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The Impact of Formal Institutions on Public Sector Efficiency: Evidence from Environmental and Healthcare Performance

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ABSTRACT

This study investigates the impact of formal institutional factors on public sector efficiency, focusing on environmental and healthcare performance—two of the most widely examined sectors in the public administration literature. The empirical analysis is based on a panel of 139 countries—33 developed and 106 developing—covering the period from 2012 to 2020. The analysis adopts a three-stage methodological framework comprising: (a) Bayesian data envelopment analysis (DEA) to estimate efficiency scores, (b) Principal component analysis (PCA) to construct a composite Public Sector Efficiency Index, and (c) a two-step generalized method of moments (GMM) approach to evaluate the influence of institutional variables, country classification (developed vs. developing), and their interactions on public sector efficiency. The findings highlight the importance of sustained efforts to reduce CO emissions and manage healthcare expenditures effectively. The results underscore the critical role of strengthening formal institutions and enhancing the human development index (HDI) to improve public sector efficiency.

Keywords: Public Sector Management, Environmental Performance, Healthcare Efficiency, CO_2 Emissions, Data Envelopment Analysis, Bayesian Methods

JEL Classifications: C5, D2, I1, Q5

1. INTRODUCTION

Public sector efficiency (PSE) is a fundamental concern for practitioners, researchers, and legislators since it directly affects social well-being, sustainable development, and economic stability. Governments worldwide are expected to satisfy the rising need for high-quality public services despite their limited funds. This means innovative policy interventions and efficient resource allocation to maximize results without compromising service quality (Afonso et al., 2005; Zervopoulos and Palaskas, 2010; Zervopoulos, 2014). An efficient public sector is essential for building trust in government, preserving budgetary restraint, and fastening economic development (Hall and Jones, 1999).

Among the several challenges public sector management faces are regulatory variations, poor accountability, and bureaucratic inefficiencies. According to Acemoglu et al. (2014), weak institutions displaying corruption and poor governance lower the public sector's efficiency and help to misallocate resources. Institutional changes and performance measuring tools like data envelopment analysis (DEA) and stochastic frontier analysis (SFA) provide a quantitative basis for evaluating efficiency levels and pointing out areas for development (Kaufmann et al., 1999). Moreover, innovative technologies like artificial intelligence (AI) and machine learning (ML) simplify resource allocation and offer predictive insights, thus enhancing decision-making processes (Medeiros and Schwierz, 2015).

1.1. Healthcare Efficiency in the Public Sector

One of the fundamental divisions of the public sector is healthcare, whose operations efficiency and quality of service directly influence population health, economic output, and government budget allocation (Afonso et al., 2005). Efficient healthcare systems guarantee fair access to high-quality medical treatments and optimal use of available resources. The World Health Organisation (WHO) underlines that inefficiencies in healthcare—such as administrative overheads, wasteful expenditure, and medical errors—can lead to major resource losses, thus lowering the effectiveness of health service delivery (WHO, 2010). DEA and SFA, among other efficiency assessment methods, let regulators evaluate hospital performance, benchmark best practices, and carry out focused interventions to improve service delivery (Kiadaliri et al., 2013).

Policy reforms and institutional quality greatly affect the effectiveness of healthcare services. Research has demonstrated that countries with established healthcare systems exhibit better health outcomes, reduced mortality rates, and higher patient satisfaction (Hauner and Kyobe, 2010). For example, China's healthcare reforms have improved healthcare efficiency despite regional disparities. Strengthening the primary healthcare system and optimizing resource allocation are key strategies for enhancing the performance of public healthcare systems globally (Zhang et al., 2017). Moreover, studies show that especially in urban areas, hospital capacity that is too high usually results in inefficiencies in healthcare. Studies of American hospitals have shown that, if improperly controlled, excess capacity may contribute to growing healthcare costs even while it can act as a buffer during an emergency (Ferrier et al., 2009).

Policies driven by cost controls, hospital ownership, and incentive systems also influence public sector healthcare efficiency. Studies have underlined how much managerial and financial incentives help to raise hospital efficiency. For instance, bureaucratic restrictions and weak market competition in publicly sponsored hospitals often result in lower efficiency levels than in private institutions (Kessler and McClellan, 2001). Conversely, as several OECD nations where healthcare systems have embraced performance-based funding models have shown, increased competition among healthcare providers has been proven to improve efficiency and service quality (Hadad et al., 2013).

Furthermore, the capacity to include process innovations and technology developments in healthcare provision usually defines hospital efficiency. By lowering wait times and allowing more exact treatment approaches, digital health solutions, including telemedicine and AI-driven diagnostics, are increasingly being used to improve efficiency. Nevertheless, the degree of success of these developments mostly relies on the quality of government and the regulatory framework applied (Neri et al., 2022). Furthermore, too strict rules or poorly crafted policy interventions can result in unexpected inefficiencies and aggravating problems in the healthcare industry (Hauner and Kyobe, 2010).

A complicated interaction of institutional governance, resource allocation, financial incentives, and technological developments ultimately defines public sector healthcare efficiency. Even if many nations have improved the efficiency of their healthcare systems, constant reforms and strategic policy interventions are required to solve inefficiencies and guarantee sustainable healthcare delivery.

1.2. Environmental Performance and Public Sector Efficiency

PSE depends fundamentally on environmental performance, especially as governments try to balance sustainability goals with economic development. Environmental policy success mainly depends on institutional frameworks, regulatory quality, and governance structures. Strong institutions are essential in reducing greenhouse gas (GHG) emissions while guaranteeing economic efficiency, claims Tateishi et al. (2020). High institutional quality countries usually show better environmental performance since governance systems help to implement policies, monitor compliance, and manage resources sustainably. Weak institutional environments, however, sometimes produce ineffective environmental policies that raise transaction costs and cause conflicts in efforts at emissions reduction (Tateishi et al., 2020).

Institutional quality shapes environmental governance's efficiency by determining regulatory control and compliance systems. As Kar et al. (2019) contend, many underdeveloped nations battle institutional traps whereby poor governance systems impede sustainable environmental management. These institutional flaws cause a difference in environmental efficiency, whereby low-income countries stay caught in a cycle of inefficiency while high-income countries keep enhancing their sustainability practices (Kar et al., 2019). Continuing institutional inefficiencies emphasize the need for specific reforms to improve governance systems, lower administrative hurdles, and promote environmental policy compliance.

Energy efficiency is another critical component of environmental performance that has major consequences for PSE (Kounetas and Zervopoulos, 2019). Achieving sustainability targets and lowering carbon emissions depend on increases in energy efficiency, claims Xu and Bao (2022). Their analysis of China's energy sector shows that spatial and institutional elements affect energy efficiency; differences in this regard reflect differences in governance effectiveness and policy execution (Xu and Bao, 2022).

Moreover, Berner et al. (2022) underline how the rebound effect—where lower energy prices result in higher consumption, so reducing environmental benefits—may offset gains in energy efficiency. This emphasizes the need for combined policies supporting strict regulatory frameworks, market-based incentives, and energy efficiency measures (Berner et al., 2022).

In the public sector, environmental efficiency calls for a complete strategy combining institutional changes, technical developments, and thorough regulations.

1.3. Contribution and Structure of the Study

This study contributes to the literature by examining the impact of formal institutions on PSE, with a specific focus on healthcare and environmental performance. These dimensions are assessed using a novel Bayesian data envelopment analysis (DEA) approach, which yields consistent estimates with the lowest mean squared error and the highest convergence rate compared to alternative efficiency estimation techniques, including the smoothed bootstrap and other Bayesian or kernel-based methods.

To the best of our knowledge, this is the first study to employ a three-stage methodology—comprising Bayesian DEA, principal component analysis (PCA), and the generalized method of moments (GMM)—to explore the effects of formal institutional factors, country classification (developed vs. developing), and their interactions on PSE. By integrating insights from governance studies, institutional economics, and public management, the study comprehensively assesses how institutional quality shapes public service outcomes.

