi i = -(1 - \sum_{j=1}^{p}\lambda_{ij}), \beta i = \sum_{j=0}^{q}\delta ij$, $\lambda_{ij}^{*} = -\sum_{m=j+1}^{p}\lambda_{im}, j = 1, 2, \ldots, p-1$. Besides, $\delta_{ij}^{*}$is as follows; $\delta_{ij}^{*} = -\sum_{m=j+1}^{q}\delta_{im}, j = 1, 2, \ldots, q-1$. The panel FMOLS method can be utilized by the following specification: $\widehat{\beta}_{GFMOLS} = N^{-1}\sum_{i=1}^{N}\beta_{FMOLSi}$, where β_{FMOLSi}computed by using individual FMOLS estimation of Eq.(1), and t-ratio of coefficients can be obtained by following specification $t_{\beta_{GFMOLS}} = N^{-1/2}\sum_{i=1}^{N} t_{\beta_{FMOLSi}}$(Erdogan, 2020). To obtain long-run coefficients with the DOLS procedure, the Eq. (1) can be reshaped as:

$$\begin{aligned} LNEF_{it} &= \beta_{0it} + \beta_1 Y_{it} + \beta_2 COR_{it} + \beta_3 NR_{it} + \beta_4 REN_{it} + \beta_5 UR_{it} \\ &+ \sum_{k=-K_i}^{K_i} a_{ikt} Y + \sum_{k=-K_i}^{K_i}\delta_{ikt} COR + \sum_{k=-K_i}^{K_i}\gamma_{ikt} NR + \sum_{k=-K_i}^{K_i}\lambda_{ikt} REN \\ &+ \sum_{k=-K_i}^{K_i}\theta_{ikt} UR + \varepsilon_{it} \end{aligned} \quad (11)$$

Where K_i, and$-K_i$ shows lags and leads, respectively. By considering the FMOLS procedure, the DOLS estimation can be done as $\widehat{\beta}_{GDOLS} = N^{-1}\sum_{i=1}^{N}\beta_{DOLSi}$, where $\beta_{DOLSi}$is obtained from OLS estimation of Eq.(7)

for each of the members. The *t*-ratio for coefficients can be obtained by the following specification: $t_{\beta_{GDOLS}} = N^{-1/2}\sum_{i=1}^{N} t_{\beta_{DOLSi}}$.

We began the empirical analysis by implementing the cross-section dependence tests. According to the results in Table 2, the null hypothesis of "no cross-section dependence" is strongly accepted for the model, however, majority of CD test results show the null hypothesis of "no cross-section dependence" is rejected for all variables. Hence, panel data estimation methods that perform under the presumption of cross-section independence can be implemented for cointegration test and cointegration estimations, whereas unit root-stationarity methods that perform under the assumption of cross-section dependence can be implemented for determining the stationarity level of the variables (Hurlin, 2004; Hurlin and Mignon, 2007; Pesaran and Tosetti, 2011).

Owing to the presence of cross-section dependence, we implemented bootstrap-based panel unit root tests and report the results in Table 3. The findings show all variables exhibit a non-stationary process at level while variables at first difference exhibit stationarity process but at varying significance level. We investigated whether cointegration exists in the model by employing the cointegration method of Pedroni (1999). The test results in Table 4 show the null hypothesis of "no cointegration" is accepted by Modified Phillips-Perron statistics, whereas rejected by Phillips-Perron and Augmented Dickey-Fuller statistics. Since most of the findings favor the alternative hypothesis of "cointegration", evidence of long-run relationships among variables is validated.

