



Effect of corruption on green growth

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Abstract

Corruption as a social and cultural epidemic is likely to influence the environmental sustainability and quality of the world we live in, where climate change threatens our survival, both now and in the future. Therefore, in this paper, we use large panel data of 123 countries between 2000 and 2017 to examine the environmental effect of corruption on green growth. Consistent with prior studies and due to the slow-changing nature of corruption, we used the pooled ordinary least square as the primary estimator. We also employ the System-Generalised Method of Moments and Two-Stage Least Square Instrumental Variable analysis to control country-specific effects and simultaneity bias caused by potential endogeneity. The results show a negative and significant relationship between corruption and green growth, suggesting that highly corrupt countries are less likely to improve the environmental consequences of rapid economic growth. Quantitatively, *ceteris paribus*, a 1% increase in corruption (control of corruption), given its standard deviation, leads to a 15.47% decrease in green growth. This is equivalent to about 0.912 US dollars per kilogram decrease in green growth. In further analyses, we find that the relationship between corruption and green growth is similar in both developed and developing countries implying that no country is immune from the environmental effect of corruption. The findings highlight the need to control corruption to achieve sustainable economic and environmentally friendly development, especially as Agenda 2030 fast approaches.

Keywords Corruption · Environment · Green growth · Natural resources

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1 Introduction

In the wake of rapid economic growth and technological advancement, the survival of humans and their environment is threatened by climate change (OECD, 2021). Consequently, policymakers and regulators worldwide are continuously advocating a growth that is sustainable for both current and future generations. Example; the Paris Agreement and the 2030 Sustainable Development Agenda (OECD, 2020). Such development called green growth incorporates the efficient and effective use of natural resources to benefit humans and the environment. Numerous factors have been found to improve or deter green growth (Tawiah et al., 2021; Zhang et al., 2021). However, these factors are primarily economic and technological such as green investment (Ren et al., 2021a), with little to no attention to how social phenomena such as corruption could affect a country's journey towards more greener growth.

By its definition, corruption, which is the abuse of power for private economic gains (Rodriguez et al., 2005; Werlin, 2016), makes it quite obvious that corruption is just an economic issue with less related to the environment. As such existing studies have either focused on the economic determinants or economic consequences of corruption (Cole, 2007; d'Agostino et al., 2016; Lalountas et al., 2011; Méon & Weill, 2010; Rodriguez et al., 2005). However, corruption as a social and cultural epidemic is likely to influence the environmental sustainability and quality of the world we live in, where climate change threatens our survival, both now and the future (Lisciandra & Migliardo, 2017). Although there is some research on how corruption affects environmental performance, these studies have primarily focused on pollution with little consideration on input–output efficiency of resources as captured in green growth (Biswas et al., 2012; Cepparulo et al., 2019; Cole, 2007; Damania et al., 2003; Fredriksson et al., 2004; Fredriksson & Svensson, 2003; Leitão, 2010; Pei et al., 2021; Song et al., 2021; Wu et al., 2021). Accordingly, in this paper, we examine the impact of corruption on the efficient use of natural assets in production and consumption.

Corruption can affect the efficient use of natural assets by weakening the stringency of environmental protection regulations and policies. Arguably, lack of or poor environmental laws leads to inefficient use of natural assets and, eventually, environmental degradation (Sinha et al., 2019; Wang et al., 2019; Yang et al., 2018; Yuan & Xiang, 2018; Zhou & Li, 2021). Besides weakening environmental regulations, corruption can also indirectly affect a country's ability to go green via other factors such as a reduction in income, poor administration, a shift of government attention, and misuse of funds for environmental projects (Biswas et al., 2012; Cole, 2007; Leitão, 2010; López and & Mitra, 2000; López, 1994; Qi & Cheng, 2018; Ren et al., 2021b; Welsch, 2004).

To examine the impact of corruption on green growth, we use large panel data of 123 countries over 18 years (2000–2017). We make use of the recent data from Organisation for Economic Co-operation and Development (OCED) on environmental performance; green growth, which measures how a country's growth is becoming greener. According to OECD (2020) statistics, green growth indicates whether economic growth is becoming greener with more efficient use of natural capital. We use the headline indicator at OECD statistics (green growth indicators). Green growth captures all areas of production, which are rarely quantified in economic models and accounting frameworks (OECD, 2021). Therefore, the green growth indicator captures more information on the environment as both an input factor and output of activity, compared to other measurements in prior studies such as emissions, which are based on the output of an activity. More so, the green growth indicator

tracks progress towards a sustainable and greener economy (OECD, 2020). Unlike prior studies, we utilize three different indicators of corruption to provide robust findings. These indicators are from three different sources, which allay the concern that our results may be driven by nature or source of corruption measurement, something which appears to be a limitation in prior studies. We also include a battery of control variables, including economic and internationalisation factors, to mitigate any concern of omitted variable bias.

Our results are as follows. First, as expected, we find corruption to be negative and significantly associated with green growth, suggesting that green growth decreases as corruption increases. Put differently, highly corrupt countries are inefficient in using their natural assets and capital in production and consumption; hence they are less likely to become greener. The results imply that corruption impedes most countries' efforts to achieve the 2030 Agenda of the Sustainable Development Goals, particularly Goal 12—*Responsible consumption and production*. In further analysis, we did not find evidence that our results are sensitive to country classification as developed or developing. However, we find that the negative relationship between corruption and green growth is much stronger in developing than developed countries, which explains why most developing countries are experiencing a downturn in green growth. We also find that the existence of natural resources does not significantly moderate our main findings that corruption is detrimental to green growth.

Although there is less concern about reverse causality between green growth and corruption, we still use three different identification strategies to address any other potential endogeneity issues, such as the effect of previous growth on current year green growth or simultaneity of the explanatory variables. The results from these estimations remain the same as in the main findings, indicating the robustness of our results in explaining the relationship between corruption and green growth.

This study is different from existing literature and makes incremental contribution without umpteenth analysis on corruption and pollution (Biswas et al., 2012; Cepparulo et al., 2019; Cole, 2007; Damania et al., 2003; Fredriksson et al., 2004; Fredriksson & Svensson, 2003; Leitão, 2010; Pei et al., 2021; Ren et al., 2021b; Song et al., 2021; Wu et al., 2021). First, unlike prior studies that focused on pollution and CO₂ emissions, we provide an understanding of how corruptions affect a country's journey towards efficient use of natural assets. We make use of the recent green growth indicator by OECD, which goes beyond the simple carbon emissions to include how a country is efficient in using natural assets to generate economic development. Green growth focuses on countries becoming greener without compromising economic development and growth. The measurement of environmental performance, such as emissions, turns to be one-sided, which assumes that the optimal environmental performance is zero emissions. Arguably, zero-emission is either difficult or near impossible because no economy can be at a standstill. Therefore, it is imperative to use performance measurement that focuses on the efficiency of generating less emission from achieving high growth. For example, Australia has high emissions, but they are more efficient in using natural assets to generate high economic growth and alternative energy sources.¹ However, most African countries have low emissions and, therefore, will be considered high environmental performers under carbon emissions performance, but they are inefficient in using their natural assets to generate economic development. Unlike previous literature (Romano et al., 2021; Leal et al., 2021; Wu et al., 2021), which only considers

¹ Pérez-Suárez & López-Menéndez (2015) find Australia to be one of the three countries expected to achieve the 2020 Kyoto targets.

environmental performance, we extend the literature by capturing the effect of corruption on overall green economic development.

Second, in contrast with prior studies, we use relatively large sample data and more control variables than other studies on corruption and environmental performance. For example, Biswas et al. (2012) used only a short time of 6 years in 100 countries; Cole's (2007) study is based on 94 countries over 13 years. Large sample data with a mix of developed and developing countries increase precision in estimations and better isolate the corruption effects.

