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# The Influence of Sustainable Socio-Economic Factors on Environmental Efficiency: An International Analysis During Turbulent Periods

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**ABSTRACT**

This research examines the impact of formal institutions, the human development index (HDI), technological progress, and trade openness on the environmental performance of various countries. The study applies a Bayesian data envelopment analysis (DEA) approach to measure environmental performance, offering consistent estimates while addressing issues of sampling bias and dimensionality, particularly given the limited sample of 56 countries (31 developed and 25 developing). The analysis employs a two-step generalized method of moments (GMM) to evaluate the influence of these factors over two periods: 2011-2019 (a period free from major global crises) and 2011-2020 (which includes the COVID-19 pandemic). The findings reveal that key drivers of environmental performance include prior environmental outcomes, country classification (developed vs. developing), corruption control in developing nations, and the HDI, which plays a more significant role during global crises, especially for developing countries.

**Keywords:** Environmental Efficiency, Corruption, Human Development Index, Data Envelopment Analysis, Bayesian Methods
**JEL Classifications:** D73, O15, Q51, Q55, Q56, Q58, R11

## 1. INTRODUCTION

The effects of climate change have led to growing concerns among governments, businesses, and academia (Rao and Riahi, 2006; Capasso et al., 2020). The environmental degradation we face has evolved into a critical issue impacting both humanity and natural ecosystems (Dogan et al., 2020). Among the adverse effects of climate change, global warming is a major focus of international environmentalists, as it brings about rising temperatures, melting glaciers, rising sea levels, and extreme weather fluctuations (Destek and Sarkodie, 2019). Addressing these issues requires stabilizing Earth's temperature, which hinges on reducing greenhouse gases (GHGs) (Tateishi et al., 2020). To avert further warming, decisive and swift actions are essential (IPCC, 2018). Globally, numerous initiatives and agreements, like the Paris Climate Agreement (COP-21) in 2015, have been introduced to combat environmental degradation by aiming to limit global warming to below 2°C (Schleussner et al., 2016). Suggested solutions include enhancing institutional quality (Khan et al., 2022), improving energy efficiency through renewable sources (Adua et al., 2021), and embracing innovative technologies (Churchill et al., 2021).

The role of institutional quality in environmental sustainability has drawn significant attention from researchers and policymakers (Salman et al., 2019; Alshehhi and Zervopoulos, 2023). According to North (1990), institutions are classified as either formal or informal, where formal institutions provide a structured set of guidelines and traditions for interaction, while informal ones consist of cultural practices passed down through tradition. Both types of institutions contribute to maintaining environmental standards (Rahman and Sultana, 2022). Formal institutions, in particular, set pollution-reduction benchmarks, thus crafting, enforcing, and monitoring relevant policies, they help reduce the environmental costs linked with economic activities (Salman et al., 2019).

Beyond institutional influence, trade significantly supports economic growth, yet its environmental effects are undeniable (Peiró-Palomino et al., 2022). Shahbaz et al. (2017) highlight that globalization has boosted economies, with both affluent and developing nations benefiting from trade openness through enhanced income and trade volume. This rise in global trade, however, promotes increased production and infrastructure expansion, thus escalating energy demands and $CO_2$ emissions. Trade openness also promotes renewable energy production by facilitating the spread of technology across borders (Zafar et al., 2019; Vural, 2021), though further analysis is required to fully understand its environmental impact (Shahbaz et al., 2017).

Energy plays a vital role in economic activities, yet reliance on fossil fuels poses environmental risks and drives a search for alternative sources (Vural, 2021). Governments are promoting renewable energy to curb emissions from economic growth (Rahman and Sultana, 2022). Nevertheless, according to REN21, renewable energy's share remains modest, accounting for just 11.2% of global final energy consumption in 2019. While this reflects an 8.7% increase over a decade, its growth remains gradual. As Rahman and Sultana (2022) note, fossil fuels remain appealing due to abundant reserves and substantial subsidies.

Contrastingly, Rogelj et al. (2013) argue that renewable energy production is key to achieving decarbonization since renewable sources are inexhaustible (Yurtkuran, 2021). Promoting renewables can thus be a crucial policy tool to shift production processes toward lower $CO_2$ emissions and better environmental outcomes (Wang et al., 2022).

Many authors underscore the role of technological innovation in expanding renewable energy adoption (Wang et al., 2022). Transitioning to alternative energy supports economic growth without harming the environment (Dauda et al., 2019), driven by technological advancements that reconcile economic growth with environmental protection (Metz et al., 2007; Hübler et al., 2012). Amid globalization, there is a shift from pure economic growth towards broader societal well-being (Sadiq et al., 2022). The Human Development Index (HDI), emphasizing human capabilities, is often used to gauge sustainable socio-economic development (Strezov et al., 2017). Sustainable development has evolved to integrate environmental conservation with economic growth for a prosperous future for people and the planet (Holden et al., 2017). Environmental degradation remains a critical threat, challenging governments to sustain growth that benefits citizens (Usman and Hammar, 2021).

The COVID-19 pandemic, beginning in 2019, profoundly affected economies worldwide (Malakar et al., 2023). In response, governments implemented lockdowns (Zhang et al., 2022), leading to economic standstills across sectors (Sun and Wang, 2021). This shifted focus from sustainable development to economic recovery (Hidalgo-Triana et al., 2023). However, while reduced human activity during lockdowns temporarily benefited the environment, increased disposable usage generated substantial waste, aggravating pollution (Khan et al., 2022).

This study is unique in examining institutional factors, country classification (developed or developing), HDI, renewable energy production, technological innovation, and trade openness on environmental performance. Prior studies typically analyzed these variables individually. Our findings highlight HDI's critical role, especially in mixed stability periods, including crises like COVID-19, and for developing nations. The Bayesian DEA model adopted in this study minimizes sampling biases, ensures reliable environmental performance estimates, and enhances model stability when applied to small samples (Alshehhi and Zervopoulos, 2023). Also, this approach enhances the quality of the findings while also facilitating the application of GMM by smoothing the typically multimodal distribution of DEA efficiencies. (Alshehhi and Zervopoulos, 2023).

The paper is organized as follows: Section 2 reviews the literature, Section 3 details the methodology (Bayesian DEA and GMM), Section 4 describes the data and variables, Section 5 presents empirical findings, and Section 6 concludes.

## 2. LITERATURE REVIEW

### 2.1. The Interplay Between Emissions, Economic Growth, and Institutional Factors

The Intergovernmental Panel on Climate Change (IPCC) has recommended reducing fossil fuel reliance to reach carbon neutrality (Khan et al., 2022). Tateishi et al. (2020) note that countries often experience conflicts due to differing priorities, objectives, knowledge bases, values, and capacities, which complicates international cooperation. They highlight that countries face the challenge of lowering $CO_2$ emissions while still pursuing economic benefits. The Environmental Kuznets Curve (EKC) illustrates an inverted U-shaped relationship between economic growth and pollution levels (Copeland and Taylor, 2004). Torras and Boyce (1998) emphasized that including institutional factors is essential for the EKC hypothesis, and many studies since then have examined the role of institutions in balancing economic growth with environmental protection (Egbetokun et al., 2020; Lægreid and Povitkina, 2018; Tamazian and Rao, 2010). These studies validate the EKC, showing that nations with robust institutions reach the pollution-reduction turning point earlier than those with weaker ones (Adams et al., 2016; Adams and Klobodu, 2017).

Research supports that developed countries with strong institutions are generally better at managing emissions (Cropper and Griffiths, 1994; Jones and Manuelli, 2001), while economic growth in developing countries with weaker institutions tends to directly correlate with higher pollution. Panayotou (1997) argued that even low-income nations can improve environmental management through quality institutions. Effective institutions help minimize the environmental impact of economic growth, thus supporting sustainable development. Torras and Boyce (1998) further found that civil liberties, political freedoms, and literacy significantly enhance environmental quality in low-income countries. Studies by Lau et al. (2014), Abid (2017), Bhattacharya et al. (2017), and Sarkodie and Adams (2018) affirm the crucial role of institutional quality in managing economic growth and reducing $CO_2$ emissions. Peiró-Palomino et al. (2022) highlighted the importance of political stability and the absence of violence for successful implementation of environmental policies. Méon and Sekkat (2008) and Yu et al. (2015) stress that economic growth benefits from institutional factors like voice, accountability, and the rule of law.

In contrast to earlier research, Alshehhi and Zervopoulos (2023) identified corruption control as the only institutional factor significantly influencing environmental performance in developing countries. This inverse relationship aligns with the "grease the wheel" theory proposed by Leff (1964). Due to strong interrelationships among institutional factors, it is challenging to analyze the impact of multiple factors simultaneously on environmental efficiency. The literature documents these high correlations (Aparicio et al., 2016; Nedić et al., 2020).