We estimated the long-run coefficients by utilizing Panel ARDL, FMOLS, and DOLS methods. The Panel ARDL, FMOLS, and DOLS estimation results in Table 5 show GDP per capita has positive and statistically significant effect on environmental pollution, hence, an increase in GDP per capita increases environmental pollution in the long-run. The deteriorating effect of economic growth may be related to an increase in resource use at the early phase of the economic development process, which is consistent with expectations and former findings (Acaravci and Akalin, 2017; Aslan et al., 2018; Destek et al., 2018; Lopez and Islam, 2008; Ozturk and Acaravci, 2013; Yilanci and Pata, 2020). Based on these three estimation results, corruption has a statistically significant and positive effect on environmental pollution. Therefore, corruption is one of the obstacles to achieving SDGs of sampled countries. This finding confirms the results of Balsalobre-Lorente et al. (2019); Faiz-Ur-Rehman Ali and Nasir (2007); Lisciandra and Migliardo (2017); Masron and Subramaniam (2018); Rehman et al. (2012); Sahli and Rejeb (2015); Sekrafi and Sghaier (2018); Sinha et al. (2019a), whereas either completely or partially in contradiction with the results presented in Akhbari and Nejati (2019); Arminen and Menegaki (2019); Azam and Khan (2017); Cole (2007); Pellegrini and Gerlagh (2006); Wang et al. (2018); Welsch (2004).

Based on the results of the three estimation methods, fossil energy consumption has a positive and statistically significant effect on environmental pollution, hence, a positive shock on non-renewable energy consumption will result in deterioration of the environmental conditions. This could be a result of the concentration of greenhouse gas emissions (GHGs) in the atmosphere and destruction of nature due to anthropogenic activities such as fossil fuel use, oil strike, and pollution of freshwater resources (IPCC, 2001). The Panel ARDL and FMOLS estimation results show renewable energy consumption has negative and statistically significant effect on environmental pollution level, whereas the DOLS estimation result shows renewable energy consumption has negative but statistically insignificant effect on environmental pollution. Because majority of findings favor the negative and statistically significant effect of renewable energy consumption, it can be regarded that an increase in renewable energy consumption mitigates environmental pollution. This may be related to reducing the effect of renewable energy consumption on carbon emissions — considered as the main cause of climate change reduction (Jebli et al., 2016), and limiting the share of fossil fuels in total energy consumption. The Panel ARDL and DOLS estimation results reveal urbanization has positive but statistically insignificant effect on environmental pollution while results from FMOLS reveal urbanization has statistically significant and positive effect on environmental degradation. Based on these findings, urbanization can be considered to have statistically insignificant effect in the long-run, hence, there is no systematic nexus between urbanization and environmental pollution in NICs.

Besides, unit root and cross-section dependence tests were applied to residuals obtained from ARDL, FMOLS, and DOLS estimators to check robustness. The findings show that cross-section independence cannot be rejected whereas residual series obtained from panel ARDL, FMOLS, and DOLS estimations follow a stationary process. It can be inferred that the effect of economic development, renewable and non-renewable energy consumption on environmental degradation is consistent with theoretical expectations and existing literature. Moreover, corruption has an environmental cost across the NIC bloc and this finding is remarkable.

5. Discussion

Within the context of empirical analysis, we observe how economic development, corruption, urbanization, non-renewable and, renewable energy utilization affect environmental degradation (Fig. 1). The empirical results highlight broad discernments with policy implications. Economic development has an aggravating effect on environmental degradation, which could be attributed to rapid industrialization since the Industrial Revolution. The unprecedented industrialization process led to an accelerated concentration of anthropogenic GHGs in the biosphere. The concentration of anthropogenic GHGs is recently estimated at 40%. Indeed, nearly half of the total anthropogenic effect occurred in the last half-century (European Commission, 2019). Moreover, the increasing concentration of GHGs spurs climate change, which threatens ecological life on land and below water. Thus, anthropogenic GHGs hamper natural resource expansion — which has vital importance for the sustainability of economic activities, health, and wellbeing of people. Besides its environmental cost, environmental degradation has an economic cost equal to nearly 2% of global GDP. Furthermore, climate change may reduce agricultural output by nearly 30%, thereby affecting almost 500 million farmers (IPCC, 2018; World Economic Forum, 2019). This implies attention should be given to the internalization of externalities created by economic development. Within this context, the majority of studies rely on the Environmental Kuznets Curve (EKC) approach—based on the premise that economic development has a reduction effect on environmental pollution in the long-run [*see*

Table 2
The Cross-Section Dependence Test Results.