The paper is structured as follows. Section 2 reviews the literature, emphasizing the interplay between institutions and both healthcare and environmental performance. It also discusses the most widely used methodologies for measuring public sector performance, including data envelopment analysis (DEA), stochastic frontier analysis (SFA), qualitative approaches, and other hybrid methods. Section 3 outlines the three-stage methodological framework for assessing PSE, incorporating a Bayesian DEA approach, principal component analysis (PCA), and a two-step generalized method of moments (GMM) procedure. Section 4 provides a detailed description of the sample and data sources. Section 5 presents the empirical results, and Section 6 concludes with policy implications, study limitations, and suggestions for future research.

2. LITERATURE REVIEW

2.1. The Interplay between Healthcare Performance and Institutions

Since governance, regulatory systems, and public policies directly affect efficiency levels, healthcare performance is intimately related to the institutional framework within which it functions. Strong institutions—defined by transparency, accountability, and efficient regulatory control—have been shown to increase the efficiency of healthcare systems, reduce mortality rates, and improve health outcomes (Hauner and Kyobe, 2010). On the other hand, poor institutions, corruption, and ineffective government help to create inefficiencies that lead to disparities in healthcare access and resource misallocation (Acemoglu et al., 2014). de Cos and Moral-Benito (2014) conducted a cross-country study showing that health system efficiency is much influenced by governance quality; better-regulated systems show reduced administrative waste and improved service delivery.

Funding models also influence the efficiency of healthcare delivery; public-sector-driven systems typically promote fair access, while market-oriented systems stress cost-containment and efficiency gains (Medeiros and Schwierz, 2015; Mitropodus et al., 2020). Germany and France, two countries with hybrid healthcare financing systems, often show better efficiency levels because of their mix of state control and market-driven competition (Retzlaff-Roberts et al., 2004). On the other hand, poor implementation of healthcare policies, weak regulatory mechanisms, and corruption in developing economies with scattered institutional frameworks challenge to ensure efficiency (Mauro, 1995).

The adoption and spread of healthcare technologies depend much on institutional quality and regulatory frameworks. Strong institutional support and well-defined laws help countries integrate data-driven healthcare policies, AI-assisted diagnostics, and electronic health records, thus improving their efficiency (Medeiros and Schwierz, 2015). By contrast, bureaucratic inefficiencies and lack of financial incentives cause delays in technological adoption in healthcare systems running weak institutional environments (Kaufmann et al., 1999). For example, hospitals' efficiency, patient outcomes, and cost-effectiveness have reportedly improved in OECD nations prioritizing AI-driven decision-making tools (Hollingsworth, 2008).

Furthermore, the effect of institutional reactions to healthcare crises, including the COVID-19 pandemic, is extensively researched. Strong institution-based crisis management, effective resource allocation, and reduced mortality rates resulting from quick regulatory interventions and open government were shown by countries with strong institutions (Kuosmanen et al., 2023). Countries with weaker institutional frameworks, on the other hand, battled poor supply chain management, delayed responses, and higher mortality rates (Feng et al., 2023). This emphasizes institutional resilience's importance in reducing health crises and guaranteeing healthcare effectiveness under crisis circumstances.

Institutional factors—such as political stability, levels of corruption, and regulatory quality—also play a significant role in shaping healthcare efficiency across different regions. Studies have shown that corruption significantly undermines healthcare efficiency by diverting resources away from essential services and inflating operational costs (Zheng et al., 2019). Strong anti-corruption laws and efficient healthcare governance systems—like those of Singapore and Sweden—help nations show better general health outcomes and higher efficiency in healthcare spending (Kessler and McClellan, 2001).

In conclusion, the interplay between healthcare performance and institutions is complex and multifaceted. Crucial determinants of healthcare efficiency are institutional strength, regulatory control, and governance quality; these affect financing models, technological acceptance, crisis management, and general system performance. Key concerns for legislators trying to guarantee sustainable public sector healthcare management and increase healthcare efficiency should be strengthening institutional frameworks and encouraging transparency.

2.2. The Interplay between Environmental Performance and Institutions

Environmental performance is closely intertwined with institutional quality since governance systems shape environmental policies, enforcement tools, and regulations. Strong institutions ensure efficient resource allocation, enforce regulatory compliance, and promote environmentally friendly practices, thus helping to reduce environmental degradation (Tateishi et al., 2020). Established countries show better environmental efficiency since government policies affect the acceptance of sustainable practices and clean technologies (Cui et al., 2022). On the other hand, inadequate institutional structures cause inefficiencies, corruption, and legal gaps, aggravating environmental problems and resource mismanagement (Lu et al., 2021).

Regulatory systems significantly affect environmental efficiency by incentivizing companies and sectors to adopt greener production methods. Empirical research indicates that strict and well-crafted environmental rules improve energy efficiency and lower carbon emissions (Suzuki and Nijkamp, 2016). On the other hand, poorly enforced laws can have unanticipated effects, including regulatory capture, in which businesses use policy manipulation to serve their own needs, producing less-than-ideal environmental results (Cui et al., 2022). The transparency and responsibility of the institutions implementing environmental policies determine their efficacy in addition to their degree of stringency.

The role of governance in energy efficiency and environmental performance is particularly evident in the electricity sector. A study by Zurano-Cervelló et al. (2019) on the European Union's electricity mix highlights that institutional frameworks significantly influence the adoption of renewable energy sources and the broader transition toward sustainable energy systems. Countries with strong governance mechanisms typically invest more in clean energy and exhibit higher energy efficiency; weaker governments struggle with inefficiencies and resistance to change (Zurano-Cervelló et al., 2019). Moreover, regulatory stability fosters innovation in the energy sector by providing long-term policy certainty encouraging investments in green technologies (Boyd and Lee, 2019).

Furthermore, political governance and corruption are essential in determining environmental performance. Corruption lowers national energy efficiency by reducing regulatory effectiveness and allowing polluting industries to evade compliance (Lu et al., 2021). Kounetas (2015) also emphasizes how different levels of environmental efficiency arise from institutional heterogeneity across European nations; more transparent and accountable governments produce better results. Improving environmental performance and guaranteeing sustainable economic development depends on strengthening institutional frameworks, raising regulatory quality, and lowering corruption.

Apart from the quality of governance, technological developments and knowledge spillovers affect the interaction between environmental performance and institutions. Stronger institutions in countries increase their likelihood of helping green technologies diffuse, lowering environmental inefficiencies, according to Kounetas (2015). This is especially important in the European setting, where eco-innovation policies have been included in institutional structures to enhance sustainability results. Furthermore, Boyd and Lee (2019) emphasize how the regulatory environment shapes companies' incentives to invest in energy-saving initiatives, determining their technology adoption in energy-intensive sectors. These results imply that the speed and success of environmental changes are much shaped by institutional capacity.

Furthermore, the function of market-based environmental policies is important in institutional influence on environmental performance. Support of strong institutions helps voluntary environmental rules, according to Cui et al. (2022), to drive long-term energy efficiency gains. Their research also implies that market-incentive policies can have conflicting effects depending on a nation's governance system. Such policies might cause rent-seeking behavior and regulatory distortions in weak institutional systems, thus lowering their expected environmental benefits. Conversely, in countries with strong legal systems and open communication channels, market-based environmental policies can efficiently promote energy efficiency while increasing economic competitiveness.

2.3. Public Sector Performance Measurement

Maintaining high-quality administrative services and ensuring the best resource allocation depends on PSE. DEA, SFA, AI- and ML-based models are among the several approaches created to evaluate public sector performance. Efficiency assessments now also include qualitative evaluations using surveys and hybrid techniques to consider contextual elements (Afonso et al., 2005). The evolution of performance-measuring approaches reflects the need for strong analytical frameworks and the increasing complexity of public service operations and delivery.

2.3.1. Data envelopment analysis (DEA)

Often applied in PSE assessment, DEA is a non-parametric technique. DEA lets policymakers benchmark public organizations, including hospitals, municipalities, and schools, by building an efficiency frontier based on best-performing decision-making units (DMUs) (Charnes et al., 1978). This approach has been widely applied in healthcare (Emrouznejad and Dey, 2011), education (Coelli et al., 2005), and government administration (Hollingsworth, 2008). Over time, researchers have refined DEA methodologies, introducing bootstrapped DEA to enhance statistical robustness and network DEA to model multi-stage processes (Coelli et al., 2005).