### 2.2. The Interplay Between Emissions, Economic Growth, and Energy

Environmental economics has widely examined the rise in environmental pollution, with various theories proposed, including the Environmental Kuznets Curve (EKC) (Yurtkuran, 2021). The EKC hypothesis suggests that industrial production leads to higher pollution and inefficient resource use during the initial stages of economic development. As nations focus on growth, they often overlook increasing greenhouse gas emissions and unsustainable resource use, particularly where environmental degradation awareness and mitigating technology are lacking.

Recent studies highlight the diverse effects of clean energy production on $CO_2$ emissions across different economies (Shahbaz et al., 2022). Most research indicates that renewable energy production generally reduces $CO_2$ emissions (Sugiawan and Managi, 2016; Gill et al., 2018; Sarkodie and Strezov, 2018; Sinha and Shahbaz, 2018; Chen et al., 2019). However, Al-Mulali et al. (2016) found that renewable energy production can sometimes increase environmental degradation. Similarly, Nguyen and Kakinaka (2019) observed that renewable energy use raises $CO_2$ emissions in low-income countries while reducing them in middle- and high-income nations. Despite these insights, studies on renewable energy production's impact on environmental performance remain relatively sparse (Yurtkuran, 2021).

Additionally, another branch of research within the emissions-growth-energy field explores how technological innovation influences energy efficiency (Herring and Roy, 2007; Jin et al., 2018; Pan et al., 2019; Chen et al., 2021). Findings suggest that technological advancements enhance energy efficiency. Many studies have narrowed their focus from the general effect of technological innovation on energy use to its specific impact on renewable energy adoption (Alvarez-Herranz et al., 2017; Li et al., 2020), as the world shifts from fossil fuels to carbon-neutral energy sources for sustainable economic growth (Solarin et al., 2022).

### 2.3. The Interplay Between Emissions, Economic Growth, and Trade

The link between environmental performance and trade openness has been widely debated for over a decade (Shahbaz et al., 2017). Central to this discussion is the positive relationship between trade openness and economic growth. The emergence of the Environmental Kuznets Curve (EKC) hypothesis in the early 1990s was a key development in understanding the trade-environment relationship.

In this context, Antweiler et al. (2001) identified three primary ways trade impacts the environment: scale, technique, and composition effects. The scale effect relates to rising pollution and resource depletion resulting from increased economic activities and consumption (Grossman and Krueger, 1994; Lopez, 1994). The technique effect suggests that as income and trade grow, improved technologies lead to cleaner production processes (Grossman and Krueger, 1996). Technological advances thus contribute to better environmental quality in economies undergoing transformation (Kozul-Wright and Fortunato, 2012). However, studies on developing countries show that when trade openness is a key driver of growth, emissions tend to rise alongside economic expansion (Lopez, 1994; Ozturk and Acaravci, 2010; Nasir and Rehman, 2011). Lastly, the composition effect highlights how a country's openness and economic structure shape its environmental impact. According to the EKC, the environmental impact of growth varies with income levels, meaning that trade openness affects the environment differently across income levels and industrial compositions. This literature on trade and environmental performance suggests the need for cross-country studies that account for income differences (Shahbaz et al., 2017).

## 3. METHODOLOGY

The methodology of this study is implemented in two stages. In the first stage, efficiency estimates are obtained using a novel Bayesian generalized directional distance function data envelopment analysis (DEA) approach. This method aims to mitigate bias in efficiency estimates, which can arise when the sample size is insufficient relative to the dimensions of the input-output space, as distorted efficiency estimates may lead to misleading conclusions. In the second stage, the efficiency estimates obtained from the first stage are used as the dependent variable, while institutional factors and their interaction effects serve as the explanatory variables in the regression model. To address potential endogeneity concerns, the two-step generalized method of moments (GMM) is applied to the linear dynamic panel data regression model. This program enables estimation and inference within the chosen panel.

### 3.1. Bayesian Data Envelopment Analysis (DEA): First Stage

In the first stage, we incorporate the generalized directional distance function (GDDF) into the Bayesian data envelopment analysis (DEA) model to achieve bias-corrected efficiency estimates. Given the small sample size—56 countries in total, with 31 developed and 25 developing—it is essential to apply a bias-correction method, as efficiency estimates in finite samples tend to show an upward bias (Banker, 1993; Simar, 2007; Zervopoulos et al., 2019). Research by Lozano and Gutiérrez (2011), Podinovski and Kuosmanen (2011), Mitropoulos et al. (2019), and Vlachos et al. (2024) supports that directional distance function DEA methods are best suited for analyses involving both desirable and undesirable outputs, as in this study. Zervopoulos et al. (2023) proposed a Bayesian DEA approach that produces consistent estimates with lower mean square error and mean absolute error compared to other bias-correction methods for efficiency analysis.

Drawing on the GDDF (Cheng and Zervopoulos, 2014), we obtain efficiencies $\theta \in (0,1]$ as follows:

$$\theta = \min \frac{1-\frac{1}{\kappa}\sum_{i=1}^{\kappa}\beta g_i / x_{io}}{1+\frac{1}{\pi+\rho}\left(\sum_{r=1}^{\pi}\beta g_r / y_{ro} + \sum_{\eta=1}^{\rho}\beta g_\eta / b_{\eta o}\right)}$$

$$s.t. \sum_{(j=1)}^{n} \lambda_j x_{ij} + \beta g_x \le x_{io} \quad i = 1,\ldots,\kappa$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - \beta g_y \ge y_{ro} \qquad r = 1,\ldots,\pi$$

$$\sum_{j=1}^{n} \lambda_j b_{\eta j} - \beta g_b = b_{\eta o} \qquad \eta = 1,\ldots,\rho$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{1}$$

$$\lambda \ge 0$$

$$g_x = 1,\ g_y = 1,\ g_b = -1$$

In this context, $g_x$, $g_y$, and $g_b$ represent the direction vectors for inputs, desirable outputs, and undesirable outputs, respectively, while $\lambda$ is the optimal intensity applied across these variable types. Additionally, $\beta_{gi}/x_{io}$ and $\beta_{g\eta}/b_{\eta o}$ indicate the proportional reduction in inputs and undesirable outputs, whereas $\beta_{gr}/y_{ro}$ represents the proportional increase in desirable outputs for the reference country, identified by the subscript $o$ in model (1).

In existing literature, the smoothed bootstrap method is the most commonly applied approach for correcting bias in DEA efficiency estimates (Simar and Wilson, 1998; 1999; 2000; Kneip et al., 2008, 2011; Simar et al., 2012). Other methods for statistical inference in efficiency estimation include the chance-constrained DEA (CCDEA) (Charnes and Cooper, 1963; Olesen and Petersen, 1995), stochastic nonparametric envelopment of data (StoNED) (Kuosmanen and Kortelainen, 2007; 2012), multi-parametric bias correction (MPBC) (Zervopoulos et al., 2019), empirical Bayesian DEA techniques (Tsionas, 2003; 2020; Tsionas and Mallick, 2019; Tsionas and Polemis, 2019), and an alternative theoretical Bayesian approach (Zervopoulos et al., 2023). Studies show that this theoretical Bayesian method provides consistent estimates with the lowest mean square errors (MSE) and mean absolute errors (MAE) among statistical inference techniques for DEA efficiencies (Zervopoulos et al., 2023).

The Bayesian DEA method used in this study, combined with the GDDF, relies on two distributional assumptions: a uniform likelihood and a beta prior. This prior is non-informative, as it does not depend on the actual DEA efficiency distribution or parameters (such as mean or standard deviation) and is unaffected by sample size.