Test	*MODEL*	EF	*Y*	*COR*	*NR*	*REN*	*UR*
LM	41.240 (0.252)	48.300 (0.083)	61.850 (0.000)	209.241 (0.000)	68.477 (0.000)	46.518 (0.113)	241.055 (0.000)
CD-Stat	−0.29 (0.765)	13.97 (0.000)	30.94 (0.000)	−1.78 (0.076)	15.05 (0.000)	29.17 (0.000)	29.10 (0.000)
LMadj	0.293 (0.769)	5.936 (0.000)	4.432 (0.000)	20.356 (0.000)	3.545 (0.000)	15.823 (0.000)	18.891 (0.000)

Note: The values in parenthesis are *p*-value for the CD test. Legend: EF — Ecological footprint per capita, Y — Gross domestic product (GDP) per capita, COR — Bayesian Corruption Index, NR — Non-renewable energy consumption per capita, REN — Renewable energy consumption per capita, and UR — Urban population.

Table 3
The Unit Root Test Results via Panel Bootstrap algorithm.

	$\bar{t}$				$\overline{WS}_s$				$\overline{Max}_s$			
	Level		1st Difference		Level		1st Difference		Level		1st Difference	
	C	C + T	C	C + T	C	C + T	C	C + T	C	C + T	C	C + T
EF	−1.591	−2.051	−5.898	−5.887	−0.944	−2.121	−5.709	−5.850	−0.925	−1.857	−5.470	−5.492
	(0.241)	(0.666)	(0.000)	(0.000)	(0.764)	(0.437)	(0.000)	(0.000)	(0.621	(0.399)	(0.000)	(0.000)
Y	0.110	−2.236	−4.416	−4.599	0.180	−1.760	−3.778	−4.204	0.429	−1.467	−3.594	−3.898
	(0.999)	(0.398)	(0.000)	(0.000)	(0.998)	0.800	(0.000)	(0.000)	(0.996)	(0.601)	(0.000)	(0.000)
COR	−1.344	−2.534	−3.212	−3.628	−1.297	−2.054	−2.710	−3.153	−0.339	−0.719	−2.453	−2.963
	(0.263)	(0.026)	(0.001)	(0.006)	(0.080)	(0.207)	(0.004)	(0.001)	(0.519)	(0.716)	(0.000)	(0.000)
NR	−1.555	−1.673	−4.656	−4.917	0.664	−1.721	−4.414	−4.768	0.334	−1.540	−4.180	−4.425
	(0.467)	(0.943)	(0.000)	(0.000)	(0.999)	(0.886)	(0.000)	(0.000)	(0.999)	(0.667)	(0.000)	(0.000)
REN	2.160	−0.573	3.997	−4.623	2.073	−0.878	−3.439	−4.168	2.442	−0.353	−3.213	−3.888
	(0.998)	(0.998)	(0.000)	(0.002)	(0.999)	(0.999)	(0.000)	(0.000)	(0.999)	(0.999)	(0.000)	(0.000)
UR	−1.453	−2.220	−2.188	−2.795	0.118	−1.567	−3.721	−3.774	0.661	−0.600	−3.475	−3.464
	(0.124)	(0.199)	(0.037)	(0.085)	(0.993)	(0.752)	(0.000)	(0.000)	(0.890)	0.745	(0.000)	(0.001)

Note: The optimal lag-length was selected as k = 2. Probability values have been obtained from 1000 bootstrap replication and shown in parenthesis (.). Legend: EF — Ecological footprint per capita, Y — Gross domestic product (GDP) per capita, COR — Bayesian Corruption Index, NR — Non-renewable energy consumption per capita, REN — Renewable energy consumption per capita, and UR — Urban population.