Despite its popularity, DEA has limitations, especially in its deterministic form, which assumes that all deviations from the efficiency frontier are caused by inefficiencies rather than external factors (Kumbhakar et al., 2000). It also supposes that all DMUs run under similar conditions, which presents a difficulty in various public sector settings (Hollingsworth, 2008). Researchers have combined DEA with parametric methods, including SFA, to overcome these restrictions and improve efficiency evaluations (Kumbhakar and Lovell, 2000; Tsionas, 2003; Boyd and Lee, 2019).

2.3.2. Stochastic frontier analysis (SFA)

By considering stochastic noise, SFA offers a substitute econometric method that separates inefficiency from statistical errors (Aigner et al., 1977). Unlike DEA, which links all inefficiencies to poor decision-making, SFA separates random fluctuations from inefficiencies to generate more consistent performance scores. In fields like healthcare (Hollingsworth, 2008), education (Coelli et al., 2005), and municipal government (Tsionas, 2003), this function makes SFA especially valuable when outside factors affect efficiency.

Two advances in SFA are semiparametric SFA, which provides more model flexibility (Kumbhakar and Lovell, 2000), and Bayesian SFA, which combines probability distributions for efficiency estimates (Tsionas, 2003). These advances improve SFA's relevance in many public sector environments. SFA, however, requires exact model specifications; thus, mistakes in functional form selection could produce skewed efficiency estimates (Afonso et al., 2005).

2.3.3. AI and ML in performance measurement

Real-time data processing, predictive analytics, and automated decision-making made possible by AI and ML have revolutionized PSE measuring (Wirtz et al., 2019). AI-driven models can handle complex, unstructured datasets, enabling the exact identification of inefficiency patterns. ML techniques—including neural networks, decision trees, and ensemble learning models—have been included in performance evaluation systems to improve predictive powers (Wirtz et al., 2019).

AI has been extensively applied in fraud detection in government spending (Wirtz et al., 2019), predictive analytics for policy planning (Eggers and Schatsky, 2017), and automation of citizen service delivery (Brynjolfsson and McAfee, 2017). AI-powered natural language processing (NLP) models also evaluate citizen satisfaction with government services employing public complaints and social media feedback (Wirtz et al., 2019). AI-based efficiency assessments, meanwhile, raise questions about algorithmic bias, lack of transparency, and ethical issues about data privacy (Eubanks, 2018). ML models' black-box character sometimes limits interpretability, which makes it challenging for legislators to support choices depending on AI-generated efficiency scores (Wirtz et al., 2019).

2.3.4. Qualitative methods and hybrid approaches

Although quantitative approaches predominate in efficiency measurement, qualitative assessments offer important contextual insights into governance quality, transparency, and institutional culture (Eubanks, 2018). Structured interviews and surveys let one measure public service accessibility, administrative efficiency, and citizen satisfaction. Applied in government service evaluations, the SERVQUAL model evaluates service quality depending on dependability, responsiveness, and empathy (Donnelly et al., 2006).

Hybrid approaches integrating DEA and SFA or combining econometric models with ML algorithms provide more comprehensive efficiency assessments (Tsionas, 2003). Whereas AI-driven frontier models improve decision-making accuracy (Wirtz et al., 2019), Bayesian DEA, for example, refines efficiency scores by including probability distributions. These combined approaches help to overcome the shortcomings of stand-alone solutions, thus strengthening the validity of efficiency assessments in local government, energy management, healthcare, and local government (Kumbhakar and Lovell, 2000).

3. METHODOLOGY

We employ a three-stage methodological framework. In the first stage, a Bayesian DEA approach obtains bias-corrected efficiency scores. The environmental and healthcare efficiency estimates produced by the Bayesian DEA exhibit smoother distributions and greater validity than those derived from non-stochastic DEA methods. This enhances the robustness of the findings and strengthens the policy implications drawn from the empirical results.

In the second stage, we apply PCA to construct a PSE index based on the environmental and healthcare efficiency scores derived from the previous stage. The values of this index are standardized to range between zero and one, consistent with conventional efficiency measures. The choice of PCA to combine environmental and healthcare efficiency scores into a single PSE index is grounded in its ability to objectively determine the weights of each component based on the variance they explain. Unlike equal averaging, which assigns arbitrary and potentially misleading equal importance to each dimension, PCA captures the intrinsic data structure and prioritizes components that contribute most to the overall variation (Jolliffe and Cadima, 2016). Similarly, unlike subjective or fixed-weight averaging, PCA avoids bias in index construction and enhances the robustness of the resulting composite score (Abdi and Williams, 2010). This method is particularly advantageous in cross-country analyses, where differences in variance across efficiency components may distort aggregated measures if treated uniformly. Therefore, PCA offers a statistically sound and data-driven alternative for synthesizing multidimensional efficiency indicators into a comprehensive index (Filmer and Pritchett, 2001; OECD, 2008).

In the third stage, the PSE index is regressed on a set of institutional factors, country classification (developed vs. developing, as defined by the International Monetary Fund and captured through a dummy variable), and their interaction terms, using a two-step GMM approach. The appropriateness of GMM results is assessed using specification, overidentification, and linear hypothesis criteria based on Arellano and Bond, Hansen J, and Wald tests.

3.1. Efficiency Estimates: A Bayesian DEA

A generalized directional distance function (GDDF) DEA model (Cheng and Zervopoulos, 2012; Cheng and Zervopoulos, 2014) is employed to determine environmental and healthcare efficiencies for each sample country [$\left\{\theta_j\right\}_{j=1}^{n} \in [\theta_L, 1]$ where $\theta_L \in (0,1)$]. We take into account inputs $x_i = (x_1, \ldots, x_m) \in \mathbb{R}_+^m$ and desirable $y_r = (y_1, \ldots, y_s) \in \mathbb{R}_+^s$ and undesirable outputs (e.g., CO_2 emissions - for environmental performance - and mortality rate under 5 years of age - for healthcare efficiency) $b_\eta = (b_1, \ldots, b_\kappa) \in \mathbb{R}_+^\kappa$. Undesirable outputs are jointly produced with desirable outputs and can be subject to regulation. In such cases, the directional distance function DEA and the generalized directional distance function (GDDF) DEA are considered the most appropriate methods for measuring efficiency (Podinovski and Kuosmanen, 2011; Zervopoulos, 2012; Zervopoulos et al., 2016; Vlachos et al., 2024).

The GDDF DEA model is as follows:

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

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

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

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

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

$\lambda \ge 0$

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

Where g_x, g_y, and g_b are the direction vectors for inputs (x), desirable outputs (y), and undesirable outputs (b), respectively, and λ is the optimal weight assigned to x,y, and b. Also, $\beta g_i/x_{io}$ and $\beta g_\eta/b_{\eta o}$ denote the proportional decrease in inputs and undesirable outputs, and $\beta g_r/y_{ro}$ expresses the proportional increase in desirable outputs of the country under review, which is identified by the subscript o in the program (1).

Despite the suitability of directional distance function DEA models for asymmetrically handling desirable and undesirable outputs, their efficiency estimates tend to be upwardly biased in finite samples—an issue common to all conventional DEA models (Banker, 1993; Zervopoulos et al., 2019).

To address the upward bias in efficiency estimates, Zervopoulos et al. (2023) developed a Bayesian DEA approach that employs a uniform likelihood and a beta prior to producing bias-corrected efficiencies based on model (1) or any conventional DEA model. Both theoretical and empirical evidence demonstrate that the Bayesian DEA estimates are consistent and outperform alternative bias-correction methods, yielding efficiency scores with significantly lower mean squared errors and higher convergence rates (Zervopoulos et al., 2023; Zacharias et al., 2024; Zervopoulos et al., 2024).

To begin, let $\{\theta_j\}_{j=1}^{v} \in [\theta_L, 1)$, where v ⊂ n, to express all sample efficiencies except the ones. Using the likelihood function of the efficiencies, we obtain the expected value (2) and the unbiased estimator (3) of the parameter θ_L, which are as follows:

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

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

Suppose the parameter θ_L is beta distributed, the prior is as follows:

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

Where γ and δ are the shape parameters of beta distribution (B).

Further details about the Bayesian DEA approach and formal proofs of the consistency of its estimates are available in Zervopoulos et al. (2023).