In particular, we apply the maximum likelihood estimator for the parameter $\theta_L \in (0,1)$ where $\left\{\theta_j\right\}_{j=1}^{k} \in [\theta_L, 1)$ and $k \subset n$ represents a subset of the sample, excluding units with efficiency scores of one. This estimator is used to determine the expected value (2) and the unbiased estimator (3) for this parameter, as expressed below.

$$\hat{\theta}_L = \theta_L + \frac{1-\theta_L}{k+1} \tag{2}$$

And $$\tilde{\theta}_L = \frac{\hat{\theta}_L(k+1)-1}{k} \tag{3}$$

Based on the distributional assumptions of this Bayesian approach, the parameter $\theta_L$ follows a beta distribution. Therefore, the prior is defined as follows:

$$f_{\theta_L}\left(\theta_L | \gamma,\delta\right) = \frac{1}{B(\gamma,\delta)}\left(\theta_L\right)^{\gamma-1}\left(1-\theta_L\right)^{\delta-1}, \quad \theta_L \in (0,1) \tag{4}$$

Next, we establish the unbiased estimator $\tilde{\theta}_L$ (3) to match the expected value of the prior, given as $E\left\{\theta_L\right\} = \frac{\gamma}{\gamma+\delta}$, in order to determine the shape parameter $\delta$ (5):

$$\delta = \frac{\left(1-\tilde{\theta}_L\right)\gamma}{\tilde{\theta}_L} \tag{5}$$

The joint probability density function (PDF) of the vector $\Theta = \left\{\theta_j\right\}_{j=1}^{k}$ is as follows:

$$f_\Theta(\Theta) = \int_0^1 f\left(\Theta|\theta_L\right) f_{\theta_L}\left(\theta_L|\gamma,\delta\right) \mathrm{d}\theta_L = \frac{B(\gamma,\delta-k)}{B(\gamma,\delta)} \tag{6}$$

Where $\delta > k$ and

$$\gamma > k\frac{\tilde{\theta}_L}{1-\tilde{\theta}_L} \tag{7}$$

Based on (6), expression (8) shows the posterior beta distribution with shape parameters $\gamma$ and $\delta - k$.

$$f_{\theta_L|\Theta}(\Theta) = \frac{f_{\Theta|\theta_L}\left(\Theta|\theta_L\right) f_{\theta_L}\left(\theta_L|\gamma,\delta\right)}{f_\Theta(\Theta)}$$
$$= \frac{1}{B(\gamma,\delta-k)}\left(\theta_L\right)^{\gamma-1}\left(1-\theta_L\right)^{(\delta-k)-1} \tag{8}$$

The posterior beta distribution represents the overestimated efficiency values, whereas the prior reflects the bias-corrected efficiency values. The connection between these two distributions is as follows:

$$E_k\left\{\theta_L|\Theta\right\} > E_k\left\{\theta_L\right\} \quad \text{as} \quad \frac{\gamma}{\gamma+\delta-k} > \frac{\gamma}{\gamma+\delta} \tag{9}$$

Where $\delta$ > k (7) should apply to prevent problems with the posterior distribution $(E_k\left\{\theta_L\left|\Theta\right.\right\} \nrightarrow 0)$.

To adjust for efficiency bias, we use a distribution ratio (10) that yields a value <1, as shown below:

$$\varphi = \frac{\tilde{\theta}_L}{\hat{\theta}_L} < 1, \text{where MLE } \hat{\theta}_L = min\Theta \tag{10}$$

Using expressions (5), (7), and (10), we obtain (11) and (12)

$$\hat{\gamma} = k\tilde{\theta}_L / (1-\varphi) \tag{11}$$

and $$\hat{\delta} = (1-\tilde{\theta}_L)\hat{\gamma} / \tilde{\theta}_L \tag{12}$$

We use the MATLAB function *betarnd* to estimate (11) and (12).

Next, we apply the MATLAB function *normfit* $(\hat{\mu},\hat{\sigma})$ to fit the ratio of the beta distribution (prior/posterior) and derive the bias-corrected efficiencies $(\theta_j^c)$ as shown in expression (13).

$$\theta_j^c = \rho^{-1}\sum_{\tau=1}^{\rho}\hat{\theta}_{j\tau} \tag{13}$$

Where $\rho$ expresses Monte Carlo iterations ($\rho$ = 1,000) and MATLAB function *normrnd* $(\theta_j\hat{\mu},\theta_j\hat{\sigma})$ is used to generate the randomly sampled efficiencies $\hat{\theta}_{j\tau}$, with $\theta_j$ values derived from the GDDF DEA model (1).

### 3.2. GMM Estimates: Second Stage

Once the environmental efficiency estimates $(\theta_j^c)$ are derived from the first stage, we use panel linear dynamic regression models to assess the influence of institutional factors and other control variables on environmental efficiency. Specifically, we apply two-step and iterative Generalized Method of Moments (GMM), which addresses potential endogeneity and feedback effects among institutional variables, control variables, and environmental efficiency (Ahn and Schmidt, 1995). To enhance the validity of GMM results, we incorporate efficiency estimates from the Bayesian DEA method discussed earlier, which range between zero and one. Using these estimates in GMM mitigates feedback effects, as their distribution notably differs from traditional "biased" efficiencies, which tend to show bias in finite samples. Studies have shown that conventional and Bayesian DEA efficiencies align asymptotically, achieving unbiased estimates (Banker, 1993; Kneip et al., 2008; Zervopoulos et al., 2023), similar to standard economic indicators like GDP per capita. Research by Glaeser et al. (2004) and Aisen and Veiga (2013) highlights feedback effects between institutional factors and GDP per capita, while Stern (2004) and Apergis and Ozturk (2015) observe inverse causality between $CO_2$ emissions and GDP per capita.

Following the panel data models proposed by Bun and Sarafidis (2015) and Phillips and Han (2019), the general GMM model used in this study, incorporating all variables, is structured as follows:

$$\begin{aligned}\theta_{j,t}^c &= a\bar{\theta}_{j,(t-1,t-2)}^c + \beta_1 z_{1,j,t-1} + \beta_2 z_{1,j,t-2} + \beta_3 z_{2,j,t-1} + \beta_4 z_{2,j,t-2}\\ &+ \beta_5 z_{3,j,t-1} + \beta_6 z_{3,j,t-2} + \beta_7 z_{4,j,t-1} + \beta_8 z_{4,j,t-2} + \beta_9 z_{5,j,t-1}\\ &+ \beta_{10} z_{5,j,t-2} + \beta_{11} z_{6,j,t-1} + \beta_{12} z_{6,j,t-2} + \beta_{13} z_{7,j,t-1} + \beta_{14} z_{7,j,t-2}\\ &+ \beta_{15} z_{8,j,t-1} + \beta_{16} z_{8,j,t-2} + \beta_{17} z_{9,j,t-1} + \beta_{18} z_{9,j,t-2} + \beta_{19} z_{10,j,t-1}\\ &+ \beta_{20} z_{10,j,t-2} + \beta_{21} z_{11,j,t-1} + \beta_{22} z_{11,j,t-2} + \tau I_{j,t} + \varphi_{p+1} d_{p+1}\\ &+ \ldots + \varphi_T d_T + \eta_j + \varepsilon_{j,t},\\ j &= 1,\ldots,n;\ t = p+1,\ldots,T;\ p = 1, 2\end{aligned} \tag{14}$$

Where the symbols of the model (14) express the variables illustrated in Table 1.

In the models presented in Table 2 of Section 5 (empirical analysis), all variable combinations, as well as interaction effects between the $z_v$ ($v$ = 1,…,11) and the country classification dummy variable ($I$), were considered. The selected models (i.e., Model 1-Model 6) shown in Table 2 meet the requirements for specification, overidentification, and linearity tests, including the Arellano and Bond test, Hansen *J*-test, and Wald test.

## 4. DATA SET AND SOURCES

This study investigates the influence of institutional quality, renewable energy generation, technological innovation, human

**Table 1: Symbols and analysis**

| Symbols | Analysis |
|---|---|
| $\theta_{j,t}^c$ | Environmental efficiency estimates obtained from model (13) for the sample countries ($j$) and time ($t$) of the review period ($t$ = p + 1,…,$T$; $p$ = 1,2) |
| $\bar{\theta}_{j,(t-1,t-2)}^c$ | Lagged ($t$–1, $t$–2) environmental efficiency estimate expressed at the aggregate level. |
| $Z_1$ | Government effectiveness (institutional factor; range: [−2.5 (weak), 2.5 (strong)]) |
| $Z_2$ | Control of corruption (institutional factor; range: [−2.5 (weak), 2.5 (strong)]) |
| $Z_3$ | Political stability (institutional factor; range: [−2.5 (weak), 2.5 (strong)]) |
| $Z_4$ | Regulatory quality (institutional factor; range: [−2.5 (weak), 2.5 (strong)]) |
| $Z_5$ | Rule of law (institutional factor; range: [−2.5 (weak), 2.5 (strong)]) |
| $Z_6$ | Voice and accountability (institutional factor; range: [−2.5 (weak), 2.5 (strong)]) |
| $Z_7$ | Human Development Index |
| $Z_9$ | Renewable energy production (GWh) |
| $Z_{10}$ | Number of patents |
| $Z_{11}$ | Trade (% of GPD) |
| $I_{j,t}$ | Country classification as developed (value 0) or developing (value 1) (dummy variable) |
| $d_{p+1}$, …, $d_T$ | Time dummies |
| $\eta_j$, $\varepsilon_{j,t}$ | Time-invariant individual-specific effect and time-variant random noise |
| $a,\beta_1,\ldots,\beta_{22}$ | Coefficients |
| $\tau$ | Country-specific impact of a country classified as developing (value 1) on $\theta_{j,t}^c$ |
| $\varphi_{p+1},\ldots,\varphi_T$ | Time dummy coefficients |
| $j$=1,…,$n$ | Sample countries |
| $t$=$p$+1,…,$T$; $p$=1,2 | Review period |