Table 4
Cointegration Test Results.

	Statistics
Modified Phillips-Perron	0.828 (0.203)
Phillips-Perron	-4.945 (0.000)
Augmented Dickey-Fuller	4.854 (0.000)

Note: Probability values of the cointegration test statistics are shown in parenthesis.

Acaravci and Akalin, 2017; Apergis and Ozturk, 2015; Aslan et al., 2018; Bello et al., 2018; Destek et al., 2018; Pata, 2018; Sarkodie and Adams, 2018; Sarkodie and Strezov, 2019; Shahbaz et al., 2016; Sharif et al., 2020]. Besides, Lopez and Islam (2008) emphasized that awareness and demand for clean environment will rise by long-term increase in income levels. Based on these approaches, it may be expected that the negative externalities of economic development may diminish by the composition and technique effects of EKC and increasing demand for sustainable ecological status in the long-run. However, ecological sustainability is at risk for irreversible damage if immediate action is not taken (United Nations, 2018). Therefore, the environmental aims of the SDGs may not be achieved under these circumstances, hence, attention could be paid to internalizing the negative effects of economic development by harmonizing economic activities with ecological sustainability.

Systemic corruption has a long-term exacerbating effect on environmental degradation. This finding may support the concept of the GTW hypothesis—where corruption has a positive effect on environmental pollution. Implying that, high levels of corruption in NICs may lead to the extension of economic activities by short-circuiting the bureaucratic process—which triggers more resource utilization—which in turn leads to ecological destruction. Besides, the exacerbating effect of corruption may be a result of corrupt officials ignoring the violation of environmental legislation for their interests. Corrupt activities of officials make enforcement of environmental legislations difficult, which in turn hampers enforcement of international treaties on sustainable environment. Hence, the effect of increasing economic activities on ecological sustainability may become more serious by the effects and violation of the legislation. Additionally, corruption makes it difficult to control the informal sector, hence, the informal production process may ignore the environmental standards and legislation, which in turn leads to overuse of ecological resources. This resonates with a recent study (Sarkodie et al., 2020b) that demonstrates that Chinese human capital is conducive for long-term environmental deterioration. International Labor Organisation (2018) reports that nearly 2 billion people are employed in the informal economy on a global scale, and more than 60% of the total informal employment is in emerging and developing

Table 5
Estimation Results.

Long-Run Estimations	Panel ARDL (Short-Run)	Panel ARDL (Long-Run)	FMOLS	DOLS
Y	–	0.689	0.572	0.665
		(0.000)	(0.000)	(0.000)
COR	–	0.463	0.253	0.415
		(0.009)	(0.000)	(0.064)
NR	–	0.257	0.383	0.277
		(0.000)	(0.000)	(0.000)
REN	–	−0.120	−0.084	−0.043
		(0.000)	(0.014)	(0.371)
UR	–	0.030	0.404	0.001
		(0.844)	(0.000)	(0.994)
ΔY	0.409	–	–	–
	(0.001)			
ΔCOR	−0.093	–	–	–
	(0.838)			
ΔNR	−0.037	–	–	–
	(0.352)			
ΔREN	0.044	–	–	–
	(0.001)			
ΔUR	−4.732	–	–	–
	(0.582)			
C	−2.688	–	–	–
	(0.000)			
Trend	−0.002	–	–	–
	(0.056)			
Cointeq.	−0.517	–	–	–
	(0.000)			
CD	–	−1.40	−1.760	−1.41
		(0.167)	(0.079)	(0.120)
$\bar{t}$	–	−5.081	−5.691	−5.677
		(0.000)	(0.000)	(0.000)