The following ratio is used to correct the bias of efficiencies:

$$\varphi = \frac{\tilde{\theta}_L}{\hat{\theta}_L} < 1 \tag{5}$$

Using the MATLAB function *betarnd*, the shape parameters are estimated as follows:

$$\hat{\gamma} = v\tilde{\theta}_L / (1-\varphi) \tag{6}$$

and

$$\hat{\delta} = (1\tilde{\theta}_L)\hat{\gamma} / \tilde{\theta}_L \tag{7}$$

To identify the bias-corrected efficiency estimates (θ_j^c), we fit ratio (5) using a normal distribution with parameters ($\hat{\mu}$, $\hat{\sigma}$) estimated by the MATLAB function *normfit*.

$$\theta_j^c = w^{-1}\sum_{\rho=1}^{w} \breve{\theta}_{j\rho} \tag{8}$$

Where w is the number of Monte Carlo iterations (ρ = 1,000), and $\breve{\theta}_{j\rho}$ are obtained randomly from the MATLAB function *normrnd* with parameters $\theta_j\hat{\mu}$ and $\theta_j\hat{\sigma}$. θ_j are determined by program (1).

3.2. Estimation of the Impact of Institutional Factors on Efficiencies: A GMM Approach

Using the methodology outlined in Section 3.1, we calculate environmental and healthcare efficiency scores for the same sample of countries. Subsequently, PCA is applied to derive PSE scores based on these two dimensions.

We employ a two-step GMM approach to estimate the effects of institutional factors on PSE. GMM is well-suited to address potential endogeneity and feedback effects between institutional variables, PSE, and unobserved heterogeneity (Ahn and Schmidt, 1995). The literature has highlighted the existence of feedback effects between institutional factors and components of PSE, such as GDP and CO_2 emissions (Glaeser et al., 2004; Stern, 2004; Aisen and Veiga, 2013; Apergis and Ozturk, 2015). While applying the GMM approach addresses endogeneity concerns, it is important to elaborate on this analysis's specific sources of potential endogeneity. One primary concern is reverse causality, where higher PSE may strengthen institutional quality—for instance, by enhancing trust in government or promoting regulatory compliance (Acemoglu et al., 2005; Kaufmann and Kraay, 2002). To mitigate issues of reverse causality between the independent and dependent variables, we construct a composite PSE index, which is standardized to range between zero and one. Another issue is omitted variable bias, whereby unobserved factors such as political stability, historical legacies, or social capital may simultaneously influence both institutional quality and public sector performance (Keefer, 2007). To mitigate these risks, GMM incorporates lagged values of the explanatory variables as instruments, using past information to correct for simultaneity and measurement error (Arellano and Bond, 1991). This dynamic panel specification helps account for feedback effects while ensuring the consistency of the estimators. In addition, including country-specific fixed effects and time dummies captures unobserved heterogeneity and time-related shocks, thereby reducing potential confounding influences (Roodman, 2009).

All combinations of institutional variables, their interaction terms, and the country classification variable (developed vs. developing) were tested to arrive at the final two-step GMM specification. This specification satisfies key econometric requirements, including model specification (Arellano and Bond, 1991), overidentification (Hansen, 1982), and linearity assumptions:

$$P_{1,j,t}^{c} = a_1 P_{1,j,t-1}^{c} + a_2 P_{1,j,t-2}^{c} + \beta_1 z_{1,j,t} + \beta_2 z_{1,j,t-1} + \beta_3 z_{2,j,t} + \beta_4 z_{1,j,t} z_{2,j,t} + \gamma_2 d_2 + \ldots + \gamma_T d_T + \eta_j + \varepsilon_{j,t} \tag{9}$$

Where $P_{1,j,t}^{c}$ expresses Bayesian DEA PSE estimates obtained from expressions (1)–(8), where $j = 1,\ldots,n$ and $t = 2,\ldots,T$ stand for the sample countries and time, respectively. Additionally, $P_{1,j,t-1}^{c}$ and $P_{1,j,t-2}^{c}$ are the lagged public sector efficiencies, serving as independent variables. Moreover, $z_{1,j,t}$ and $z_{1,j,t-1}$ express the control of corruption and its lag, and $z_{2,j,t}$ is the country classification (dummy-coded variable, where zero is assigned to developed countries and one to developing countries). The dummy variables $d_2,\ldots,d_T$ denote time and capture the possible effect of events that can bias the estimates. Also, η_j and $\varepsilon_{j,t}$ stand for time-invariant individual-specific effect and random noise, respectively.

The classification of countries into developed and developing follows established literature (Angelopoulos et al., 2008; Halkos and Tzeremes, 2010; Aparicio et al., 2016) and is based on the International Monetary Fund (IMF) definition (https://www.imf.org/en/Publications/WEO/weo-database/2022/April/select-aggr-data).

4. SAMPLE AND DATA DESCRIPTION

The sample used in this study comprises 139 countries, classified into 33 developed and 106 developing economies. The review period spans from 2012 to 2020. Extending the analysis beyond 2020 would significantly reduce the sample size, as energy-related data—such as energy consumption and CO_2 emissions—are not yet available for many of the countries included in the sample.

Acknowledging that PSE in this study is derived from environmental and healthcare components, we consider two inputs—labor (Solow, 1956) and energy consumption (Kounetas and Zervopoulos, 2019)—and two outputs—Gross Domestic Product (GDP) (Swan, 1956) and CO_2 emissions (Kounetas and Zervopoulos, 2019; Ashehhi and Zervopoulos, 2025). The economic variables, labor, and GDP are obtained from the World Development Indicators database (https://databank.worldbank.org/source/world-development-indicators), while the environmental variables, energy consumption and CO_2 emissions, are sourced from the Enerdata-Odyssee database (https://www.enerdata.net/solutions/database-odyssee.html).

All input and output variables concerning healthcare efficiency are obtained from the World Development Indicators database. In line with the literature, we use two inputs: health expenditure per capita and total health expenditure as a percentage of GDP (Evans et al., 2001; Cheng and Zervopoulos, 2014). The two outputs are life expectancy at birth (desirable output) and the mortality rate of children under 5 years of age (undesirable output) (Afonso and Aubyn, 2005; Grosskopf et al., 2006).

Additionally, six standard formal institutional factors were incorporated into the regression model following the efficiency estimation and the construction of the PSE index. These include (a) control of corruption, (b) government effectiveness, (c) political stability, (d) rule of law, (e) regulatory quality, and (f) voice and accountability. The selection of these institutional variables, originally proposed by Kaufmann et al. (1999), is supported by the extant literature (Méon and Weill, 2005; Aparicio et al., 2016; Nedić et al., 2020), and the data are sourced from the World Governance Indicators (WGI) database (https://www.worldbank.org/en/publication/worldwide-governance-indicators). These continuous variables range from −2.5 to 2.5, with lower values indicating weaker governance performance and higher values reflecting stronger governance quality.

Descriptive statistics for the environmental performance variables, healthcare efficiency variables, and institutional factors are presented in Tables 1-3, respectively. Additionally, (Figures 1a-d, 2a-d, and 3a-f) illustrate the trends of these variables across all sample countries, as well as separately for developed and developing economies.

Based on Table 1 and Figure 1a-d, both developed and developing countries experienced economic growth between 2012 and 2020 despite the adverse effects of the COVID-19 pandemic in 2020. Specifically, developing countries recorded a compound annual growth rate (CAGR) of 2.8% over the review period, while developed countries achieved a more modest CAGR of 1%. Both groups of countries succeeded in reducing CO_2 emissions during this period. Notably, developing countries attained a −0.1% CAGR in CO_2 emissions despite a 4.2% increase in energy consumption. In contrast, developed countries achieved a 0.2% reduction in CO_2 emissions alongside a 0.1% decrease in energy consumption from 2012 to 2020.