**Table 2: GMM results**

| Variables | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| | 2011-2019 | 2011-2020 | 2011-2019 | 2011-2020 | 2011-2019 | 2011-2020 |
| $\bar{\theta}^{c}_{j,(t-1,t-2)}$ | 0.2099**** | −0.2962**** | 0.1966** | 0.1401** | 0.1201** | 0.2542** |
| $z_{1,j,t-1}$ | −0.0055 | −0.0429 | −0.0049 | 0.0316 | −0.0042 | −0.0067 |
| $z_{1,j,t-2}$ | −0.0359 | −0.0423** | −0.0400 | −0.0329 | 0.0151* | −0.0061 |
| $z_{2,j,t-1}$ | 0.0162 | 0.0382 | −0.0270 | −0.0024 | −0.2080 | −0.1705 |
| $z_{2,j,t-2}$ | 0.0160 | 0.0447 | 0.0079 | 0.0109 | −0.0074 | 0.0229* |
| $I_{j,t}$ | −0.0752**** | <10E−04**** | −0.0586**** | −0.0447**** | <10E−04**** | <10E−04* |
| $I_{j,t} \times z_{2,j,t-1}$ | −0.7371**** | −0.0098 | 0.0474 | −0.0806 | −0.0034 | 0.0100 |
| $z_{5,j,t-1}$ | | | 0.0059 | 0.0328 | | |
| $z_{5,j,t-2}$ | | | 0.0523 | 0.0754* | | |
| $z_{5,j,t-1} \times z_{2,j,t-1}$ | | | 0.0265 | 0.0170 | | |
| $I_{j,t} \times z_{5,j,t-1}$ | | | −0.0627 | −0.0088 | | |
| $z_{7,j,t-1}$ | | | | | 0.0074* | 0.0073*** |
| $z_{7,j,t-2}$ | | | | | 0.0009 | −0.0081 |
| $z_{7,j,t-1} \times z_{2,j,t-1}$ | | | | | 0.0530 | 0.0400 |
| $I_{j,t} \times z_{7,j,t-1}$ | | | | | 0.0074* | 0.0073*** |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 504 | 560 | 504 | 560 | 504 | 560 |
| Years | 2011-2019 | 2011-2020 | 2011-2019 | 2011-2020 | 2011-2019 | 2011-2020 |
| Arellano and Bond test | 0.5838 | 0.7316 | 0.3808 | 0.3050 | 0.7322 | 0.4230 |
| Hansen J-test | 0.1084 | 0.1453 | 0.0911 | 0.0957 | 0.2038 | 0.1430 |
| Wald test | 0.0000 | 0.0064 | 0.0000 | 0.0000 | 0.0036 | 0.0001 |
| GMM estimation | Two-step | Iterative | Two-step | Two-step | Iterative | Iterative |

Coefficients are significant at the 0.10 level (denoted by *), by 0.05 level (denoted by **), by 0.01 level (denoted by ***), and by 0.00001 level (denoted by ****)

development, and trade openness on environmental efficiency, focusing on both the pre-pandemic and pandemic periods. The analysis spans 2011-2020 due to data availability, covering a sample of 56 countries, with 31 classified as developed and 25 as developing, based on the International Monetary Fund (IMF) criteria (https://www.imf.org/en/Publications/WEO/weo-database/2022/April/select-aggr-data).

Environmental efficiency is assessed from a neoclassical perspective of economic efficiency, rooted in the theories of Solow (1956) and Swan (1956), while addressing critiques of GDP per capita's limitations in reflecting complex economic systems, especially in wealthier nations (Ayres, 1996). Specifically, GDP is considered a desirable output of production, while gross fixed capital formation and labor serve as inputs, as informed by Halkos and Tzeremes (2010). Additionally, total energy consumption and $CO_2$ emissions are included, acting as an input and an undesirable output, respectively, based on Kounetas and Zervopoulos (2019).

The study incorporates formal institutional indicators (Kaufmann et al., 1999) such as (1) voice and accountability, (2) political stability, (3) government effectiveness, (4) regulatory quality, (5) rule of law, and (6) control of corruption to represent institutional quality, a method commonly used in literature (Aparicio et al., 2016; Khan et al., 2022; Peiró-Palomino et al., 2022). These indicators are scored on a scale from −2.5 to 2.5, representing varying levels of institutional quality, and are sourced from the Worldwide Governance Indicators (WGI) database (www.govindicators.org).

Aligned with Tateishi et al. (2020), the human development index (HDI) is included, capturing three core aspects of human development: (1) long and healthy life, (2) education, and (3) a reasonable standard of living (UNDP, 2020; https://hdr.undp.org/data-center/human-development-index#/indicies/HDI)). Additionally, following Vural (2021), the study uses the number of patent applications, both domestic and international, as an indicator of technological innovation. Trade openness is calculated using the sum of real exports and imports as a percentage of GDP. Patents and trade openness data are sourced from the World Bank Development Indicators database (https://databank.worldbank.org/source/world-development-indicators). Data on renewable energy production, energy consumption, and $CO_2$ emissions (in millions of kWh and tons, respectively) are drawn from the Enerdata-Odyssey database.

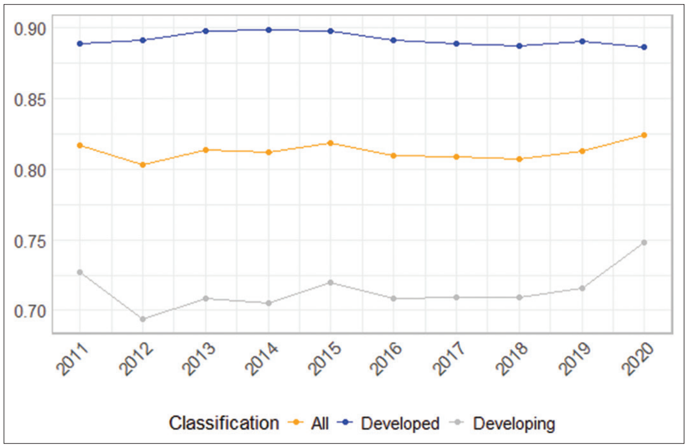
Detailed statistical information on the dataset used in this study is available in Table ES1 of the Electronic Supplement.

## 5. EMPIRICAL ANALYSIS

In this study, environmental efficiency serves as the dependent variable for the linear dynamic panel data models (Model 1-Model 3), estimated using the Bayesian DEA method outlined in Section 3 (expressions [1]-[13]). On average, environmental efficiency showed a marginal annual increase of 0.10% between 2011 and 2020, primarily driven by the year 2020, which was influenced by the COVID-19 pandemic (Figure 1). Excluding the pandemic period and focusing on 2011-2019, the average annual growth rate in environmental efficiency across all countries in the sample (both developed and developing) actually decreased by 0.05%.

Previous research by Hidalgo-Triana et al. (2023) emphasized the positive impact of COVID-19 on environmental performance,

**Figure 1:** Efficiency estimates




CAGR: 0.10% (total); −0.03% (developed); 0.28% (developing)

attributing it to a notable reduction in economic activity (GDP). However, our findings (refer to Figure 1 and Table A1 in the Appendix) indicate that this positive effect was confined to developing countries, which saw a 4.4% improvement in environmental performance between 2019 and 2020 (with a compound annual growth rate of 0.28% for 2011-2020). In contrast, developed countries experienced a negative impact from COVID-19 on their environmental performance, with a 0.05% decline between 2019 and 2020 (CAGR 2011-2020: −0.03%).

Table 2 presents result for two distinct periods: (a) the reduced period from 2011 to 2019, which excludes major global crises like the Global Financial Crisis and COVID-19, and (b) the extended period from 2011 to 2020, which includes potential COVID-19 effects. Despite the significant impact of COVID-19 on the global economy and environmental performance, variables such as lagged environmental performance, country classification, and corruption control consistently influence environmental performance in both periods under review (2011-2019 and 2011-2020).