Third, unlike prior studies that focus on environmental regulations or the indirect effect via other factors, we focus on the direct effect on green growth. By focusing on green growth, we provide the direct effect of corruption on the attainment of Agenda 2030 on Sustainable Development Goals (Goal 12). Our study, therefore, informs policymakers of the need to address corruption in order to meet the 2030 Sustainable Development Goals deadline. The Sustainable Development Goals (SDGs) have five themes with seventeen goals, expected to be achieved by 2030. SDGs were adopted by 193 countries to promote economic development, ensure social inclusion and protect the environment (Maes et al., 2019; United Nations Development Programme, 2020). Specifically, *Goal 12: Responsible consumption and production*, indicate efficient use of natural assets and resources for achieving economic growth (United Nations Sustainable Development Goals, 2020).

The remainder of the paper is as follows. The literature review is presented in Sect. 2, and the research method is presented in Sect. 3. In Sect. 4, we present and discuss the empirical results. Section 5 concludes the paper with policy implications and suggestions for future research.

2 Literature review

Corruption, as societal cancer, affects almost every aspect of a country (International Federation of Accountants, 2017). Empirical evidence has shown that corruption in any form is bad for almost every aspect of the society with few exceptions (for debate on greasing the wheel hypothesis Egger & Winner, 2005; Kato & Sato, 2015; Méon & Weill, 2010). For example, findings of the economic consequences of corruption show that corruption negatively affects economic growth and economic development (d'Agostino et al., 2016; Rodriguez et al., 2005; Werlin, 2016). Also, there is evidence that corrupt countries turn to have weak regulations and enforcement capabilities, which lead to waste of funds and other resources (Sinha et al., 2019; Wang et al., 2019; Yang et al., 2018; Yuan & Xiang, 2018).

Though dominated by pollution studies, existing literature on the corruption-environment nexus provides a two-strand on how corruption affects the environment. The first strand of literature provides evidence on how corruption weakens the formulation and implementation of environmental regulation and hence leads to a poor environment (Hassenforder et al., 2015; Pei et al., 2021; Zhou et al., 2019) Damania et al., 2003; Du & Li, 2019; Cole, 2007; Fredriksson et al., 2004; Fredriksson & Svensson, 2003; López and Mitra, 2000; Chen et al., 2018). Cole et al. (2006) find that high corruption negatively impacts environmental stringency, creating a pollution haven for foreign direct investment. Fredriksson et al. (2004) argue that corruption reduces the stringency of environmental regulations because it shifts the government's attention from welfare towards bribes for purchasing public influence. Similarly, Chen et al., (2018) reports that environmental regulation is effective only when shadow economy and corruption are

controlled. However, Fredriksson and Svensson (2003) show that the negative effect of corruption on the stringency of environmental regulations disappear when political instability increases. In effect, the authors argue that corruption mitigates the negative effect of political instability on the environment. Du and Li (2019) find that decentralisation and corruption weaken the environmental regulations on overcapacity of energy in Chinese firms, suggesting excessive energy consumption by firms in corrupt areas. According to Cepparulo et al. (2015), decarbonisation is only effective when there are multi-level governance institutions rather than external instruments. Hao et al. (2021) found that local corruption negatively affects environmental decentralisation on air pollution in China. Similarly, Hao et al. (2020) report that corruption aggravates the negative effect of resource misallocation on total environmental efficiency.

The second strand of the literature explains how corruption aggravates the effect of other factors on the environment. Some scholars have found that corruption increases the per capita income required to turn economic development to improve the environment under the Environmental Kuznets Curve (EKC). The EKC hypothesis posits that the environment suffers at the beginning of economic development, but as income increases, the environment improves. Hence there is an inverted U-shaped relationship between economic development and the environment (Cole, 2007; Leitão, 2010; López and Mitra, 2000; López, 1994; Welsch, 2004). López (1994) theoretical argument supports the inverted U-shaped relationship between income and environmental quality. According to this theoretical argument, López (1994) argues that the relationship between economic growth and the environment depends on how easy and flexible one can change between conventional factors and pollution in the production, and the relative degree of curvature of income utility. Empirical evidence shows that at a lower elasticity of substitution and relative curvature coefficient, high income increases pollution (López and Mitra, 2000; López, 1994). For example, Leitão (2010) finds that corruption is significantly associated with a critical income threshold at which SO₂ emissions reduce. Sinha et al. (2019) report an inverted N-shaped EKC in emerging economics, arguing that corruption increases environmental degradation by reducing the positive impact of renewable energy consumption. Biswas et al. (2012) find that the relationship between the shadow economy and pollution is dependent on the level of corruption, implying that corruption only affects pollution in the shadow economy. According to case studies by Desai (1998), corruption causes environmental degradation because corruption makes it cheaper for firms to buy government officials or regulators than to comply with environmental laws.

Damania et al. (2003) find a high degree of corruptibility to increase the negative impact of trade liberalisation on the environment. Lapatinas et al. (2011) suggest that corruption decreases the quality of the environment because environmental protection involves a huge investment in technology, which could be a breeding ground for rent-seeking activity. They argue that in a corrupt country, the budget allocated for environmental protection is less likely to achieve a meaningful outcome for the environment, probably due to the long gestation period of such investments. Other scholars have also provided evidence on how the rent-seeking behaviour of corrupt officials negatively impacts the implementation of renewable energy solutions (Burritt et al., 2009; Geng et al., 2010). Sinha et al. (2019) argue that corruption impedes the growth of renewable energy but may increase the use of fossil fuels. Corruption decreases environmental sustainability through deforestation due to illegal logging, timbering and smuggling of forest products (Koyuncu & Yilmaz, 2008). Liu and Dong (2021) report that corruption affects haze pollution via economic development.

Welsch (2004) argues that while findings of corruption directly increasing pollution are plentiful and unambiguous, the indirect negative effect via other factors is dominated by only direct effect. Similarly, Cole et al. (2006) also find that the indirect negative effect of corruption on SO₂ and CO₂ approaches zero. That is, the indirect effect of corruption only holds when the direct relationship is stronger. Hence, direct analysis between corruption and the environment provides more evidence for policy formulation and decision-making.

Although the above discussion provides plentiful and unanimous evidence that corruption negatively affects the environment, the effect of corruption on green growth may not be straightforward. Because, unlike prior studies, where the measurement of environmental performance is one side (mostly emissions), green growth is a two-way measurement that combines both economic and environmental performance. Hence, if corruption leads to high emission, but economic development also increases, then, the country could still be more efficient in using its natural assets than a low corrupt country with low emission and low economic development. Thus, findings from prior studies indicating a negative impact of corruption may be due to the fact that low corrupt countries are not utilising their natural assets due to low economic growth, which results in low emission, but that will not necessarily lead to a greener environment. Having said this, there is also empirical evidence that corruption retard economic growth and economic development. Therefore, it is more logical to expect corruption to exacerbate green growth because green growth measures the interaction of economic and environmental performance, and both are negatively affected by corruption. Since economic growth and economic development are essential for human survival, so emissions of any kind are inevitable; hence focus should be on the efficient use of natural assets rather than simple emissions as environmental performance.

From the above discussion, we observe that the key measurement of environmental performance is; pollution and carbon emission. However, these indicators are one-sided, which assumes that optimal environmental performance is zero emissions. Nevertheless, such an assumption is neither achievable nor close to reality because emissions are inevitable once humans live. Arguably, an indicator that captures the input–output efficiency on the use of resources will provide a better and more reliable understanding of how corruption affects the environment.

Existing literature is also limited by the small sample size and short period. For example, Biswas et al. (2012) used only a short time of 6 years in 100 countries; Cole's (2007) study is based on 94 countries over 13 years. Most studies (Hao et al., 2020, 2021) are also limited to single country analysis, which does not provide insight into cross-country trends. Large sample data with a mix of developed and developing countries increase precision in estimations and better isolate the corruption effects.

In addition to using a novel and more comprehensive indicator of environmental performance as well as a large sample size, we employ rigorous econometric modelling that enhances the robustness of our study compared with prior studies.

In sum, our current study fills at least two research gaps, mainly using a more comprehensive and novel measure of corruption than prior studies. Using a large sample size and a longer period to increase the precision and accuracy of the analyses.