Table 2 and Figures 2a-d highlight the efforts made by both developed and developing countries to improve healthcare outcomes. Specifically, the mortality rate of the under-five age group declined on average by 2.8% in developing countries and

Table 1: Descriptive statistics for environmental performance variables (2012-2020)

Country classification	Statistics	Labor, in millions (input)	Energy consumption, in million tons of oil equivalent (input)	Gross domestic product, in million USD (desirable output)	CO_2 emissions, in metric tons (undesirable output)
All	Average	21.70	140.86	531,209.50	208.94
	Minimum	0.03	0.02	229.37	0.10
	Maximum	781.08	7,027.59	21,539,982.00	11,710.50
	St. deviation	80.20	598.60	1,993,992.04	1,047.75
	N	1251			
Developed	Average	14.91	260.09	1,398,202.37	76.06
	Minimum	0.19	1.95	9,609.53	0.21
	Maximum	167.95	4,042.84	21,539,982.00	641.12
	N	297			
Developing	Average	23.82	103.74	261,296.63	250.31
	Minimum	0.03	0.02	229.37	0.10
	Maximum	781.08	7,027.59	14,687,744.16	11,710.50
	N	954			
All	CAGR	0.007	0.023	0.017	-0.001
Developed	CAGR	0.004	-0.001	0.010	-0.002
Developing	CAGR	0.008	0.042	0.028	-0.001

Table 2: Descriptive statistics for healthcare efficiency variables (2012-2020)

Country classification	Statistics	Health expenditure per capita (input)	Health expenditure percentage of GDP (input)	Life expectancy at birth (desirable output)	Mortality rate under five (undesirable output)
All	Average	1240.92	6.38	71.84	31.11
	Minimum	15.89	1.51	47.84	2.10
	Maximum	11758.42	19.69	84.56	147.60
	St. Deviation	1988.73	2.71	8.21	32.57
	N	1251			
Developed	Average	4124.59	9.13	81.03	3.88
	Minimum	746.00	3.33	73.78	2.10
	Maximum	11758.42	18.76	84.56	7.10
	N	297			
Developing	Average	343.17	5.53	68.98	39.59
	Minimum	15.89	1.51	47.84	2.90
	Maximum	2435.45	19.69	80.99	147.60
	N	954			
All	CAGR	0.015	0.016	0.002	−0.028
Developed	CAGR	0.015	0.013	0.001	−0.017
Developing	CAGR	0.015	0.017	0.002	−0.028

Table 3: Descriptive statistics for institutional factors (2012-2020)

Country classification	Statistics	Control of corruption	Government effectiveness	Political stability	Rule of law	Regulatory quality	Voice and accountability
All	Average	−0.01	0.04	−0.07	0.00	0.06	−0.02
	Minimum	−1.65	−2.17	−2.70	−1.85	−2.13	−2.26
	Maximum	2.40	2.28	1.62	2.12	2.25	1.74
	St. Deviation	1.02	0.99	0.90	0.98	0.96	0.97
	N	1251					
Developed	Average	1.35	1.37	0.80	1.39	1.38	1.19
	Minimum	−0.19	0.12	−1.10	0.05	0.14	−0.21
	Maximum	2.40	2.28	1.62	2.12	2.25	1.74
	N	297					
Developing	Average	−0.43	−0.38	−0.34	−0.43	−0.36	−0.39
	Minimum	−1.65	−2.17	−2.70	−1.85	−2.13	−2.26
	Maximum	1.65	1.50	1.28	1.35	1.54	1.15
	N	954					
All	CAGR	−1.976	−0.157	0.005	−0.046	−0.088	−0.020
Developed	CAGR	−0.007	−0.008	−0.013	−0.006	0.001	−0.004
Developing	CAGR	−0.002	0.008	−0.007	−0.008	0.018	−0.006

Figure 1: Trends in environmental performance variables. (a) Labor (input), (b) Energy consumption (input), (c) Gross domestic product (desirable output), (d) CO_2 emissions (undesirable output)

Figure 2: Trends in healthcare efficiency variables. (a) Health expenditure per capita (input), (b) Health expenditure, percentage of GDP (input), (c) Life expectancy at birth (desirable output), (d) Mortality rate under five (undesirable output)

by 1.7% in developed countries over the review period. However, developed countries exhibit significantly higher levels of health expenditure per capita and health expenditure as a percentage of GDP compared to their developing counterparts.

Concerning institutional factors, developed countries consistently report positive scores throughout the review period (Table 3 and Figure 3a-f). In contrast, institutions in developing countries are generally perceived as weak, with average scores falling below zero—an observation previously noted by Alshehhi and Zervopoulos (2023). Notably, government effectiveness in developing countries improved significantly between 2012 and 2020, with a compound annual growth rate (CAGR) of 8%. In contrast, developed countries experienced an 8% decline in this indicator over the same period. Additionally, one of the most widely studied institutional variables—control of corruption—shows a negative CAGR for both groups: −0.7% for developed countries and −0.2% for developing countries (Table 3).

It is worth highlighting that a strong positive correlation exists among most institutional factors over the 2012-2020 period (Table 4). This finding is consistent with previous studies in the literature (Aparicio et al., 2016; Nedić et al., 2020; Alshehhi and Zervopoulos, 2023; Alshehhi and Zervopoulos, 2025).

Figure 3: Trends in institutional factors. (a) Control of corruption, (b) Government effectiveness, (c) Political stability, (d) Rule of law, (e) Regulatory quality, (f) Voice and accountability

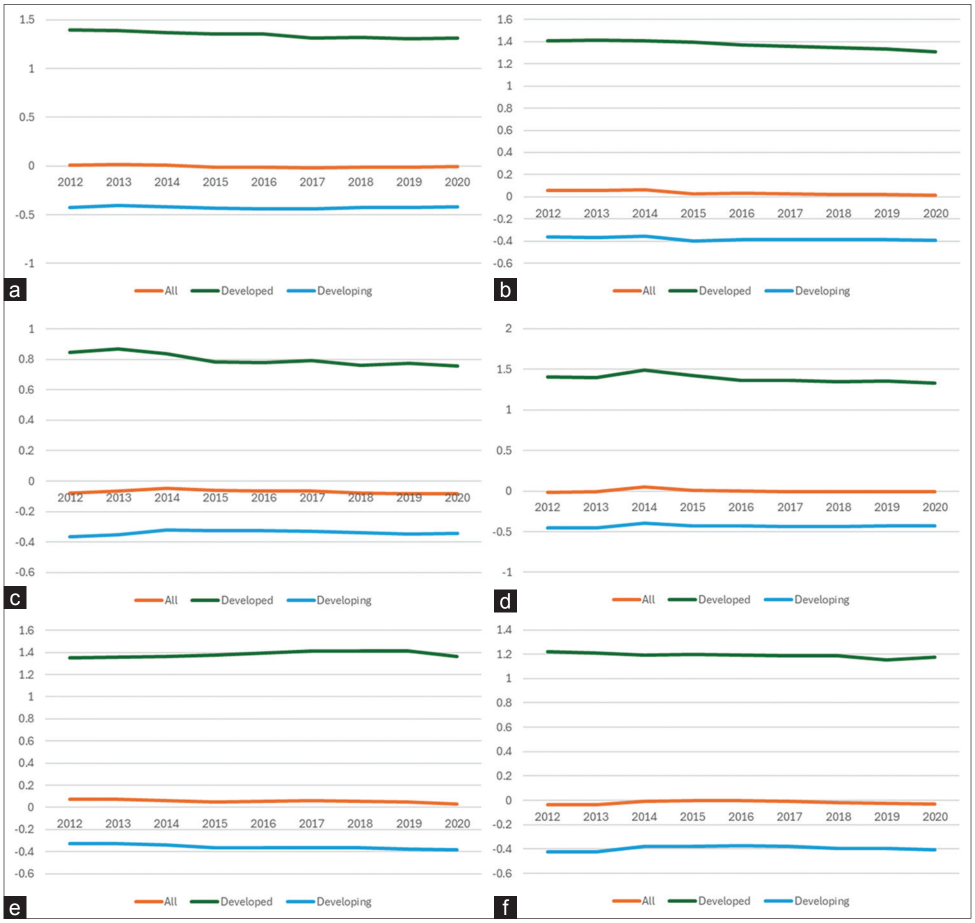

Table 4: Institutions correlation coefficients (2012-2020)

Institutional factors	[1]	[2]	[3]	[4]	[5]	[6]
[1] Control of corruption	1.000					
[2] Government effectiveness	0.913**	1.000				
[3] Political stability	0.773**	0.743**	1.000			
[4] Rule of law	0.941**	0.942**	0.757**	1.000		
[5] Regulatory quality	0.871**	0.933**	0.702**	0.925**	1.000	
[6] Voice and accountability	0.761**	0.732**	0.675**	0.768**	0.762**	1.000

5. EMPIRICAL RESULTS

The two selected components of PSE—environmental performance and healthcare efficiency—are derived using the methodology outlined in Section 3.1. As illustrated in Figure 4a (additional details are provided in Table A1 in the Appendix), environmental performance declined in both developed and developing countries over the review period. A comparison of the compound annual growth rates (CAGR) for the periods 2012-2019 and 2012-2020 reveals the negative impact of the COVID-19 pandemic, with the latter period showing more pronounced declines. In contrast, healthcare efficiency improved in both country groups between 2012 and 2019. However, the COVID-19 pandemic significantly affected the healthcare sector, as evidenced by a sharp decline in healthcare efficiency between 2019 and 2020 (Figure 4b; additional details are provided in Table A2 in the Appendix).