Across all six models shown in Table 2—which were the only models passing the Arellano and Bond, Hansen J, and Wald tests among various combinations tested—lagged environmental performance ($\bar{\theta}^{c}_{j,(t-1,t-2)}$) consistently has a positive impact on current environmental performance. However, in the extended period for Model 1, lagged environmental performance shows a significant negative effect on current environmental performance. This persistence underscores the importance of historical environmental policies and practices in shaping present-day efficiency. Countries with a history of effective environmental management are likely to continue benefiting from established infrastructures, regulatory frameworks, and societal norms that prioritize sustainability. This aligns with the findings of Banker (1993) and Kneip et al. (2008), who emphasize the enduring influence of past efficiencies on current performance metrics. Nevertheless, Model 1 for the extended period is unsuitable for conclusions on environmental performance, as it assigns a negative and statistically significant coefficient (at the 0.05 level) to government effectiveness ($z_{1,j,t-2}$), which contradicts established literature.

For both periods, most models show that country classification ($I_{j,t}$) has a significantly negative effect on environmental performance, indicating that developing countries (coded as one) perform worse environmentally than developed countries. This disparity can be attributed to several factors inherent to developing economies, including weaker institutional frameworks. Adams and Klobodu (2017) and Salman et al. (2019) have previously highlighted how institutional quality and economic structures in developing nations often lag behind, impeding their ability to implement and sustain effective environmental policies. Additionally, the interaction between country classification and corruption control ($I_{j,t} \times z_{2,j,t-1}$) significantly negatively impacts environmental performance (Model 1 for 2011-2019), suggesting that anti-corruption efforts in developing countries may hinder environmental performance. This finding aligns with the "grease the wheel" theory suggesting that in certain contexts, corruption can facilitate economic activities that inadvertently benefit environmental performance by accelerating project approvals and reducing bureaucratic delays (Leff, 1964; Méon and Weill, 2010) and supports findings from Alshehhi and Zervopoulos (2023).

Moreover, HDI ($z_{7,j,t-1}$) and its interaction with country classification ($I_{j,t} \times z_{7,j,t-1}$) show a significantly positive impact on environmental performance (Model 3). HDI, which measures a country's health, education, and wealth (as per the IMF World Economic Outlook database; https://www.imf.org/en/Publications/WEO/weo-database/2022/April/select-aggr-data), proves crucial during both stable and crisis periods, such as 2011-2020, particularly for developing nations. In developed countries, high HDI levels contribute to greater public awareness, cleaner technologies, and robust innovation, while in developing countries, improvements in HDI enable communities to prioritize sustainability as health outcomes, education, and incomes improve. During crises like COVID-19, countries with higher HDI were better equipped to balance immediate needs with long-term sustainability goals. As suggested by Holden et al. (2017) and Strezov et al. (2017), incorporating HDI into environmental frameworks ensures that human development aligns with sustainability, making it an essential tool for achieving integrated socio-economic and environmental progress (Sadiq et al., 2022).

Additionally, Table 2 indicates that the rule of law positively affects environmental performance (Model 2, 2011-2020) at a 0.10 significance level, highlighting the importance of public trust in governance and regulatory bodies for environmental outcomes. A strong rule of law ensures that environmental regulations are not only well-designed but also effectively implemented and adhered to. This enhances accountability and deters environmentally harmful practices. The significance of this variable aligns with studies by Yu et al. (2015) and Khan et al. (2022), which highlight how legal institutions underpin successful environmental governance.

In contrast to previous studies, this research did not find trade, technological innovation, or renewable energy production to have a significant effect on environmental performance. Only the models presented in Table 2 satisfied the GMM specification, overidentification, and linearity tests, despite testing all discussed variable combinations.

## 6. CONCLUSION

This study explores the influence of formal institutional factors and additional variables—including the human development index (HDI), renewable energy production, patents, and trade—on countries' environmental performance. The sample includes 56 countries, divided into 31 developed and 25 developing countries. Two periods are analyzed: (a) 2011-2019, which is unaffected by major global crises, and (b) 2011-2020, which includes the impact of COVID-19 in the final year. Environmental performance is estimated using three inputs (labor, gross fixed capital formation, and energy consumption) and two outputs (GDP as a desirable outcome and $CO_2$ emissions as an undesirable by-product). A novel Bayesian DEA approach was applied to achieve reliable, bias-free estimates that address the sample's limited size and the uneven distribution between developed and developing countries. The effects of these variables on environmental performance were assessed using two-step and iterative GMM methods.

The findings indicate that COVID-19 significantly disrupted economic activities, leading to declines in GDP, energy consumption, $CO_2$ emissions, and trade. Developed countries have substantially reduced $CO_2$ emissions without negatively impacting their GDP and invested heavily in renewable energy. In contrast, developing countries showed notable progress in improving their HDI. Developed countries consistently outperformed developing ones across institutional factors, with positive scores for formal institutions, while developing countries often displayed negative scores throughout the period. Furthermore, developed countries exhibited better environmental performance than developing countries from 2011 to 2020.

According to the GMM estimates, key drivers of environmental performance in both periods (2011-2019 and 2011-2020) included lagged environmental performance, country classification (developed vs. developing), and corruption control (relevant mainly for developing countries). These findings are robust across multiple models that tested different variable combinations. The study emphasizes the importance of HDI, particularly its combined effect with country classification, on environmental performance, highlighting the role of sustainable socio-economic development. The importance of HDI becomes even more pronounced during global crises, especially for developing nations. Additionally, inflation's impact on environmental performance differs by country type: it negatively affects developed countries while positively affecting developing countries with high corruption levels.

Based on these insights, policymakers are encouraged to focus on improving HDI, particularly for developing nations, by investing in health, education, and well-being. The study shows that HDI has significantly increased in developing countries between 2011 and 2020. Governments should also work to address key environmental performance drivers, particularly by reducing $CO_2$ emissions, which have increased substantially in developing countries between 2011 and 2019. Notably, developed countries have managed to reduce $CO_2$ emissions without compromising GDP growth.

A limitation of this study is the small sample size, constrained by data availability for the review period. However, the Bayesian DEA approach helps minimize potential distortions, ensuring the validity of the findings. Future research could extend the analysis to include more years affected by COVID-19, providing deeper insights into the effects of global crises on environmental performance. Incorporating a difference-in-differences approach (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021) may also allow for comparisons between periods with and without global crises.

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## APPENDIX

**Table A1: Efficiencies**

| Years | All | Developed | Developing |
|---|---|---|---|
| 2011 | 0.8165 | 0.8887 | 0.7269 |
| 2012 | 0.8031 | 0.8913 | 0.6937 |
| 2013 | 0.8132 | 0.8975 | 0.7086 |
| 2014 | 0.8121 | 0.8983 | 0.7053 |
| 2015 | 0.8181 | 0.8974 | 0.7198 |
| 2016 | 0.8095 | 0.8909 | 0.7086 |
| 2017 | 0.8086 | 0.8884 | 0.7095 |
| 2018 | 0.8073 | 0.8867 | 0.7089 |
| 2019 | 0.8127 | 0.8907 | 0.7161 |
| 2020 | 0.8243 | 0.8860 | 0.7477 |
| Average | 0.8125 | 0.8916 | 0.7145 |
| CAGR (2011-2020) | 0.0010 | −0.0003 | 0.0028 |
| CAGR (2011-2019) | −0.0005 | 0.0002 | −0.0017 |