3 Materials and methods

This section comprises sample data, variables & proxies, and the model and estimation methods.

3.1 Sample data

The population for the study includes all 134 countries in the OECD database on the environment. We sample 123 countries by dropping 6 countries with missing data on green growth and another 5 countries with missing data on corruption and other control variables. The remaining sample yields unbalanced data panel data of 2214 country-year observations between 2000 and 2017. A full list of sample countries is presented in “Appendix”. Data are collected from different sources, including OECD statistics; World Development Indicators, Worldwide Governance Indicators; Transparency International, and Quality of Government database.

3.2 Variables and proxies

3.2.1 Dependent variable

We use the recently developed environmental and resource productivity indicator by the OECD to measure green growth. The OECD defines green growth as the efficient use of natural capital or assets for production and consumption. It measures how economic growth is becoming greener and captures areas usually not included in economic and accounting measurements of a country’s performance. It is the headline indicator at OECD statistics (green growth indicators).

3.2.2 Independent variable

The main independent variable is corruption. To ensure that the measurement of corruption does not drive our results, we use three widely corruption indicators, namely, control of corruption, corruption perception index, and the Bayesian corruption index. Although all these three sources do not measure actual corruption, they are known to reflect the level of corruption in the country (Treisman, 2007). In fact, Transparency International (2020) posits that in the absence of any accurate measurement of actual corruption, perception-based measurement offers a more meaningful assessment of corruption.

Control of corruption is one of the six Worldwide Governance Indicators developed by Kaufmann & Kraay (2018). According to the authors, control of corruption is the perception of the extent to which public power is exercised for private gain in both petty or large corruption. The score ranges between -2.5 and $+2.5$, with higher values indicating low corruption. For simplicity and easy interpretation, we use the reciprocal format, which ranges from 0 to 5, with higher values indicating a high level of corruption. The rescaling is calculated as 2.5 minus the original score of the country.

The *Corruption perception index* by Transparency International is our second measure of corruption. This index is calculated from 10 different sources, and it represents the perception of business people and experts on the level of corruption in the country. The corruption perception index ranges between 0 and 100, with higher values indicating low corruption. As done in control of corruption, we use the reciprocal form of the index to obtain a consistent and straightforward interpretation of the results. We take the reverse format ranging from 0 to 100, where high values indicate high corruption.

Our final measure of corruption is the *Bayesian corruption index* from the Quality of Government database. Although this index has not attracted much popularity as the first two, it is also generated from rich sources and methodology. Bayesian corruption index is based on opinions of companies, non-governmental organisations and officials on the level of corruption in a country. Information for computing the index is collected from 20 different surveys. Like the corruption perception index, the Bayesian corruption index ranges between 0 and 100 but with high values indicating a high level of corruption.

3.2.3 Control variables

Given the multi-dimensional nature of environmental issues, green growth is likely to be influenced by different factors, including economic, internationalisation, institutional, and energy-related factors. We admit that it is not possible to control all factors that drive green growth. Therefore, we include a battery of variables that parsimoniously control other factors influencing green growth. The first sets of control variables are economic-related factors, which include *Economic development* and *Economic growth*. We proxy economic development with GDP per capita and economic growth with the annual GDP growth rate. Following prior studies, we expect economic development and economic growth to have a negative effect on green growth because large development and growth require the rapid depletion of natural assets (Shahbaz et al., 2015). The next set of control is the internationalisation comprising of trade openness and foreign direct investment. *Trade openness* is measured by the sum of total export and import as a percentage of GDP, and *Foreign direct investment* is measured by the ratio of net inflow of foreign direct investment to GDP. Following the pollution haven (Pethig, 1976) and pollution halo hypothesis (Birdsall & Wheeler, 2016) and recent literature (Ren et al., 2021a), we expect the relationship between internationalisation and green growth to go either way. We also include the level of *Energy consumption* measured by the use of primary energy to control for the energy-related factors on green growth. Arguably the efficient use of natural assets largely depends on the number of people using it and availability of the assets. Therefore, we account for *Forest area*, *Population* and *Population growth* in the model to control for variations in availability and end-users of natural assets among the countries. Description and sources of all variables are presented in Table 1.

3.3 Model and estimation method

We use the following model to test the impact of corruption on green growth

$$\begin{aligned}
 \text{Green growth}_{it} = & a + \beta_1(\text{Corruption})_i + \beta_2(\text{Economic development})_i \\
 & + \beta_3(\text{Economic growth})_i + \beta_4(\text{Trade openness})_i \\
 & + \beta_5(\text{Foreign direct investment})_i + \beta_6(\text{Energy consumption})_i \\
 & + \beta_7(\text{Population})_i + \beta_8(\text{Population growth})_i + \beta_9(\text{Forest area})_i + \varepsilon_{it}
 \end{aligned}
 \tag{1}$$

where *Corruption* takes on three different measurements of corruption in separate models. Each *i* represents a country, and ε_{it} is the associated error. All variables are defined in Table 1.

Table 1 Description and sources of variables

| Variable name | Measurement | Source |
|---------------------------|--|---------------------------------|
| Green growth | Measures how a country's growth is becoming greener. The headline indicator at OECD statistics (green growth indicators) (US dollars per kilogram) | OECD Statistics |
| Control of corruption | Corruption measurement as part of governance indicators ranging from +2.5 to -2.5 | Worldwide Governance Indicators |
| Corruption perception | Perception-based measurement of corruption which ranges between 0 and 100 | Transparency International |
| Bayesian corruption | Bayesian corruption index also ranges between 0 and 100 | Quality of Government database |
| Economic development | Gross domestic product divided by population | World Development Indicators |
| Economic growth | Annualised growth in gross domestic product | World Development Indicators |
| Trade openness | The sum of import and export as a percentage of gross domestic product | World Development Indicators |
| Foreign direct investment | The net inflow of foreign direct investment as a percentage of gross domestic product | World Development Indicators |
| Energy consumption | Energy use refers to the use of primary energy before transformation to other end-use fuels, which is equal to indigenous production plus imports and stock changes, minus exports and fuels supplied to ships and aircraft engaged in international transport | World Development Indicators |
| Population | The estimated headcount of residents living in the country | World Development Indicators |
| Population growth | Annualised growth in population | World Development Indicators |
| Forest area | Forest area is land under natural or planted stands of trees of at least 5 m in situ, whether productive or not, and excludes tree stands in agricultural production systems and trees in urban parks and gardens. Measure as the percentage of the total land | World Development Indicators |
| Resource rent | Total natural resources rents are the sum of oil rents, natural gas rents, coal rents (hard and soft), mineral rents, and forest rents as a percentage of gross domestic product | World Development Indicators |

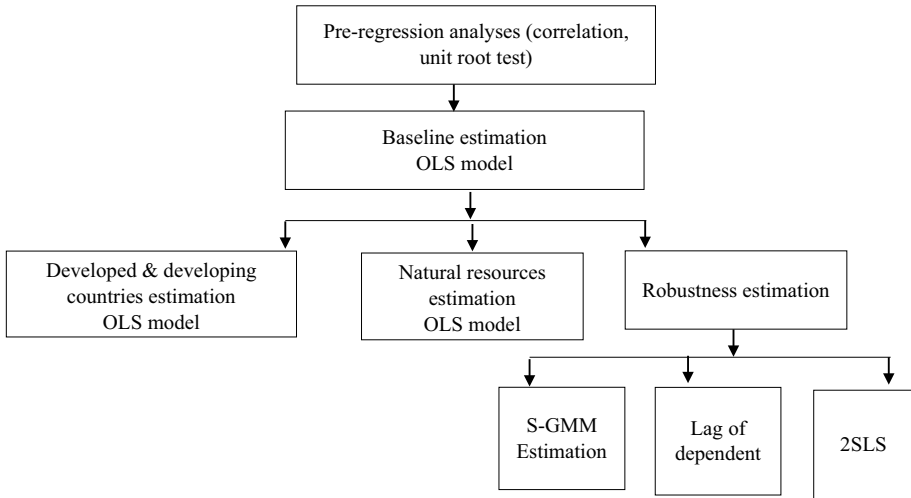


Fig. 1 Conceptual framework

3.3.1 Identification strategies

The panel estimation approach adopted in this study uses three-step strategies. Figure 1 presents the conceptual framework of the estimations. First, the panel unit root tests are applied to test the degree of integration of the variables. To do this, we performed the panel-persistent parameter ρ_i are identical across all cross sections, where $\rho_i = \rho$ for all variables.