While the paper acknowledges the potential impact of the COVID-19 pandemic, it is important to elaborate on how 2020 may bias the results, particularly in environmental and healthcare performance domains. The pandemic brought about unprecedented disruptions in both sectors: healthcare systems faced severe strain due to the surge in patient volumes, while environmental indicators were temporarily altered due to lockdowns, mobility restrictions, and reductions in industrial activity (Barouki et al., 2021; He et al., 2020). These shocks may distort efficiency scores, especially if they reflect temporary or crisis-driven patterns rather than underlying institutional performance. For instance, a sudden reduction in CO_2 emissions in 2020 may misleadingly indicate improved environmental efficiency despite economic contraction rather than effective governance. Similarly, healthcare inefficiencies in some countries may have been amplified by systemic overload rather than pre-existing institutional weaknesses. To address this, the

Figure 4: Trends of public sector performance. (a) Environmental performance CAGR 2012-2019: −0.011 (all); −0.012 (developed); −0.011 (developing); CAGR 2012-2020: −0.015 (all); −0.018 (developed); −0.014 (developing), (b) Healthcare efficiency CAGR 2012-2019: 0.002 (All); 0.001 (developed); 0.003 (developing); CAGR 2012-2020: −0.0003 (all); −0.0013 (developed); 0.0000 (developing)

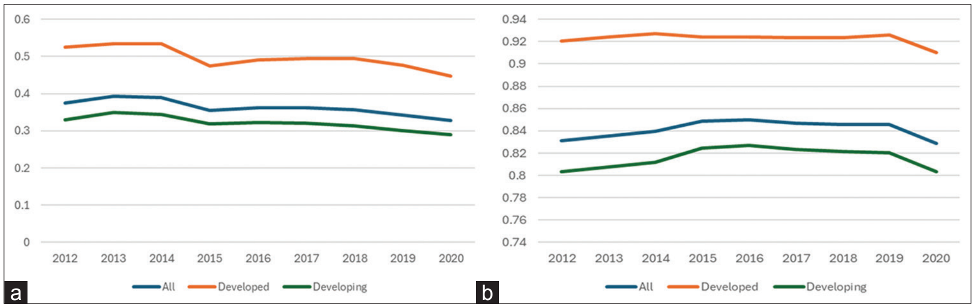

Table 5: Effects on PSE (2012-2020)

Variables & Tests	(9a)	(9b)[1]
$P^c_{1,j,t-1}$	0.4301***	0.3991***
$P^c_{1,j,t-2}$	0.2110***	0.1918***
$z_{1,j,t}$	0.0414	0.0219
$z_{1,j,t-1}$	−0.0043	−0.0093
$z_{2,j,t}$	−0.1103***	−0.1091***
$z_{1,j,t}z_{2,j,t}$	−0.0109*	−0.0112*
$z_{3,j,t}$		−0.0102
$z_{3,j,t-1}$		0.0148
Year dummies	Yes	Yes
Observations	1251	1251
Arellano and bond test	−0.3729	−0.2800
P-value	0.3733	0.4001
Hansen J-test	115.61	128.35
P-value	0.3455	0.3202
Wald test	121.12	119.08
P-value	<10-4	<10-4

empirical analysis includes year-fixed effects, which help control for time-specific shocks such as the pandemic. Nevertheless, 2020 is interpreted cautiously, recognizing that its trends may not reflect structural realities but short-term anomalies triggered by a global health crisis (Gössling et al., 2021). Future studies may benefit from separating pandemic years or applying robustness checks that exclude 2020 to ensure consistency of findings.

Following the estimation of the PSE index ($P^c_{1,j,t}$), as introduced in Section 3, we regress this index on formal institutional factors and the country classification variable using a two-step GMM approach. The structure and implementation of the GMM are detailed in Section 3.2.

Among the various models incorporating alternative combinations of institutional factors and interaction effects, only Models (9a) and (9b), presented in Table 5, satisfy the GMM specification, overidentification, and linearity assumptions. Furthermore, model (9b) is employed as a robustness check to validate the results of model (9a).

1 The two-step GMM model (9b) is as follows:

$$P^c_{1,j,t} = a_1 P^c_{1,j,t-1} + a_2 P^c_{1,j,t-2} + \beta_1 z_{1,j,t} + \beta_2 z_{1,j,t-1} + \beta_3 z_{2,j,t} + \beta_4 z_{1,j,t} z_{2,j,t} + \beta_5 z_{3,j,t}$$
$$+ \beta_6 z_{3,j,t-1} + \gamma_2 d_2 + \ldots + \gamma_T d_T + \eta_j + \varepsilon_{j,t}$$

where ${}_{3,j,t}$ and $z_{3,j,t-1}$ express government effectiveness and its time lags (j=1,...n and t=2,...T).

According to models (9a) and (9b), developing countries ($z_{2,j,t}$) PSE ($P^c_{1,j,t}$) is lower than that of their developed counterparts by 11.03% and 10.91%, respectively, over the review period 2012-2020, considering the remaining independent variables fixed. Previous years' PSE reports had the most considerable effect on the current PSE. Specifically, drawing on the model (9a), every 1% increase in the previous year's PSE ($P^c_{1,j,t-1}$) can lead to a 0.43% improvement in the current year's efficiency ($P^c_{1,j,t}$). Additionally, the same increase in 2 year's back, PSE ($P^c_{1,j,t-2}$) is expected to yield a 0.21% expansion of the current year's efficiency ($P^c_{1,j,t}$).

The findings of this research align with existing literature on economic and environmental performance (Apergis and Ozturk, 2015; Ozturk et al., 2019; Alshehhi and Zervopoulos, 2023; Alshehhi and Zervopoulos, 2024). Furthermore, the results support the "grease the wheels" hypothesis originally proposed by Leff (1964) and further developed by Méon and Weill (2005, 2010), extending its applicability to the context of PSE.

According to the estimates presented in Table 5, a country's classification (developed vs. developing) emerges as the second most significant determinant of PSE, with developed countries consistently outperforming their developing counterparts. As shown in Figure 3, developed countries exhibit, on average, stronger institutional quality than developing ones—highlighting the indirect role formal institutions play in shaping PSE.

In light of these findings, governments should prioritize strengthening the factors influencing their country's classification, including improvements in the Human Development Index (https://hdr.undp.org/data-center/country-insights#/ranks).

6. CONCLUSION AND POLICY IMPLICATIONS

This study sheds light on the effects of formal institutions on PSE, as measured through environmental performance and healthcare efficiency. These two sectors are among the most widely studied areas in the public sector management literature (Alqasimi et al., 2025), and the framework is grounded in the work of Afonso et al. (2005). A three-stage methodology facilitated both efficiency estimation and regression analysis, comprising (a) a Bayesian Generalized directional distance function (GDDF) data envelopment analysis (DEA) approach to estimate environmental and healthcare efficiency; (b) principal component analysis (PCA) to construct the PSE index based on the efficiency scores derived from the Bayesian method; and (c) a two-step generalized method of moments (GMM) regression analysis.

In line with the existing literature, the variables used to estimate the two components of PSE are: (a) for environmental performance - labor, energy consumption, GDP, and CO_2 emissions; and (b) for healthcare efficiency - health expenditure per capita, health expenditure as a percentage of GDP, life expectancy at birth, and the under-five mortality rate. The regression analysis incorporated six standard formal institutional indicators proposed by Kaufmann et al. (1999): (a) control of corruption, (b) government effectiveness, (c) political stability, (d) rule of law, (e) regulatory quality, and (f) voice and accountability. The sample consisted of 139 countries—33 developed and 106 developing—from 2012 to 2020.