Note: Probability values are shown in parenthesis. The FMOLS and DOLS specification includes constant and trend and based on the heterogeneity of long-run variance, estimated by using the Parzen kernel and Andrews bandwidth method. Optimal lag and lead for DOLS estimation were fixed at 1 by using the Schwarz info criterion. Optimal lag-length for Panel ARDL estimations was fixed at 1 for all variables by using the Akaike info criterion. Legend: EF — Ecological footprint per capita, Y — Gross domestic product (GDP) per capita, COR — Bayesian Corruption Index, NR — Non-renewable energy consumption per capita, REN — Renewable energy consumption per capita, UR — Urban population. CD— CD test (Pesaran, 2004) and $\bar{t}$— Bootstrap IPS statistic.

countries including NICs. On the one hand, reducing the high level of informal employment levels may have economic consequences while on the other hand, the existence of a high level of informal employment has consequences for employees, society and environment. Hence, corruption may pose a risk for both achieving ecological sustainability and decent work outlined in the SDGs. Indeed, Transparency International

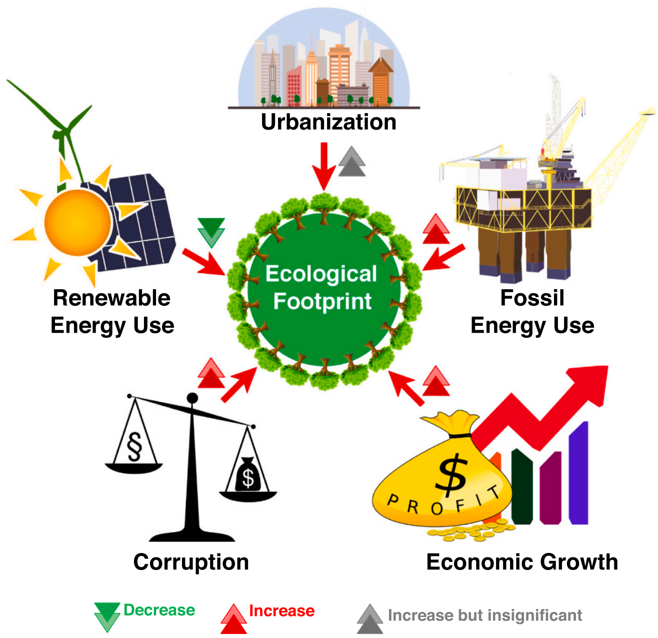

Fig. 1. Graphical summary of the Empirical Results.

(2017) reports that the achievement of all SDGs depends on the success of the fight against corruption. Within this scope, mitigating corruption is essential for clean environment and safe future across NICs. Thus, governments could pass legislation to combat corruption whereas regulatory bodies may have a core significance in monitoring the implementation of laws. Besides, the establishment of an independent judiciary in NICs which deals with corrupt and opportunistic behaviors could significantly contribute to the success of anti-corruption policies.

Fossil fuel energy use has a positive effect on environmental pollution, which is consistent with expectations and former literature (Bekun et al., 2019; Alola et al., 2019). The polluting effect of fossil fuels on environmental pollution is widely known, and non-renewable energy sources are already prevalently used in NICs with an average share of 79.16% in the energy mix (World Bank, 2020). Besides, there is a growing energy demand in NICs because of rapid economic development. Therefore, the determination of energy composition and reducing negative externalities of non-renewable energy utilization is a challenging issue in NICs. A ban on the utilization of non-renewable energy sources can be an option but unfavorable and challenging because of welfare and developmental concerns (Erdogan, 2020; Sinha et al., 2020). Reducing the share of non-renewable energy use by increasing productivity can be another alternative, but this option may not be achieved unless governments and private sector take common initiatives. Renewable energy diminishes environmental pollution, hence, promoting renewable energy production and consumption can be an effective option for decreasing the environmental burden. Sadorsky (2009) emphasized that non-renewable energy supply is vulnerable to exogenous shocks including price fluctuations, political decisions, monopoly pricing, and terrorist attacks. Thus, renewable energy can be an effective tool for ensuring energy security, diversifying energy inputs, avoiding energy scarcity, and achieving the clean energy policy objective of the SDGs, particularly in developing countries (Owusu and Asumadu, 2016). Moreover, renewable energy investment can create new job opportunities but the financial cost of establishing renewable energy production facilities affects the feasibility of the projects (Sinha et al., 2020). Therefore, the determination of both government and private investment composition may be a challenging issue for NICs.