LLC (2002) are expressed as follows:

$$\Delta y_{it} = \alpha y_{it-1} + \sum_{j=1}^{\rho_i} \gamma_{ij} y_{it-j} + X'_{it} \delta + \varepsilon_{it} \tag{2}$$

Note that $\Delta y_{it} = y_{it} - y_{it-1}$ and the assumption is that $\alpha = \rho - 1$ and therefore, $\rho_i = \rho$ for all. For brevity, the results are untabulated.

Second, consistent with Beck and Katz (2011) and Plümer and Troeger (2011) argument that corruption is a slow-changing variable, we use pooled regression, the commonly used estimator in corruption studies. One of the unique attributes of the pooled regression model is that it incorporates times series for several cross sections (Podestà, 2006). This includes repeated observation on fixed units, which indicates that data containing both cross-sectional data on N spatial unit and T of time formed a data of NxT observations (Podestà, 2006). This can be expressed as:

$$y_{it} = x'_{it} \beta + \alpha + \varepsilon_{it} \tag{3}$$

Third, we applied the System-Generalised Method of Moments (S-GMM) by (Arellano & Bond, 1991) and Two-Stage Least Square (2SLS) for robustness. There is less likelihood of reverse causality between corruption and green growth. That is, our dependent variable is less likely to cause variation in corruption. However, other potential endogeneity concerns may bias the results. For instance, one may argue that contemporary green growth is mainly dependent on its previous year. Therefore, the linearity assumption of our regression analysis could be violated, and the OLS model may lead to spurious estimations. To mitigate and possibly eliminate such concerns, we adopt three robust identification techniques. First, we include the lagged of the dependent variable as a control in the baseline model. Second, we follow prior studies such as Pei et al. (2021) to employ the System-Generalised Method of Moments (S-GMM) by (Arellano & Bond, 1991). According to Arellano and Bond (1991), S-GMM has the advantage of controlling for the presence of country-specific effects. More so, S-GMM control for simultaneity bias caused by potential endogeneity. The standard system GMM in levels (1) and first difference (2) are summarised as follows:

$$Y_{it} = \sigma_0 + \sigma_1 Y_{it-\tau} + \sigma_2 X1_{it} + \sigma_3 X2_{it} + \sigma_4 X3_{it} + \sum_{h=1}^5 \delta_j W_{h,i,t-\tau} + \eta_i + \xi_t + \varepsilon_{it} \quad (4)$$

$$\begin{aligned}
 Y_{it} - Y_{it-\tau} = & \sigma_1 (Y_{it-\tau} - Y_{it-2\tau}) + \sigma_2 (X1_{it-\tau} - X1_{it-2\tau}) + \sigma_3 (X2_{it-\tau} - X2_{it-2\tau}) \\
 & + \sigma_4 (X3_{it-\tau} - X3_{it-2\tau}) \sigma_1 Y_{it-\tau} + \sigma_2 X1_{it} + \sigma_3 X2_{it} + \sigma_4 X3_{it} \\
 & + \sum_{h=1}^5 \delta_j (W_{h,i,t-\tau} - W_{h,i,t-2\tau}) + (\xi_t - \xi_{t-2\tau}) + (\varepsilon_{it} - \varepsilon_{it-2\tau})
 \end{aligned} \quad (5)$$

Note that Y_{it} is the dependent variable of country i at period t ; σ_0 is a constant, while τ represents the coefficient of autoregression which presents specifications that take into cognizant the issues in degrees of freedom. The coefficients $X1, X2, X3$ are independent variables; W show the vector of control variables, η_i is the country-specific effect, ξ_t is the time-specific constant and ε_{it} the error term. In the third and final endogeneity check, we instrument corruption with legal origin and religious background in a 2SLS model deal with potential missing institutional characteristics of a country (Shao et al., 2013).

Consistent with Tawiah and Karungi, (2020), to further check the sanity of our results, we calculate the economic significance of corruption to show by how much corruption affects green growth. The economic significance is calculated as follows

$$\text{Economic significance} = \frac{(\text{Coefficient} * \text{standard deviation})}{\text{Mean of green growth}} \times 100$$

4 Results and discussion

This section comprises descriptive statistics and correlation, main results, sensitivity analyses, the effect of natural resources and endogeneity checks.

Table 2 Descriptive statistics

| Variables | (1) <i>N</i> | (2) Mean | (3) p25 | (4) p50 | (5) p95 | (6) SD |
|---------------------------|-----------------|-------------|------------|------------|------------|-----------|
| Green growth | 2214 | 5.901 | 3.343 | 4.963 | 13.26 | 3.630 |
| Control of corruption | 2214 | 2.404 | 1.695 | 2.714 | 3.748 | 1.040 |
| Corruption perception | 1469 | 50.43 | 30 | 57 | 79 | 22.78 |
| Bayesian corruption | 2208 | 45.37 | 32.58 | 50.53 | 65.59 | 16.58 |
| Economic development | 2210 | 8.647 | 7.474 | 8.612 | 10.88 | 1.492 |
| Economic growth | 2214 | 3.918 | 1.937 | 3.841 | 10.000 | 3.632 |
| Trade openness | 2214 | 85.87 | 55.62 | 77.60 | 163.8 | 51.43 |
| Foreign direct investment | 2110 | 2.607 | 0.0511 | 0.523 | 11.94 | 7.413 |
| Energy consumption | 1862 | 2648 | 650.4 | 1615 | 8512 | 2944 |
| Population | 2214 | 16.31 | 15.24 | 16.17 | 18.89 | 1.629 |
| Population growth | 2214 | 1.322 | 0.414 | 1.159 | 3.634 | 1.398 |
| Forest area | 2091 | 30.67 | 11.03 | 31.13 | 68.41 | 21.89 |

Table 3 Correlation matrix

| Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|-------|-------|-------|-------|-------|-------|-------|-------|-------|------|
| Control of corruption | 1 | | | | | | | | | |
| BayeCorruption percep- sian corruption | 0.98 | 1 | | | | | | | | |
| Economic development | -0.71 | -0.74 | -0.77 | 1 | | | | | | |
| Economic growth | 0.24 | 0.29 | 0.18 | -0.3 | 1 | | | | | |
| Trade openness | -0.28 | -0.29 | -0.31 | 0.29 | 0.02 | 1 | | | | |
| Foreign direct investment | -0.35 | -0.38 | -0.33 | 0.34 | -0.04 | 0.39 | 1 | | | |
| Energy consumption | -0.56 | -0.61 | -0.6 | 0.68 | -0.1 | 0.17 | 0.21 | 1 | | |
| Population | 0.26 | 0.33 | 0.27 | -0.27 | 0.1 | -0.44 | -0.18 | -0.31 | 1 | |
| Population growth | 0.2 | 0.2 | 0.1 | -0.19 | 0.16 | -0.02 | -0.04 | 0.13 | 0 | 1 |
| Forest area | -0.01 | -0.03 | 0.08 | -0.01 | -0.06 | -0.04 | -0.1 | -0.11 | -0.05 | -0.2 |

4.1 Descriptive statistics and correlation

The descriptive statistics of the variables are displayed in Table 2. The statistics include the mean, 25th percentile, median, 95th percentile, and standard deviation. The mean of green growth is 5.901, with a median of 4.963 and 95th percentile of 13.26, indicating large variations in growth among the sample countries. We can also observe a similar trend among the three measurements of corruption. The mean of all the corruption indicators is around the average score of their respective measurement scale, suggesting that corruption is widespread globally, and all three sources capture similar corruption levels. However,