Despite efforts by both developed and developing countries to reduce CO_2 emissions, environmental performance declined over the review period. In contrast, healthcare efficiency improved between 2012 and 2019. However, a downturn was observed between 2019 and 2020 due to the severe negative impact of the COVID-19 pandemic on healthcare systems worldwide. Notably, developing countries significantly reduced the under-five mortality rate, while life expectancy at birth marginally increased. A concern for the healthcare sector remains the rising health expenditure per capita, which increased on average by 1.5% annually during the study period. As highlighted in the literature and confirmed in this study, developed countries consistently demonstrate stronger institutional quality compared to developing countries.

The GMM results reveal that the most significant determinant of current PSE is the efficiency achieved in previous years. Based on the two components of the PSE index—environmental and healthcare performance—policy recommendations include intensifying efforts to reduce CO_2 emissions and energy consumption, alongside better management of healthcare expenditures. While an aging population, particularly in developed countries, may limit reductions in healthcare spending due to rising pharmaceutical and medical technology costs, gains in life expectancy and reductions in under-five mortality can enhance healthcare efficiency.

In addition to the influence of lagged efficiency, country classification and the control of corruption—moderated by country classification—play a crucial role. These findings underscore the importance of strengthening formal institutions and improving the human development index (HDI), essential for a country's advancement to developed status. As demonstrated in this study and supported by a growing body of literature, developed countries maintain, on average, significantly stronger formal institutions than their developing counterparts.

The findings of this study offer important practical implications for both international organizations and national governments seeking to enhance public sector performance. Institutions such as the international monetary fund (IMF), United Nations Development programme (UNDP), and World Bank can use the study's PSE index and institutional diagnostics as empirical tools to monitor governance reforms and assess country-level progress in healthcare and environmental performance. The results also inform the design and targeting of institutional development initiatives, particularly in developing countries where efficiency gaps are most pronounced. For instance, identifying regulatory quality and corruption control as key determinants of efficiency can guide technical assistance and capacity-building efforts. At the national level, governments may apply the analytical framework to benchmark their performance, identify areas of institutional weakness, and design tailored policy interventions. In doing so, the study supports evidence-based reform strategies aligned with the broader objectives of sustainable development and inclusive governance.

This study is not without limitations. First, the review period (2012–2020) could be extended to include additional years impacted by the COVID-19 pandemic. Although the descriptive statistics clearly indicate the pandemic's adverse effects on efficiency, incorporating data beyond 2020 could yield further insights into the evolving role of institutional factors and their interactions with country classification. Second, the variables used to estimate environmental and healthcare efficiency and the exclusive focus on these two sectors present another limitation. Future research could expand the variable set to include capital stock and sector-specific gross value added for environmental performance, as well as literacy rates and maternal mortality ratios for healthcare efficiency. Moreover, other sectors—such as education, infrastructure, and transportation—could be integrated into broader PSE assessments. Lastly, future studies may also consider the role of informal institutions, including citizen sentiment and cultural norms, in complementing the analysis of formal institutional impacts.

REFERENCES

Abdi, H., Williams, L.J. (2010), Principal component analysis. Wiley Interdisciplinary Reviews: Computational Statistics, 2(4), 433-459.

Acemoglu, D., Gallego, F.A., Robinson, J.A. (2014), Institutions, human capital, and development. Annual Review of Economics, 6(1), 875-912.

Acemoglu, D., Johnson, S., Robinson, J.A. (2005), Institutions as a fundamental cause of long-run growth. In: Aghion, P., Durlauf, S., editors. Handbook of Economic Growth. Vol. 1A. Netherlands: Elsevier. p385-472.

Afonso, A., Aubyn, M.S. (2005), Non-parametric approaches to education and health efficiency in OECD countries. Journal of Applied Economics, 8(2), 227-246.

Afonso, A., Schuknecht, L., Tanzi, V. (2005), Public sector efficiency: An international comparison. Public Choice, 123(3-4), 321-347.

Ahn, S.C., Schmidt, P. (1995), Efficient estimation of models for dynamic panel data. Journal of Econometrics, 68, 5-27.

Aigner, D., Lovell, C.A.K., Schmidt, P. (1977), Formulation and estimation of stochastic frontier production function models. Journal of Econometrics, 6(1), 21-37.

Aisen, A., Veiga, F.J. (2013), How does political instability affect economic growth? European Journal of Political Economy, 29, 151-167.

Alqasimi, S.A., Zervopoulos, P.D., Sharker, A.E., Fousteris, A.E. (2025), A review of the impact of institutions on public sector efficiency. International Review of Management and Marketing, 15(3), 352-390.

Alshehhi, J.M., Zervopoulos, P.D. (2023), The effect of institutional factors on environmental efficiency: A cross-country analysis using a Bayesian data envelopment analysis approach. Journal of Cleaner Production, 395, 136401.

Alshehhi, J.M., Zervopoulos, P.D. (2024), The role of institutional factors in shaping environmental performance: Evidence from developed and developing countries. In: Lecture Notes in Operations Research. Berlin: Springer. p97-108.

Alshehhi, J.M., Zervopoulos, P.D. (2025), The influence of sustainable socio-economic factors on environmental efficiency: An international analysis during turbulent periods. International Journal of Energy Economics and Policy, 15(1), 165-179.

Angelopoulos, K., Philippopoulos, A., Tsionas, E. (2008), Does public sector efficiency matter? Revisiting the relation between fiscal size and economic growth in a world sample. Public Choice, 137(1), 245-278.

Aparicio, S., Urbano, D., Audretsch, D. (2016), Institutional factors, opportunity entrepreneurship and economic growth: Panel data evidence. Technological Forecasting and Social Change, 102, 45-61.

Apergis, N., Ozturk, I. (2015), Testing environmental Kuznets curve hypothesis in Asian countries. Ecological Indicators, 52, 16-22.

Arellano, M., Bond, S. (1991), Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. The Review of Economic Studies, 58(2), 277-297.

Banker, R. D. (1993), Maximum likelihood, consistency and data envelopment analysis: A statistical foundation. Management Science, 39(10), 1265-1273.

Barouki, R., Kogevinas, M., Audouze, K., Belesova, K., Bergman, A., Birnbaum, L., & Slama, R. (2021), The COVID-19 pandemic and global environmental change: Emerging research needs. Environment International, 146, 106272.

Berner, A., Bruns, S., Moneta, A., Stern, D.I. (2022), Do energy efficiency improvements reduce energy use? Empirical evidence on the economy-wide rebound effect in Europe and the United States. Energy Economics, 110, 105939.

Boyd, G.A., Lee, J.M. (2019), Measuring plant level energy efficiency and technical change in the U.S. metal-based durable manufacturing sector using stochastic frontier analysis. Energy Economics, 81, 159-174.

Brynjolfsson, E., McAfee, A. (2017), The Business of Artificial Intelligence. Harvard Business Review. Available from: https://hbr.org/2017/07/the-business-of-artificial-intelligence

Charnes, A., Cooper, W.W., Rhodes, E. (1978), Measuring the efficiency of decision making units. European Journal of Operational Research, 2(6), 429-444.

Cheng, G., Zervopoulos, P.D. (2012), A Generalized Directional Distance Function in Data Envelopment Analysis and its Application to a Cross-Country Measurement of Health Efficiency. MPRA Paper 42068. Available from: https://mpra.ub.uni-muenchen.de/42068

Cheng, G., Zervopoulos, P.D. (2014), Estimating the technical efficiency of health care systems: A cross-country comparison using the directional distance function. European Journal of Operational Research, 238(3), 899-910.

Coelli, T., Rao, D.S.P., O'Donnell, C.J., Battese, G.E. (2005), An Introduction to Efficiency and Productivity Analysis. 2nd ed. Berlin: Springer.

Cui, S., Wang, Y., Zhu, Z., Zhu, Z., Yu, C. (2022), The impact of heterogeneous environmental regulation on the energy eco-efficiency of China's energy-mineral cities. Journal of Cleaner Production, 350, 131553.

de Cos, P.H., Moral-Benito, E. (2014), Determinants of health-system efficiency: evidence from OECD countries. International Journal of Health Care Finance and Economics, 14(1), 69-93.