6. Conclusion and policy implications

The impact of corruption on economic development and social issues has received much attention and debate from politicians and economists for decades. The effect of corruption on environmental degradation and climate change situated at the heart of the SDGs has attracted the interest of researchers and growing body of scientific literature. There is a progressive discussion on whether corruption hamper efforts against environmental degradation, which in turn, becloud the attainment of the environmental aims of the SDGs. In this sense, we examined the effects of corruption on environmental degradation in NICs aimed at contributing to the growing literature. The empirical results of our study and its corresponding policy implications are as follows: first, economic growth has an aggravating effect on environmental degradation. To reduce the environmental cost of economic growth and economic cost of the environment, governments could adopt a more inclusive and eco-friendly developmental approach that encourages substitution of pollutant-production technology based on nonrenewable resources with technologies that use clean and renewable resources.

Corruption is a global canker with interest to both politicians/governments, and civil societies. Therefore, empowering civil societies may affect efforts of governmental organizations and regulatory bodies. Freedom of the press could improve access to information—typically about ecological issues, thus, contribute to the prevention of corruptive practices on ecological issues. To reduce the distorting effects of corruption on the environment, the informal sector should be minimized. However, along with reforms aimed at reducing the informal sector, policymakers could consider the welfare of individuals working in the informal sector. Reducing social security premiums, taxes, and increasing subsidies for the formal sector can be policy options to reduce the size of informal sector and protect the welfare of members of the informal sector (Fortin et al., 1997; Giles and Tedds, 2002; Dabla-Norris et al., 2008; Saraçoğlu, 2020).

The use of renewable energy instead of non-renewable energy in the production process can be an effective option for decreasing the environmental burden. To increase the accessibility and affordability of renewable energy in NICs, the financial burden of renewable energy facilities could be addressed by establishing an international fund for renewable energy investments. Policymakers could consider establishing financial mechanisms, thus, credits for renewable energy investments can be provided by low cost and mega projects, which cannot be implemented by the national budget could be considered (Reboredo, 2015; Erdogan, 2020; Sinha et al., 2020). Besides, increasing productivity by replacing vintage technologies and facilities with more efficient models, improving operational and infrastructure use—will reduce demand for fossil fuels, hence, improve energy efficiency and decline environmental degradation. Following these purposes, policymakers could consider increasing the budget of Research and Development (R&D) programs and subsidize private R&D activities.

This paper has some limitations—first, due to data availability across NICs, several explanatory variables related to production technology and environmental degradation—including energy prices, and renewables were not included in the empirical analysis. Future studies could consider these variables, which may provide comprehensive information about drivers of environmental pollution in NICs. Moreover, this study focuses on the demand side of the environment, thus, further studies may consider focusing on both demand and supply side of the environment by adopting ecological deficit as proxy for ecological bearing capacity.

CRediT authorship contribution statement

Guray Akalin: Investigation, Writing – original draft, Writing – review & editing. **Sinan Erdogan**: Conceptualization, Formal analysis, Writing – original draft. **Samuel Asumadu Sarkodie**: Writing – original draft, Visualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Appendix

The maximum lag-length for panel ARDL estimation procedure was determined by using information criteria. According to the results (Table A1) maximum lag-length for ARDL estimation was determined as 2.

Table A1
Lag-length Selection Criteria.

Lag	LogL	AIC	SC	HQ
0	−291.002	2.200	2.279	2.232
1	3466.182	−25.364	−24.804	−25.139
2	3871.881	−28.102	-27.063*	-27.685*
3	3932.989	-28.288*	−26.769	−27.678

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