Table 4 Main results

| Variables | (1) Control of corruption | (2) Corruption perception index | (3) Bayesian corruption index |
|-------------------------------------|------------------------------|------------------------------------|----------------------------------|
| Control of corruption | -0.878*** (0.115) | | |
| Corruption perception | | -0.0868*** (0.00638) | |
| Bayesian corruption index | | | -0.0455*** (0.00664) |
| Economic development | -0.635*** (0.0945) | 0.00619 (0.109) | -0.520*** (0.0888) |
| Economic growth | -0.00213 (0.0200) | 0.0105 (0.0225) | -0.00894 (0.0201) |
| Trade openness | -0.00594*** (0.00164) | -0.00901*** (0.00180) | -0.00674*** (0.00165) |
| Foreign direct investment | 0.0292*** (0.0105) | 0.0289** (0.0123) | 0.0333*** (0.0105) |
| Energy consumption | -0.000401*** (3.49e-05) | -0.000316*** (4.83e-05) | -0.000413*** (3.51e-05) |
| Population | -0.182*** (0.0503) | -0.490*** (0.0577) | -0.193*** (0.0504) |
| Population growth | 0.829*** (0.0523) | 1.330*** (0.0757) | 0.783*** (0.0522) |
| Forest area | 0.0530*** (0.00332) | 0.0369*** (0.00405) | 0.0555*** (0.00335) |
| Intercept | 15.15*** (1.303) | 13.19*** (1.486) | 14.43*** (1.297) |
| Year effect | Yes | Yes | Yes |
| Country effect | Yes | Yes | Yes |
| Economic significance of corruption | -15.47 | -33.50 | 12.78 |
| Observations | 1767 | 1210 | 1767 |
| R-squared | 0.325 | 0.322 | 0.321 |

Standard errors in parentheses

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

the large standard deviation and high value of the 95th percentile highlight the different levels of corruption across the sample countries. To mitigate the effect of outliers, all variables are winsorized in the 1st and 99th percentile.

The Pearson pairwise correlation matrix is presented in Table 3. Except for correlation among the three corruption indicators, none of the coefficients is higher than the threshold to possess any multicollinearity issue (Field, 2000; Tabachnick & Fidell, 2007). To further

check the appropriateness of the variables against multicollinearity, we performed the Variance Inflation Factor analysis (VIF), and the un-tabulated results show that none of the variables has high VIF to indicate any threat of multicollinearity.

4.2 Main results

The results of the OLS estimations are presented in Table 4. The coefficient of corruption is negative and highly significant at 1% in all the columns (-0.878^{***} , -0.0868^{***} , -0.0455^{***}), indicating a negative relationship between corruption and green growth. The results imply that green growth decreases as corruption increases. Thus, countries with high corruption are more likely to have low efficiency in utilising natural capital and assets for economic development. Corruption, which is the abuse of power for private gain, is likely to lead to wasteful use of natural assets because corrupt people are less likely to think of the next generation and concentrate on what they get now. Also, corruption leads to weak environmental regulations to address the inefficient use of natural assets and capital. Even countries with good environmental regulation may not realise green growth when corruption is high because corrupt officials can take bribes for users to bypass the law. This is particularly true in the case of natural assets and capital, where the immediate effect of any corrupt practices is less obvious in the short term. Another channel through which corruption affects green growth is the negative influence of corruption on government attitude towards the environment. Corruptibility is likely to force the government to focus on addressing society's concern on the economic consequence of corruption, which is mostly short term than the long-term effect on sustainable economic growth. The results are consistent with prior studies on the negative consequence of corruption on the environment (Burritt et al., 2009; Geng et al., 2010).

The results of the economic significance are presented as an additional line in Table 4. Our results are not only statistically significant but also economically significant in explaining the relationship between corruption and green growth. For example, in column 1, a 1% increase in corruption (control of corruption), given its standard deviation, leads to a 15.47% decrease in green growth. This is equivalent to about 0.912 US dollars per kilogram decrease in green growth. Similarly, given its standard deviation, a 1% increase in the Bayesian corruption index (column 3) leads to a 12.78% (about 0.754 US dollars per kilogram) decrease in green growth. These are significant figures given that the average green growth is 5.90.

The results of most of the control variables came out as expected by standard assumption. For example, *Trade openness* is negative and significant, leaning support to the pollution haven hypothesis, whereas the positive results of *Foreign direct investment* lean support to the pollution halo hypothesis. We find *Energy consumption* and *Population* to decrease green growth, but *Forest area* increases green growth.

4.3 Sensitivity analyses

4.3.1 Developed and developing countries

One advantage of using a large sample size is the ability to employ a sub-sampling technique in testing whether the results are sensitive to a particular group of countries. Given

Table 5 Sensitive to country classification

| Variables | Developed countries | | | Developing | | |
|--|----------------------------|----------------------------|---------------------------|---------------------------|-------------------------|---------------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Control of corruption | Corruption perception | Bayesian corruption | Control of corruption | Corruption perception | Bayesian corruption |
| (A) <i>Developed versus developing countries</i> | | | | | | |
| Control of corruption | -0.255** (0.129) | -0.0227*** (0.00670) | | -0.523*** (0.199) | -0.0252** (0.0103) | |
| Corruption perception | | | | | | |
| Bayesian corruption index | | | -0.0150** (0.00740) | | | -0.0336*** (0.0116) |
| Economic development | 2.100*** (0.181) | 2.162*** (0.188) | 2.073*** (0.182) | -1.094*** (0.131) | -0.383*** (0.134) | -1.060*** (0.124) |
| Economic growth | 0.0460* (0.0242) | 0.0428 (0.0279) | 0.0443* (0.0243) | -0.000902 (0.0283) | 0.0676** (0.0271) | -0.00592 (0.0284) |
| Trade openness | 0.00574*** (0.00145) | 0.00930*** (0.00166) | 0.00579*** (0.00145) | -0.0159*** (0.00273) | -0.0258*** (0.00306) | -0.0172*** (0.00276) |
| Foreign direct investment | -0.0231*** (0.00805) | -0.00584 (0.00968) | -0.0230*** (0.00804) | 0.0327 (0.0207) | -0.0259 (0.0225) | 0.0359* (0.0206) |
| Energy consumption | -0.000463*** (3.97e-05) | -0.000851*** (5.92e-05) | -0.00046*** (3.97e-05) | -0.00029*** (5.41e-05) | 8.50e-05 (6.33e-05) | -0.00022*** (5.47e-05) |
| Population | -0.0839 (0.0609) | 0.0890 (0.0723) | -0.0789 (0.0612) | -0.327*** (0.0753) | -0.812*** (0.0742) | -0.337*** (0.0745) |
| Population growth | 0.0460 (0.0804) | -0.127 (0.118) | 0.0354 (0.0785) | 0.872*** (0.0767) | 1.384*** (0.0922) | 0.848*** (0.0761) |
| Forest area | 0.0110** (0.00447) | 0.0226*** (0.00488) | 0.0109** (0.00446) | 0.0726*** (0.00474) | 0.0610*** (0.00545) | 0.0749*** (0.00489) |