## ELECTRONIC SUPPLEMENT

**Table ES1: Descriptive statistics**

| Group | Statistics | Labor (in millions) (%) | Gross fixed capital formation (in millions of $, constant 2017) (%) | Energy consumption (in millions of kWh) (%) | GDP (in millions of $, constant 2017) (%) | $CO_2$ (in millions of tons of $CO_2$) (%) | Voice and accountability[1] (%) | Political stability[1] (%) | Government effectiveness[1] (%) | Regulatory quality[1] (%) | Rule of law[1] (%) | Control of corruption[1] (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **2011** | | | | | | | | | | | | |
| Overall | Min | 0.18 | 1291.64 | 1866.00 | 5577.00 | 2.58 | −1.907 | −2.810 | −1.078 | −1.177 | −1.190 | −1.219 |
| | Max | 1.34 | 1504.64 | 5151.00 | 8561.11 | 4.92 | −0.102 | −1.201 | 0.409 | 0.496 | 0.490 | −0.094 |
| | Average | 25.31 | 185776.08 | 225970.88 | 881808.17 | 346.38 | 0.569 | 0.256 | 0.821 | 0.832 | 0.707 | 0.676 |
| | St. Dev. | 64.27 | 439367.33 | 544523.63 | 2309790.82 | 793.56 | 0.894 | 0.942 | 0.886 | 0.784 | 0.952 | 1.075 |
| | N | 56 | | | | | | | | | | |
| Developed | Min | 0.18 | 1504.64 | 1866.00 | 8561.11 | 2.58 | −0.10 | −1.20 | 0.41 | 0.50 | 0.49 | −0.09 |
| | Max | 157.16 | 3086680.01 | 3885019.00 | 16636956.92 | 5415.29 | 1.626 | 1.393 | 2.241 | 1.971 | 1.949 | 2.400 |
| | Average | 15.93 | 267689.88 | 289463.92 | 1314868.92 | 378.95 | 1.151 | 0.788 | 1.441 | 1.376 | 1.402 | 1.403 |
| | St. Dev. | 30.26 | 571922.55 | 704949.36 | 3034689.31 | 979.89 | 0.385 | 0.537 | 0.487 | 0.415 | 0.453 | 0.728 |
| | N | 31 | | | | | | | | | | |
| Developing | Min | 1.34 | 1291.64 | 5151.00 | 5577.00 | 4.92 | −1.907 | −2.810 | −1.078 | −1.177 | −1.190 | −1.219 |
| | Max | 457.50 | 518847.50 | 856239.00 | 1616398.76 | 1852.97 | 1.074 | 1.072 | 1.247 | 1.459 | 1.366 | 1.529 |
| | Average | 36.93 | 84202.97 | 147239.52 | 344812.85 | 305.99 | −0.154 | −0.404 | 0.053 | 0.156 | −0.155 | −0.226 |
| | St. Dev. | 89.82 | 118779.41 | 215955.56 | 414793.31 | 489.76 | 0.816 | 0.923 | 0.625 | 0.578 | 0.649 | 0.675 |
| | N | 25 | | | | | | | | | | |
| **2012** | | | | | | | | | | | | |
| Overall | Min | 0.19 | 1518.70 | 1946.00 | 5572.08 | 2.72 | −1.866 | −2.677 | −0.902 | −1.070 | −1.129 | −1.149 |
| | Max | 1.34 | 1766.57 | 5120.00 | 8913.63 | 5.72 | 0.053 | −1.079 | 0.280 | 0.527 | 0.393 | −0.183 |
| | Average | 25.50 | 192079.33 | 227959.59 | 897632.43 | 348.21 | 0.592 | 0.275 | 0.830 | 0.841 | 0.710 | 0.697 |
| | St. Dev. | 64.34 | 466280.89 | 539016.06 | 2359117.14 | 779.63 | 0.894 | 0.932 | 0.863 | 0.780 | 0.956 | 1.078 |
| | N | 56 | | | | | | | | | | |
| Developed | Min | 0.19 | 1518.70 | 1946.00 | 8913.63 | 2.72 | 0.05 | −1.08 | 0.28 | 0.53 | 0.39 | −0.18 |
| | Max | 157.84 | 3298732.18 | 3830933.00 | 17016393.93 | 5230.33 | 1.728 | 1.401 | 2.220 | 1.966 | 1.958 | 2.390 |
| | Average | 16.02 | 275716.25 | 288041.36 | 1331696.78 | 374.29 | 1.185 | 0.803 | 1.429 | 1.377 | 1.404 | 1.418 |
| | St. Dev. | 30.36 | 608223.66 | 695700.59 | 3100957.85 | 950.25 | 0.395 | 0.541 | 0.477 | 0.398 | 0.482 | 0.742 |
| | N | 31 | | | | | | | | | | |
| Developing | Min | 1.34 | 1766.57 | 5120.00 | 5572.08 | 5.72 | −1.866 | −2.677 | −0.902 | −1.070 | −1.129 | −1.149 |
| | Max | 457.75 | 544473.77 | 874739.00 | 1704595.76 | 2021.20 | 1.088 | 1.049 | 1.264 | 1.539 | 1.392 | 1.582 |
| | Average | 37.26 | 88369.54 | 153458.20 | 359392.65 | 315.86 | −0.144 | −0.380 | 0.087 | 0.176 | −0.150 | −0.198 |
| | St. Dev. | 89.86 | 124859.91 | 224440.22 | 434805.86 | 512.09 | 0.788 | 0.904 | 0.621 | 0.604 | 0.641 | 0.683 |
| | N | 25 | | | | | | | | | | |
| **2013** | | | | | | | | | | | | |
| Overall | Min | 0.19 | 1517.06 | 1950.00 | 6180.30 | 2.39 | −1.876 | −2.603 | −0.897 | −1.068 | −1.109 | −1.163 |
| | Max | 1.36 | 1785.20 | 5404.00 | 9401.50 | 5.49 | 0.037 | −1.101 | 0.361 | 0.633 | 0.441 | −0.068 |
| | Average | 25.71 | 196113.17 | 230259.35 | 914110.05 | 349.62 | 0.580 | 0.276 | 0.840 | 0.842 | 0.714 | 0.699 |
| | St. Dev. | 64.78 | 481949.70 | 544988.50 | 2401495.25 | 792.75 | 0.901 | 0.946 | 0.853 | 0.791 | 0.949 | 1.060 |
| | N | 56 | | | | | | | | | | |
| Developed | Min | 0.19 | 1517.06 | 1950.00 | 9401.50 | 2.39 | 0.04 | −1.10 | 0.36 | 0.63 | 0.44 | −0.07 |
| | Max | 158.25 | 3416444.75 | 3871735.00 | 17329814.71 | 5342.99 | 1.738 | 1.454 | 2.190 | 1.970 | 1.980 | 2.407 |

*(Contd...)*

**Table ES1:** ***(Continued)***

| Group | Statistics | Labor (in millions) (%) | Gross fixed capital formation (in millions of $, constant 2017) (%) | Energy consumption (in millions of kWh) (%) | GDP (in millions of $, constant 2017) (%) | $CO_2$ (in millions of tons of $CO_2$) (%) | Voice and accountability[1] (%) | Political stability[1] (%) | Government effectiveness[1] (%) | Regulatory quality[1] (%) | Rule of law[1] (%) | Control of corruption[1] (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | **2013** | | | | | | |
| | Average | 16.10 | 281189.67 | 289131.21 | 1350573.40 | 376.26 | 1.178 | 0.825 | 1.434 | 1.386 | 1.402 | 1.404 |
| | St. Dev. | 30.46 | 629375.05 | 702856.19 | 3157123.43 | 970.40 | 0.390 | 0.541 | 0.445 | 0.402 | 0.478 | 0.728 |
| | N | 31 | | | | | | | | | | |
| Developing | Min | 1.36 | 1785.20 | 5404.00 | 6180.30 | 5.49 | −1.876 | −2.603 | −0.897 | −1.068 | −1.109 | −1.163 |
| | Max | 461.05 | 552977.39 | 883046.00 | 1813453.06 | 2061.22 | 1.106 | 0.973 | 1.265 | 1.491 | 1.368 | 1.541 |
| | Average | 37.62 | 90618.29 | 157258.24 | 372895.49 | 316.59 | −0.161 | −0.404 | 0.105 | 0.169 | −0.139 | −0.176 |
| | St. Dev. | 90.49 | 127337.71 | 230471.36 | 453857.49 | 510.92 | 0.798 | 0.904 | 0.633 | 0.615 | 0.642 | 0.686 |
| | N | 25 | | | | | | | | | | |
| | | | | | | **2014** | | | | | | |
| Overall | Min | 0.20 | 1653.76 | 2005.00 | 6429.00 | 2.37 | −1.882 | −2.401 | −0.866 | −1.009 | −0.962 | −1.128 |
| | Max | 1.34 | 2097.53 | 5352.00 | 10119.17 | 5.48 | −0.099 | −1.040 | 0.300 | 0.329 | 0.374 | −0.130 |
| | Average | 25.92 | 202246.74 | 232159.72 | 934789.34 | 349.47 | 0.560 | 0.254 | 0.842 | 0.847 | 0.782 | 0.682 |
| | St. Dev. | 65.18 | 504788.89 | 549281.57 | 2454389.09 | 803.53 | 0.897 | 0.922 | 0.837 | 0.816 | 0.975 | 1.033 |
| | N | 56 | | | | | | | | | | |
| Developed | Min | 0.20 | 1653.76 | 2005.00 | 10119.17 | 2.37 | −0.10 | −1.04 | 0.30 | 0.33 | 0.37 | −0.13 |
| | Max | 158.91 | 3591825.30 | 3895216.00 | 17726282.04 | 5390.69 | 1.684 | 1.468 | 2.183 | 2.233 | 2.130 | 2.256 |
| | Average | 16.19 | 290291.73 | 287472.47 | 1376830.74 | 370.69 | 1.149 | 0.788 | 1.418 | 1.393 | 1.489 | 1.368 |
| | St. Dev. | 30.58 | 660047.03 | 706128.70 | 3226507.94 | 976.76 | 0.387 | 0.521 | 0.452 | 0.463 | 0.527 | 0.712 |
| | N | 31 | | | | | | | | | | |
| Developing | Min | 1.34 | 2097.53 | 5352.00 | 6429.00 | 5.48 | −1.882 | −2.401 | −0.866 | −1.009 | −0.962 | −1.128 |
| | Max | 464.10 | 567372.75 | 970454.00 | 1947834.06 | 2234.90 | 1.138 | 0.843 | 1.435 | 1.494 | 1.433 | 1.489 |
| | Average | 38.00 | 93070.95 | 163571.92 | 386658.01 | 323.17 | −0.171 | −0.409 | 0.127 | 0.170 | −0.095 | −0.169 |
| | St. Dev. | 91.07 | 130143.30 | 243505.63 | 476191.40 | 534.57 | 0.808 | 0.885 | 0.624 | 0.628 | 0.621 | 0.671 |
| | N | 25 | | | | | | | | | | |
| | | | | | | **2015** | | | | | | |
| Overall | Min | 0.20 | 2175.31 | 2114.00 | 6678.18 | 1.67 | −1.843 | −2.483 | −0.915 | −0.994 | −0.989 | −1.150 |
| | Max | 1.33 | 2554.95 | 5372.00 | 11091.43 | 5.34 | −0.162 | −1.095 | 0.177 | 0.410 | 0.277 | −0.087 |
| | Average | 26.15 | 208371.71 | 234515.25 | 958232.81 | 348.32 | 0.561 | 0.218 | 0.845 | 0.850 | 0.747 | 0.683 |
| | St. Dev. | 65.59 | 522242.81 | 550002.35 | 2518599.09 | 787.48 | 0.905 | 0.935 | 0.839 | 0.821 | 0.965 | 1.039 |
| | N | 56 | | | | | | | | | | |
| Developed | Min | 0.20 | 2554.95 | 2114.00 | 11091.43 | 1.67 | −0.16 | −1.09 | 0.18 | 0.41 | 0.28 | −0.09 |
| | Max | 159.91 | 3722979.00 | 3895365.00 | 18206020.74 | 5248.04 | 1.688 | 1.525 | 2.236 | 2.261 | 2.089 | 2.276 |
| | Average | 16.28 | 298783.80 | 288301.16 | 1407312.99 | 366.17 | 1.155 | 0.750 | 1.431 | 1.413 | 1.450 | 1.384 |
| | St. Dev. | 30.76 | 682974.68 | 705351.70 | 3311013.87 | 951.16 | 0.396 | 0.535 | 0.459 | 0.443 | 0.530 | 0.719 |
| | N | 31 | | | | | | | | | | |
| Developing | Min | 1.33 | 2175.31 | 5372.00 | 6678.18 | 5.34 | −1.843 | −2.483 | −0.915 | −0.994 | −0.989 | −1.150 |
| | Max | 466.84 | 604426.92 | 1022223.00 | 2103587.81 | 2256.36 | 1.152 | 0.875 | 1.509 | 1.345 | 1.344 | 1.280 |
| | Average | 38.39 | 96260.72 | 167820.72 | 401373.39 | 326.19 | −0.176 | −0.442 | 0.119 | 0.152 | −0.125 | −0.187 |
| | St. Dev. | 91.62 | 135293.86 | 250925.54 | 499800.61 | 537.89 | 0.813 | 0.909 | 0.598 | 0.618 | 0.595 | 0.637 |
| | N | 25 | | | | | | | | | | |
| | | | | | | **2016** | | | | | | |
| Overall | Min | 0.21 | 1927.33 | 2117.23 | 6967.73 | 1.36 | −1.728 | −2.483 | −0.896 | −0.941 | −1.023 | −1.079 |