Table 5 (continued)

| Variables | Developed countries | | | Developing | | |
|----------------------------------|---------------------------|----------------------------|----------------------------|----------------------------|---------------------|---------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Control of corruption | -14.02*** (2.009) | -16.07*** (2.146) | -13.70*** (2.034) | 20.13*** (1.849) | 19.33*** (1.906) | 20.42*** (1.859) |
| Year effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Country effect | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 521 | 459 | 521 | 1246 | 751 | 1246 |
| R-squared | 0.468 | 0.513 | 0.468 | 0.361 | 0.465 | 0.361 |
| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
| | Africa | Americas | Asia | | | Europe |
| <i>(B) Geographical clusters</i> | | | | | | |
| Corruption | -0.135*** (0.0331) | -0.0158*** (0.00160) | -0.0390*** (0.0121) | -0.0428*** (0.00708) | | |
| Economic development | -0.843*** (0.331) | 0.331*** (0.0247) | -1.030*** (0.164) | 0.699*** (0.110) | | |
| Economic growth | 0.0132 (0.0594) | 0.0795** (0.0379) | -0.00556 (0.0306) | 0.00555 (0.0186) | | |
| Trade openness | -0.0115 (0.0104) | 0.00426 (0.00464) | -0.00223 (0.00226) | -0.0114*** (0.00168) | | |
| Foreign direct investment | -0.0872 (0.0940) | -0.256** (0.106) | 0.190*** (0.0487) | -0.00939*** (0.00261) | | |
| Energy consumption | -0.00193*** (0.000515) | -0.000423*** (6.24e-05) | -0.000169*** (5.08e-05) | -0.000319*** (3.79e-05) | | |
| Population | 1.185*** | 0.00326 | -0.433*** | -0.473*** | | |

Table 5 (continued)

| Variables | (1) | (2) | (3) | (4) |
|---|--------------------------------|--------------------------------|--------------------------------|----------------------------------|
| | Africa | Americas | Asia | Europe |
| Population growth | (0.256) 1.974*** (0.338) | (0.103) 0.827*** (0.216) | (0.0846) 0.0727 (0.0583) | (0.0667) 0.220*** (0.0654) |
| Forest area | 0.132*** (0.0117) | 0.00156 (0.00775) | 0.0335*** (0.00538) | 0.00551 (0.00439) |
| Intercept | 3.053*** (1.978) | 2.609*** (0.637) | 21.83*** (2.471) | 9.532*** (1.477) |
| Year effect | Yes | Yes | Yes | Yes |
| Country effect | Yes | Yes | Yes | Yes |
| Observations | 362 | 346 | 429 | 630 |
| R-squared | 0.564 | 0.295 | 0.316 | 0.355 |
| Variables | (1) | (2) | (3) | (3) |
| | Intitutional quality | High quality | High quality | Low quality |
| <i>(C) Accounting for institutional quality</i> | | | | |
| Corruption | -0.0548*** (0.00760) | -0.0346*** (0.00697) | -0.0346*** (0.00697) | -0.0401*** (0.0146) |
| Institutional quality | -0.0169 (0.0346) | | | |
| Economic development | -0.835*** (0.0988) | 0.448*** (0.110) | | -1.678*** (0.176) |
| Economic growth | -0.0346* (0.0208) | 0.0104 (0.0187) | | 0.0283 (0.0363) |
| Trade openness | -0.00367** | -0.00827*** | | -0.00656** |

Table 5 (continued)

| Variables | (1) | (2) | (3) |
|---------------------------|---|---|--|
| | Intuituional quality | High quality | Low quality |
| Foreign direct investment | (0.00173) 0.00458 | (0.00171) -0.00913*** | (0.00317) 0.102* |
| Energy consumption | (0.00463) -0.000341*** (3.90e-05) | (0.00317) -0.000415*** (3.44e-05) | (0.0591) -0.000212*** (7.34e-05) |
| Population | -0.128** (0.0573) | -0.305*** (0.0594) | -0.380*** (0.101) |
| Population growth | 0.607*** (0.0498) | 0.505*** (0.0678) | 0.650*** (0.0898) |
| Forest area | 0.0607*** (0.00383) | 0.0139*** (0.00400) | 0.0871*** (0.00591) |
| Intercept | 16.37*** (1.457) | 8.787*** (1.332) | 24.87*** (2.670) |
| Year effect | Yes | Yes | Yes |
| Country effect | Yes | Yes | Yes |
| Observations | 1767 | 796 | 791 |
| R-squared | 0.284 | 0.217 | 0.459 |

Standard errors in parentheses

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

that both our dependent and independent variable varies significantly between developed and developing countries, we re-run the model separately on developed and developing countries. We focus on developed and developing countries because both groups appear to be at extreme ends of the dependent and independent variables. For example, corruption is everywhere but is more pervasive in developing countries than in developed countries (Hellman & Schankerman, 2000). Although developed countries are the major contributors to climate change, they are improving in green growth faster than in developing countries. Indeed, while most developed countries are experiencing an increase in green growth, developing countries are on a decreasing trend (OECD, 2020). Given these contrasting differences and the fact that 89 out of the 123 countries are developing countries, our baseline results could be biased by the dominating characteristics of developing countries. Therefore, we provide separate regression estimations for developed and developing countries. The results are presented in Table 5. The results of developed countries are presented in columns 1 to 3, while the results of developing countries are displayed in columns 4 to 6. The coefficient of all different measurements of corruption is negative and highly significant at 5% or less for both developed and developing countries. Therefore, our baseline finding of the negative association between corruption and green growth still holds and is not sensitive to countries been classified as developed and developing. However, the coefficient of corruption in developing countries appears to be relatively larger than in developed countries. The results highlight that, although corruption negatively affects green growth, the impact is much stronger in developing countries than in developed countries.

4.3.2 Grouping countries by geographical location

Although large samples offer numerous advantages, it is not without challenges such as geographical heterogeneity, which may bias the results. To overcome this challenge, we employ sub-sampling techniques to run additional analyses based on the geographical location of the sample countries. We sub-sample the countries into 4 clusters; Africa, Americas, Asia and Europe. The results are presented in Table 5B. The results remain consistent with the main findings that corruption is negatively associated with green growth. Thus, regardless of the geographical location of the country, corruption decreases green growth.

4.3.3 Accounting for institutional quality

In our third and final sensitivity analyses, we investigate whether the country's institutional quality matters in the relationship between corruption and green growth. Following prior studies (Tawiah, 2021; Tawiah et al., 2021; Tunyi et al., 2020), we construct the institutional quality variable from the World Governance Indicators by Kaufmann and Kraay (2018). We take the average of the five governance indicators (excluding corruption because it is the main variable in our analyses). We use two different identification approaches to account for the effect of institutional quality on our results. First, we include institutional quality as a control variable, and the results are presented in column 1 of Table 5C. In the second approach, we group the countries into high and low-quality countries based on the median institutional quality value of the total sample. The results

Table 6 The effect of natural resources

| Variables | (1) Control of corruption | (2) Corruption perception | (3) Bayesian corruption |
|-----------------------------|------------------------------|------------------------------|----------------------------|
| Control of corruption | -1.030*** (0.127) | | |
| CCP*Natural resources | 0.0539*** (0.00740) | | |
| Corruption perception index | | -0.0250*** (0.00721) | |
| CPI*Natural resources | | 0.00332*** (0.000659) | |
| Bayesian corruption index | | | -0.0557*** (0.00701) |
| BCI*Natural resources | | | 0.00281*** (0.000384) |
| Natural resources | -0.172*** (0.0236) | -0.218*** (0.0479) | -0.160*** (0.0206) |
| Economic development | -0.624*** (0.0952) | -0.0382 (0.108) | -0.506*** (0.0876) |
| Economic growth | 0.00851 (0.0199) | 0.00718 (0.0228) | 0.00295 (0.0199) |
| Trade openness | -0.00719*** (0.00163) | -0.00971*** (0.00180) | -0.00737*** (0.00163) |
| Foreign direct investment | 0.0156 (0.0105) | 0.0192 (0.0124) | 0.0187* (0.0105) |
| Energy consumption | -0.000330*** (3.59e-05) | -0.000351*** (4.85e-05) | -0.000343*** (3.58e-05) |
| Population | -0.217*** (0.0498) | -0.488*** (0.0571) | -0.209*** (0.0496) |
| Population growth | 0.919*** (0.0574) | 1.277*** (0.0802) | 0.903*** (0.0575) |
| Forest area | 0.0486*** (0.00332) | 0.0354*** (0.00402) | 0.0501*** (0.00337) |
| Intercept | 16.04*** (1.316) | 14.66*** (1.501) | 15.04*** (1.285) |
| Year effect | Yes | Yes | Yes |
| Country effect | Yes | Yes | Yes |
| Observations | 1767 | 1210 | 1767 |
| R-squared | 0.346 | 0.337 | 0.343 |

Standard errors in parentheses

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

of the high and low-quality sub-sample are presented in columns 2 and 3, respectively, of Table 5C. Corruption remains negative and highly significant in all three columns,

indicating that our main finding of the negative relationship between corruption and green growth is robust.