*(Contd...)*

**Table ES1:** ***(Continued)***

| Group | Statistics | Labor (in millions) (%) | Gross fixed capital formation (in millions of \$, constant 2017) (%) | Energy consumption (in millions of kWh) (%) | GDP (in millions of \$, constant 2017) (%) | $CO_2$ (in millions of tons of $CO_2$) (%) | Voice and accountability[1] (%) | Political stability[1] (%) | Government effectiveness[1] (%) | Regulatory quality[1] (%) | Rule of law[1] (%) | Control of corruption[1] (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **2016** | | | | | | | | | | | | |
| | Max | 1.30 | 2615.68 | 5328.00 | 11466.49 | 5.08 | −0.150 | −0.795 | 0.158 | 0.148 | 0.135 | −0.102 |
| | Average | 26.39 | 212833.83 | 238938.38 | 978759.33 | 348.25 | 0.549 | 0.194 | 0.828 | 0.855 | 0.732 | 0.693 |
| | St. Dev. | 66.02 | 533825.86 | 555430.04 | 2560787.57 | 776.63 | 0.892 | 0.932 | 0.826 | 0.829 | 0.932 | 1.025 |
| | N | 56 | | | | | | | | | | |
| Developed | Min | 0.21 | 2615.68 | 2117.23 | 11466.49 | 1.36 | −0.15 | −0.79 | 0.16 | 0.15 | 0.14 | −0.10 |
| | Max | 161.84 | 3802207.08 | 3922011.00 | 18509601.05 | 5142.64 | 1.665 | 1.519 | 2.206 | 2.181 | 2.050 | 2.284 |
| | Average | 16.44 | 305056.74 | 290809.04 | 1432261.51 | 362.29 | 1.144 | 0.739 | 1.413 | 1.433 | 1.407 | 1.385 |
| | St. Dev. | 31.12 | 697395.66 | 710039.29 | 3365074.31 | 933.07 | 0.392 | 0.512 | 0.451 | 0.469 | 0.507 | 0.715 |
| | N | 31 | | | | | | | | | | |
| Developing | Min | 1.30 | 1927.33 | 5328.00 | 6967.73 | 5.08 | −1.728 | −2.483 | −0.896 | −0.941 | −1.023 | −1.079 |
| | Max | 469.54 | 655552.07 | 1085748.00 | 2277266.45 | 2299.47 | 1.118 | 0.664 | 1.415 | 1.373 | 1.129 | 1.172 |
| | Average | 38.73 | 98477.42 | 174618.76 | 416416.63 | 330.83 | −0.188 | −0.483 | 0.102 | 0.139 | −0.105 | −0.165 |
| | St. Dev. | 92.14 | 143169.43 | 262689.03 | 527444.18 | 541.66 | 0.782 | 0.896 | 0.562 | 0.579 | 0.590 | 0.619 |
| | N | 25 | | | | | | | | | | |
| **2017** | | | | | | | | | | | | |
| Overall | Min | 0.21 | 2114.28 | 2319.59 | 7298.00 | 1.53 | −1.691 | −2.406 | −0.709 | −0.860 | −1.058 | −1.056 |
| | Max | 1.30 | 2668.68 | 5623.10 | 12736.88 | 5.38 | −0.169 | −0.888 | 0.274 | 0.240 | 0.075 | −0.079 |
| | Average | 26.56 | 221030.59 | 241445.06 | 1004852.30 | 351.94 | 0.546 | 0.228 | 0.831 | 0.868 | 0.723 | 0.668 |
| | St. Dev. | 66.34 | 553921.23 | 553583.12 | 2618753.62 | 777.57 | 0.900 | 0.912 | 0.807 | 0.828 | 0.937 | 1.011 |
| | N | 56 | | | | | | | | | | |
| Developed | Min | 0.21 | 2668.68 | 2319.59 | 12736.88 | 1.53 | −0.17 | −0.89 | 0.27 | 0.24 | 0.07 | −0.08 |
| | Max | 163.40 | 3947417.64 | 3886956.08 | 18927118.51 | 5084.83 | 1.694 | 1.616 | 2.223 | 2.167 | 2.069 | 2.245 |
| | Average | 16.57 | 316501.96 | 291579.06 | 1466000.87 | 360.72 | 1.147 | 0.761 | 1.403 | 1.455 | 1.410 | 1.352 |
| | St. Dev. | 31.40 | 723003.29 | 704731.02 | 3440034.05 | 922.50 | 0.400 | 0.518 | 0.461 | 0.466 | 0.500 | 0.710 |
| | N | 31 | | | | | | | | | | |
| Developing | Min | 1.30 | 2114.28 | 5623.10 | 7298.00 | 5.38 | −1.691 | −2.406 | −0.709 | −0.860 | −1.058 | −1.056 |
| | Max | 471.68 | 706699.18 | 1149181.89 | 2432015.44 | 2431.76 | 1.122 | 0.807 | 1.418 | 1.350 | 1.149 | 1.136 |
| | Average | 38.95 | 102646.10 | 179278.90 | 433028.07 | 341.05 | −0.199 | −0.433 | 0.122 | 0.141 | −0.129 | −0.181 |
| | St. Dev. | 92.55 | 152839.35 | 272418.09 | 555310.67 | 567.07 | 0.781 | 0.864 | 0.531 | 0.553 | 0.578 | 0.595 |
| | N | 25 | | | | | | | | | | |
| **2018** | | | | | | | | | | | | |
| Overall | Min | 0.21 | 2215.76 | 2390.22 | 7572.25 | 1.56 | −1.696 | −2.269 | −0.680 | −0.864 | −1.036 | −0.949 |
| | Max | 1.25 | 2816.65 | 5402.56 | 13505.45 | 5.60 | −0.084 | −0.912 | 0.291 | 0.414 | 0.139 | −0.025 |
| | Average | 26.76 | 228690.35 | 246906.68 | 1030850.07 | 355.54 | 0.540 | 0.242 | 0.839 | 0.861 | 0.716 | 0.675 |
| | St. Dev. | 66.63 | 576741.45 | 574746.73 | 2691122.45 | 799.60 | 0.896 | 0.864 | 0.798 | 0.821 | 0.933 | 1.006 |
| | N | 56 | | | | | | | | | | |
| Developed | Min | 0.21 | 2816.65 | 2390.22 | 13505.45 | 1.56 | −0.08 | −0.91 | 0.29 | 0.41 | 0.14 | −0.03 |
| | Max | 164.63 | 4119951.45 | 4042840.01 | 19479574.02 | 5210.13 | 1.696 | 1.534 | 2.231 | 2.226 | 2.079 | 2.211 |
| | Average | 16.71 | 325703.87 | 296683.67 | 1498798.01 | 361.55 | 1.139 | 0.733 | 1.396 | 1.445 | 1.395 | 1.355 |
| | St. Dev. | 31.66 | 752364.86 | 730728.85 | 3535238.75 | 942.84 | 0.398 | 0.510 | 0.461 | 0.453 | 0.509 | 0.710 |
| | N | 31 | | | | | | | | | | |
| Developing | Min | 1.25 | 2215.76 | 5402.56 | 7572.25 | 5.60 | −1.696 | −2.269 | −0.680 | −0.864 | −1.036 | −0.949 |