4.4 The effect of natural resources

Our dependent variable, green growth, is defined by the efficient use of natural assets and capital in production and consumption. According to the OECD database, the index captures environmental and resources productivity, natural assets base, the environmental dimension of quality of life, economic opportunities and policy responses, and socio-economic context of environmental sustainability). Natural resources appear to form a significant part of a country's natural assets and capital. However, not every country has the same level of natural resources. Some countries such as Australia, Canada, Russia, and Saudi Arabia are considered natural resource-rich countries, while countries like Germany, and Singapore have little or no natural resources. Having a natural resource can either be beneficial or detrimental to green growth. Natural resource generates a considerable amount of income that a country can use to finance modern technologies such as renewable energy sources. Also, the endowment of natural resources indicates that the country has a large natural asset base. On the other hand, the rapid extraction of natural resources leads to the depletion of that resources and can destroy other natural assets and habitats like forest areas.

Therefore, we expect the moderating effect of natural resources to go either way. To empirically test the effect of natural resources on the baseline results, we generate a two-way interaction term between natural resources rent and each of the corruption indicators. If our expectation that natural resources change the relationship between green growth and corruption, then the interaction term should be significant and larger or in the opposite direction to the main corruption in the same model.

The results are presented in Table 6. The coefficient of the moderating term under the three different corruption indicators is negative and significant ($CCP * \text{Natural resources} = -0.0539^{***}$; $CPI * \text{Natural resources} = -0.00332^{***}$; $BCI * \text{Natural resources} = -0.00281^{***}$). Similarly, the coefficient of the main corruption variable remains negative and significant but larger than the moderating term. The results, therefore, suggest that the existence of natural resources does not significantly change the relationship between corruption and green growth. This is also evident by the negative coefficient of *Natural resources*.

4.5 Endogeneity check

As stated earlier, there is less likelihood of reverse causality between the dependent and independent variables. However, as in any kind of growth, the previous year's growth is more likely to influence the current year growth. For example, a country will like to achieve consistent growth over many years; hence prior year will determine how it works towards current year growth in order to maintain consistency. Therefore, to allay any concern of potential endogeneity due to the prior year's performance, we include a one-year lag of the dependent variable (green growth) in the model as a control variable. The results are presented in columns 1–3 of Table 7. The coefficient of corruption in all three different measurement remains negative and highly significant at 5%. Also, as expected, the lagged of green growth is positive and highly significant at 1%. The results in columns 1–3,

Table 7 (A) Endogeneity check—lagged dependent and S-GMM, (B) two-stage least squares

| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---------------------------|---------------------------|--------------------------|----------------------------|----------------------------|----------------------------|----------------------------|
| | Control of corruption | Corruption perception | Bayesian corruption | Control of corruption | Corruption perception | Bayesian corruption |
| (A) | | | | | | |
| Control of corruption | -0.0610** (0.0241) | | | -0.302*** (0.0272) | | |
| Corruption perception | | -0.00259** (0.00129) | | | -0.00331** (0.00131) | |
| Bayesian corruption | | | -0.00316** (0.00138) | | | -0.0157*** (0.00149) |
| Lagged Green growth | 0.978*** (0.00491) | 0.985*** (0.00581) | 0.978*** (0.00489) | 0.700*** (0.0178) | 0.822*** (0.0184) | 0.701*** (0.0178) |
| Economic development | 0.0257 (0.0201) | 0.0401* (0.0224) | 0.0338* (0.0187) | -0.163*** (0.0224) | 0.0365 (0.0225) | -0.123*** (0.0203) |
| Economic growth | 0.0187*** (0.00410) | 0.0181*** (0.00448) | 0.0183*** (0.00410) | 0.0256*** (0.00432) | 0.0249*** (0.00493) | 0.0238*** (0.00430) |
| Trade openness | -0.000211 (0.000338) | -3.47e-05 (0.000365) | -0.000264 (0.000340) | -0.00176*** (0.000335) | -0.00147*** (0.000395) | -0.00201*** (0.000339) |
| Foreign direct investment | 0.00260 (0.00213) | 0.00313 (0.00246) | 0.00285 (0.00212) | 0.00703*** (0.00237) | 0.00471* (0.00284) | 0.00801*** (0.00236) |
| Energy consumption | -1.87e-05** (7.40e-06) | -1.65e-05* (9.75e-06) | -1.94e-05*** (7.44e-06) | -0.000123*** (9.40e-06) | -6.64e-05*** (1.08e-05) | -0.000127*** (9.58e-06) |
| Population | -0.00569 (0.0104) | -0.00895 (0.0119) | -0.00647 (0.0104) | -0.0547*** (0.01000) | -0.0887*** (0.0143) | -0.0588*** (0.0100) |
| Population growth | -0.0285** (0.0115) | -0.0176 (0.0171) | -0.0320*** (0.0114) | 0.179*** (0.0173) | 0.189*** (0.0283) | 0.164*** (0.0167) |
| Forest area | -0.000979 (0.000733) | -0.000866 (0.000842) | -0.000831 (0.000742) | 0.0138*** (0.00114) | 0.00520*** (0.00104) | 0.0146*** (0.00118) |
| Intercept | 0.230 | 0.0395 | 0.176 | 4.504*** | 2.234*** | 4.239*** |

Table 7 (continued)

| Variables | First stage | | | Second stage | | |
|---------------------------|-----------------------|-----------------------|----------------------|----------------------------|----------------------------|----------------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Control of corruption | Corruption perception | Bayesian corruption | Control of corruption | Corruption perception | Bayesian corruption |
| Observations | (0.282) | (0.314) | (0.278) | (0.373) | (0.391) | (0.361) |
| R-squared | 1656 | 1133 | 1656 | 1656 | 1133 | 1656 |
| | 0.973 | 0.974 | 0.973 | 122 | 81 | 122 |
| | Second stage | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Control of corruption | Corruption perception | Bayesian corruption | Control of corruption | Corruption perception | Bayesian corruption |
| (B) Corruption | 0.113*** (0.014) | 0.221*** (0.06) | 0.157*** (0.0043) | -0.415*** (0.147) | -0.132*** (0.00794) | -0.0281*** (0.0106) |
| Religion | 0.024*** (0.004) | 0.058*** (0.006) | 0.020*** (0.0018) | | | |
| Legal origin | -0.015 (0.112) | -0.740** (0.360) | -0.335 (0.96) | -0.321*** (0.116) | 0.283*** (0.124) | -0.314*** (0.117) |
| Economic development | -0.006 (0.001) | 0.065 (0.060) | -0.818 (1.40) | -0.00987 (0.0220) | -0.0127 (0.0221) | -0.0118 (0.0221) |
| Economic growth | 0.001*** (0.001) | 0.029*** (0.005) | 0.012** (0.006) | -0.00889*** (0.00199) | -0.0170*** (0.00216) | -0.00915*** (0.00198) |
| Trade openness | -0.004 (0.003) | -0.073** (0.027) | -0.0004 (0.21) | 0.00229 (0.00407) | 0.0342*** (0.0103) | 0.00242 (0.00407) |
| Foreign direct investment | 0.000*** (0.000) | -0.001*** (0.000) | 0.001*** (4.32) | -0.000363*** (4.07e-05) | -0.000221*** (4.67e-05) | -0.000372*** (4.10e-05) |

Table 7 (continued)

| Variables | First stage | | | Second stage | | |
|-------------------|-----------------------|-----------------------|---------------------|------------------------|------------------------|------------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Control of corruption | Corruption perception | Bayesian corruption | Control of corruption | Corruption perception | Bayesian corruption |
| Population | -0.011** (0.004) | -3.365*** (0.169) | -0.032 (0.22) | -0.228*** (0.0580) | -0.549*** (0.0630) | -0.226*** (0.0583) |
| Population growth | -0.059*** (0.005) | -3.365*** (0.232) | -1.50*** (8.35) | 0.676*** (0.0594) | 1.173*** (0.0795) | 0.658*** (0.0594) |
| Forest area | 0.001*** (0.000) | 0.022* (0.011) | 0.074*** (0.008) | 0.0381*** (0.00387) | 0.0225*** (0.00419) | 0.0397*** (0.00393) |
| Intercept | 2.889 (0.109) | 6.903*** (2.367) | 13.49*** (1.562) | 13.03*** (1.494) | 11.67*** (1.588) | 13.27*** (1.583) |
| Observations | 1352 | 994 | 1352 | 1352 | 994 | 1352 |
| R-squared | 0.946 | 0.917 | 0.798 | 0.246 | 0.267 | 0.245 |

Standard errors in parentheses

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

therefore, suggest that our findings of corruption negatively impacting green growth are robust after accounting for the effect of previous green growth on the current year.

Next, to further check the robustness of our model to potential endogeneity, we use the System-Generalised Method of Moments, which controls for the simultaneity of the explanatory variables. Following (Cuadrado-Ballesteros et al., 2019), we use the one-year lag values of corruption and the predetermined variables as the instrumental variables in the S-GMM model. The results are presented in columns 4–6 of Table 7A. Similar to that of the lagged variable model, the coefficient of corruption is negative and significant at 5% or less, suggesting that corruption impair green growth.

In the third and final robustness check for endogeneity, we employ the Two-Stage Least Squares instrumental variable identification strategy to deal with missing institutional characteristics of a country (Shao et al., 2013). Consistent with prior studies, we instrument the potential endogeneity variable (corruption) with historical institutions such as religion and legal origin (La Porta et al., 2008; Treisman, 2007). The results are presented in Table 7B. The first 3 columns contain the results of the first stage estimation, and the second stage is presented in columns 4–6. The coefficient of corruption remains negative and highly significant at 1% in all cases, indicating that our main results are not sensitive to potential endogeneity problems.

Putting all together, the results in Table 7A, B confirm our baseline finding that corruption is negatively and significantly associated with a decrease in green growth.

5 Policy and managerial implications

In sum, our results imply that corruption is impairing global efforts towards achieving sustainable development and fighting against climate change. More importantly, most countries are less like to meet the Agenda 2030 deadline of the Sustainable Development Goals due to the widespread corruption, especially in developing countries. Therefore, controlling corruption is essential, not only to mitigate its negative impact on economic growth but to facilitate sustainable development and a better environment for current and future generations. First, developing countries should strengthen citizens demand for anti-corruption and empower them to hold the government accountable. This can be achieved through the development of community monitoring initiatives. Second, development of minimum standards and guidelines for ethical procurement and build procurement practice via training, monitoring and research. Third, the countries should ratify various treaties on prevention and combating corruption to have a shared roadmap of implementing governance and anti-corruption policies. Forth, the government of these countries should create and enforce laws that address the proceeds of corruption, crime and money laundering.

For developed countries, there is a need to step up existing measures to control corruption. First, one of the strong causes of corruption in developed countries is impunity. Hence, an end to impunity is necessary, and this can be achieved through effective law enforcement to ensure that the corrupt persons are punished and break the cycle of impunity. A strong legal framework, law enforcement branches and an independent court system will help law enforcement. Second, a reform of public administration and finance management such as disclosure of budget information, which prevents waste and misappropriation of resources, will help curb corruption and promote green economic development. Third, countries should imbibe the tradition of government openness, press freedom, transparency and access to information. Through access to information, the government can increase the

responsiveness of its bodies and increase public participation in government, which will help curb corruption and improve green economic development.

6 Conclusion

This paper has used a more recent environmental performance indicator to establish how corruption affects environmental sustainability, an issue that threatens humans' survival. Although there is a considerable amount of literature on the topic, they are mostly limited to the effect of corruption on pollution-related issues, which is just one side measurement of environmental performance. We argue that emission is near-inevitable as long as human breath and needs economic resources to survive, hence relevance should be given to the amount of emission generated in relation to an achieved economic development and economic growth. Focusing on only emissions makes most African countries appear environmentally responsible and countries like Australia and Canada less responsible. Nevertheless, in reality, most African countries use more natural assets and capital to generate less development, whereas Australia and Canada generate high development and economic growth with less natural assets and capital, which makes them more environmentally sustainable in the long run.

Following these arguments, we use large panel data on 123 countries over 18 years to examine the relationship between corruption and green growth, a more robust and long-term view of environmental performance. Consistent with expectation, we find that corruption is negative and significantly associated with green growth. The results imply that corruption retards the efficient use of natural assets in production and consumption. The results are robust to different sources and measurements of corruption, suggesting that the nature of the corruption indicator does not drive our findings. To allay concerns that our results may be influenced by the dominance of developing countries in the sample, we conduct further analysis using the sub-sampling technique between developed and developing countries. The results show that no country is immune to the negative effect of corruption on green growth regardless of being a developed or developing country. However, the effect is more pronounced in developing, which explains why environmental sustainability is low in developing countries even though emission is low. To further check the robustness of the findings and mitigate any potential endogeneity problems, we conduct additional analyses using two robust identification strategies, including the lagged of dependent variable and S-GMM. The results from both estimation techniques are not qualitatively different from the main findings that corruption is detrimental to green growth.

Our study makes an incremental contribution by extending the corruption-environmental quality nexus by considering how corruption interacts with long-run environmentally and economically sustainable growth. Our measure of environmental performance, green growth, is notably different from commonly used pollution-based measurements in prior studies. Future studies can examine other institutional factors such as quality of regulations, political stability, political ideology, and ethical framework on green growth.

Appendix

See Table 8.

Table 8 List of countries

| | | | | | |
|------------------------|-----------------|-------------------|-----------------|--------------------|----------------------|
| Albania | Canada | Georgia | Kuwait | Nigeria | Spain |
| Algeria | Chile | Germany | Kyrgyz Republic | Norway | Sri Lanka |
| Angola | China | Ghana | Latvia | Oman | Suriname |
| Argentina | Colombia | Greece | Lebanon | Pakistan | Sweden |
| Armenia | Congo, Dem. Rep | Guatemala | Lithuania | Panama | Switzerland |
| Australia | Congo, Rep | Honduras | Luxembourg | Paraguay | Tanzania |
| Austria | Costa Rica | Hungary | Malaysia | Peru | Thailand |
| Azerbaijan | Cote d'Ivoire | Iceland | Malta | Philippines | Togo |
| Bahrain | Croatia | India | Mauritius | Poland | Trinidad and Tobago |
| Bangladesh | Cyprus | Indonesia | Mexico | Portugal | Tunisia |
| Belarus | Czech Republic | Iran, Islamic Rep | Moldova | Qatar | Ukraine |
| Belgium | Denmark | Iraq | Mongolia | Romania | United Arab Emirates |
| Benin | Dominica | Ireland | Morocco | Russian Federation | United Kingdom |
| Bolivia | Ecuador | Israel | Mozambique | Saudi Arabia | United States |
| Bosnia and Herzegovina | Egypt, Arab Rep | Italy | Myanmar | Senegal | Uruguay |
| Botswana | El Salvador | Jamaica | Namibia | Serbia | Uzbekistan |
| Brazil | Estonia | Japan | Netherlands | Singapore | Vietnam |
| Brunei Darussalam | Ethiopia | Jordan | New Zealand | Slovak Republic | Yemen, Rep |
| Bulgaria | Finland | Kazakhstan | Nicaragua | Slovenia | Zambia |
| Cambodia | France | Kenya | Niger | South Africa | Zimbabwe |
| Cameroon | Gabon | Korea, Rep | | | |

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