*(Contd...)*

**Table ES1:** ***(Continued)***

| Group | Statistics | Labor (in millions) (%) | Gross fixed capital formation (in millions of $, constant 2017) (%) | Energy consumption (in millions of kWh) (%) | GDP (in millions of $, constant 2017) (%) | $CO_2$ (in millions of tons of $CO_2$) (%) | Voice and accountability[1] (%) | Political stability[1] (%) | Government effectiveness[1] (%) | Regulatory quality[1] (%) | Rule of law[1] (%) | Control of corruption[1] (%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | **2018** | | | | | | |
| | Max | 473.42 | 785871.18 | 1233017.98 | 2588974.10 | 2557.87 | 1.108 | 0.803 | 1.430 | 1.335 | 1.092 | 1.152 |
| | Average | 39.24 | 108393.58 | 185183.21 | 450594.63 | 348.09 | −0.203 | −0.367 | 0.148 | 0.137 | −0.126 | −0.169 |
| | St. Dev. | 92.90 | 165775.80 | 287036.93 | 583619.04 | 594.91 | 0.777 | 0.830 | 0.544 | 0.547 | 0.578 | 0.590 |
| | N | 25 | | | | | | | | | | |
| | | | | | | **2019** | | | | | | |
| Overall | Min | 0.22 | 2313.26 | 2479.31 | 7920.62 | 1.67 | −1.660 | −2.265 | −0.682 | −0.828 | −1.052 | −0.950 |
| | Max | 1.27 | 3053.80 | 5839.18 | 14297.02 | 6.04 | −0.206 | −0.793 | 0.349 | 0.530 | 0.184 | 0.043 |
| | Average | 27.11 | 232384.25 | 246651.36 | 1050240.20 | 351.89 | 0.523 | 0.244 | 0.841 | 0.863 | 0.723 | 0.673 |
| | St. Dev. | 67.85 | 593263.35 | 567441.09 | 2748870.00 | 789.76 | 0.888 | 0.829 | 0.778 | 0.788 | 0.924 | 0.995 |
| | N | 56 | | | | | | | | | | |
| Developed | Min | 0.22 | 3053.80 | 2479.31 | 14297.02 | 1.67 | −0.21 | −0.79 | 0.35 | 0.53 | 0.18 | 0.04 |
| | Max | 166.36 | 4248643.25 | 3964472.69 | 19925436.12 | 5116.13 | 1.655 | 1.639 | 2.221 | 2.162 | 2.058 | 2.170 |
| | Average | 16.85 | 332473.53 | 292520.28 | 1524571.69 | 352.76 | 1.109 | 0.720 | 1.390 | 1.437 | 1.397 | 1.347 |
| | St. Dev. | 31.98 | 774629.64 | 716557.96 | 3611714.30 | 925.24 | 0.412 | 0.508 | 0.444 | 0.387 | 0.499 | 0.693 |
| | N | 31 | | | | | | | | | | |
| Developing | Min | 1.27 | 2313.26 | 5839.18 | 7920.62 | 6.04 | −1.660 | −2.265 | −0.682 | −0.828 | −1.052 | −0.950 |
| | Max | 482.70 | 798075.43 | 1316767.19 | 2685747.84 | 2555.51 | 1.096 | 0.772 | 1.377 | 1.224 | 1.075 | 1.107 |
| | Average | 39.83 | 108273.54 | 189773.90 | 462069.16 | 350.81 | −0.203 | −0.345 | 0.161 | 0.150 | −0.112 | −0.162 |
| | St. Dev. | 94.70 | 165919.68 | 299976.28 | 599930.87 | 599.39 | 0.776 | 0.775 | 0.520 | 0.530 | 0.576 | 0.595 |
| | N | 25 | | | | | | | | | | |
| | | | | | | **2020** | | | | | | |
| Overall | Min | 0.21 | 2114.32 | 2368.12 | 7255.42 | 1.61 | −1.609 | −1.785 | −0.798 | −0.785 | −1.080 | −1.115 |
| | Max | 1.20 | 2820.69 | 5847.23 | 13103.39 | 6.55 | −0.204 | −0.850 | 0.394 | 0.503 | 0.236 | 0.056 |
| | Average | 26.35 | 221512.30 | 241772.57 | 1001780.71 | 325.55 | 0.524 | 0.238 | 0.776 | 0.817 | 0.690 | 0.659 |
| | St. Dev. | 64.72 | 581639.24 | 558215.16 | 2648613.20 | 717.33 | 0.908 | 0.802 | 0.812 | 0.780 | 0.927 | 1.006 |
| | N | 56 | | | | | | | | | | |
| Developed | Min | 0.21 | 2820.69 | 2368.12 | 13103.39 | 1.61 | −0.20 | −0.85 | 0.39 | 0.50 | 0.24 | 0.06 |
| | Max | 164.74 | 4182801.18 | 3903674.41 | 19247056.78 | 4573.23 | 1.724 | 1.492 | 2.325 | 2.213 | 2.066 | 2.268 |
| | Average | 16.70 | 321069.88 | 285848.08 | 1454120.54 | 319.72 | 1.127 | 0.725 | 1.355 | 1.381 | 1.363 | 1.342 |
| | St. Dev. | 31.69 | 760981.30 | 705345.55 | 3482939.79 | 829.97 | 0.425 | 0.489 | 0.465 | 0.423 | 0.491 | 0.670 |
| | N | 31 | | | | | | | | | | |
| Developing | Min | 1.20 | 2114.32 | 5847.23 | 7255.42 | 6.55 | −1.609 | −1.785 | −0.798 | −0.785 | −1.080 | −1.115 |
| | Max | 457.78 | 715041.63 | 1293951.19 | 2508593.75 | 2384.78 | 1.125 | 0.843 | 1.317 | 1.086 | 0.942 | 1.134 |
| | Average | 38.32 | 98060.89 | 187118.93 | 440879.33 | 332.77 | −0.224 | −0.366 | 0.059 | 0.117 | −0.144 | −0.188 |
| | St. Dev. | 89.85 | 150787.58 | 294247.67 | 566386.79 | 563.94 | 0.781 | 0.699 | 0.520 | 0.500 | 0.599 | 0.638 |
| | N | 25 | | | | | | | | | | |
| Overall | CAGR | 0.45 | 1.97 | 0.75 | 1.43 | −0.69 | −0.90 | −0.81 | −0.62 | −0.20 | −0.27 | −0.27 |
| Developed | CAGR | 0.53 | 2.04 | −0.14 | 1.12 | −1.87 | −0.23 | −0.92 | −0.68 | 0.04 | −0.31 | −0.49 |
| Developing | CAGR | 0.41 | 1.71 | 2.70 | 2.77 | 0.94 | 4.28 | −1.09 | 1.19 | −3.15 | −0.79 | −2.05 |