Donnelly, M., Kerr, N.J., Rimmer, R., Shiu, E.M. (2006), Assessing the quality of police services using SERVQUAL. Policing, 29(1), 92-105.

Eggers, W. D., & Schatsky, D. (2017), AI-augmented government: Using cognitive technologies to redesign public sector work. Deloitte Insights. Available from: https://www2.deloitte.com/us/en/insights/focus/cognitive-technologies/artificial-intelligence-government.html

Emrouznejad, A., & Dey, P. K. (2011), Performance measurement in the health sector: uses of frontier efficiency methodologies and multi-criteria decision making. Journal of Medical Systems, 35, 977-979.

Eubanks, V. (2018), Automating Inequality: How High-tech Tools Profile, Police, and Punish the Poor. New York: St. Martin's Press.

Evans, D.B., Tandon, A., Murray, C.J., Lauer, J.A. (2001), Comparative efficiency of national health systems: Cross national econometric analysis. BMJ, 323(7308), 307-310.

Feng, Q.Q., Ao, Y.B., Chen, S.Z., Martek, I. (2023), Evaluation of the allocation efficiency of medical and health resources in China's rural three-tier healthcare system. Public Health, 218, 39-44.

Ferrier, G.D., Leleu, H., Valdmanis, V.G. (2009), Hospital capacity in large urban areas: Is there enough in times of need? Journal of Productivity Analysis, 32(2), 103-117.

Filmer, D., Pritchett, L.H. (2001), Estimating wealth effects without expenditure data--or tears: An application to educational enrollments in states of India. Demography, 38(1), 115-132.

Glaeser, E.L., La Porta, R., Lopez-de-Silanes, F., Shleifer, A. (2004), Do institutions cause growth? Journal of Economic Growth, 9, 271-303.

Gössling, S., Scott, D., Hall, C.M. (2021), Pandemics, tourism and global change: A rapid assessment of COVID-19. Journal of Sustainable Tourism, 29(1), 1-20.

Grosskopf, S., Self, S., Zaim, O. (2006), Estimating the efficiency of the system of healthcare financing in achieving better health. Applied Economics, 38(13), 1477-1488.

Hadad, S., Hadad, Y., Simon-Tuval, T. (2013), Determinants of healthcare system's efficiency in OECD countries. The European Journal of Health Economics, 14(2), 253-265.

Halkos, G.E., Tzeremes, N.G. (2010), Corruption and economic efficiency: Panel data evidence. Global Economic Review, 39(4), 441-454.

Hall, R. E., & Jones, C. I. (1999), Why do some countries produce so much more output per worker than others?. The Quarterly Journal of Economics, 114(1), 83-116.

Hansen, L.P. (1982), Large sample properties of generalized method of moments estimators. Econometrica, 50(4), 1029-1054.

Hauner, D., Kyobe, A. (2010), Determinants of government efficiency. World Development, 38(11), 1527-1542.

He, G., Pan, Y., Tanaka, T. (2020), The short-term impacts of COVID-19 lockdown on urban air pollution in China. Nature Sustainability, 3, 1005-1011.

Hollingsworth, B. (2008), The measurement of efficiency and productivity of health care delivery. Health Economics, 17(10), 1107-1128.

Jolliffe, I.T., Cadima, J. (2016), Principal component analysis: A review and recent developments. Philosophical Transactions. Series A, Mathematical, Physical, and Engineering Sciences, 374(2065), 20150202.

Kar, S., Roy, A., Sen, K. (2019), The double trap: Institutions and

economic development. Economic Modelling, 76, 243-259.
Kaufmann, D., Kraay, A. (2002), Growth without governance. Economia, 3(1), 169-229.
Kaufmann, D., Kraay, A., Zoido-Lobaton, P. (1999), Aggregating Governance Indicators. World Bank Working Paper #2195.
Keefer, P. (2007), Clientelism, credibility, and the policy choices of young democracies. American Journal of Political Science, 51(4), 804-821.
Kessler, D., McClellan, M. (2001), The Effects of Hospital Ownership on Medical Productivity. National Bureau of Economic Research. Working Paper 8537.
Kiadaliri, A.A., Jafari, M., Gerdtham, U.G. (2013), Frontier-based techniques in measuring hospital efficiency in Iran: A systematic review and meta-regression analysis. BMC Health Services Research, 13(1), 312.
Kneip, A., Park, B. U., & Simar, L. (1998), A note on the convergence of nonparametric DEA estimators for production efficiency scores. Econometric Theory, 14(6), 783-793.
Kounetas, K. (2015), Heterogeneous technologies, strategic groups and environmental efficiency technology gaps for European countries. Energy Policy, 83, 277-287.
Kounetas, K., Zervopoulos, P.D. (2019), A cross-country evaluation of environmental performance: Is there a convergence-divergence pattern in technology gaps? European Journal of Operational Research, 273(3), 1136-1148.
Kumbhakar, S.C., Lovell, C.A.K. (2000), Stochastic Frontier Analysis. Cambridge: Cambridge University Press.
Kuosmanen, T., Tan, Y., Dai, S. (2023), Performance analysis of English hospitals during the first and second waves of the coronavirus pandemic. Health Care Management Science, 26(3), 447-460.
Leff, N.H. (1964), Economic development through bureaucratic corruption. The American Behavioral Scientist, 8(3), 8-14.
Lu, W.M., Kweh, Q.L., Nourani, M., Lin, C.Y. (2021), Political governance, corruption perceptions index, and national dynamic energy efficiency. Journal of Cleaner Production, 295, 126505.
Mauro, P. (1995), Corruption and growth. The Quarterly Journal of Economics, 110(3), 681-712.
Medeiros, J., Schwierz, C. (2015), Efficiency estimates of health care systems in the EU. European Commission Economic Papers, 549, 1-26.
Méon, P.G., Weill, L. (2005), Does better governance foster efficiency? An aggregate frontier analysis. Economics of Governance, 6(1), 75-90.
Méon, P.G., Weill, L. (2010), Is corruption an efficient grease? World Development, 38(3), 244-259.
Mitropoulos, P., Zervopoulos, P.D., Mitropoulos, I. (2020), Measuring performance in the presence of noisy data with targeted desirable levels: Evidence from healthcare units. Annals of Operations Research, 294(1-2), 537-566.
Nedić, V., Despotović, D., Cvetanović, S., Djukić, T., Petrović, D. (2020), Institutional reforms for economic growth in the Western Balkan countries. Journal of Policy Modeling, 42(5), 933-952.
Neri, M., Cubi-Molla, P., Cookson, G. (2022), Approaches to measure efficiency in primary care: A systematic literature review. Applied Health Economics and Health Policy, 20(1), 19-33.
OECD. (2008), Handbook on Constructing Composite Indicators. Paris: OECD Publishing.
Ozturk, I., Al-Mulali, U., Solarin, S.A. (2019), The control of corruption and energy efficiency relationship: An empirical note. Environmental Science and Pollution Research, 26(17), 17277-17283.
Podinovski, V.V., Kuosmanen, T. (2011), Modelling weak disposability in data envelopment analysis under relaxed convexity assumptions. European Journal of Operational Research, 211(3), 577-585.
Retzlaff-Roberts, D., Chang, C.F., Rubin, R.M. (2004), Technical efficiency in the use of health care resources: A comparison of OECD countries. Health Policy, 69(1), 55-72.
Roodman, D. (2009), A note on the theme of too many instruments. Oxford Bulletin of Economics and Statistics, 71(1), 135-158.
Solow, R.M. (1956), A contribution to the theory of economic growth. The Quarterly Journal of Economics, 70(1), 65-94.
Stern, D.I. (2004), The rise and fall of the environmental Kuznets curve. World Development, 32(8), 1419-1439.
Suzuki, S., Nijkamp, P. (2016), An evaluation of energy-environment-economic efficiency for EU, APEC and ASEAN countries: Design of a Target-Oriented DFM model with fixed factors in Data Envelopment Analysis. Energy Policy, 88, 100-112.
Swan, T.W. (1956), Economic growth and capital accumulation. Economic Record, 32(2), 334-361.
Tateishi, H.R., Bragagnolo, C., de Faria, R.N. (2020), Economic and environmental efficiencies of greenhouse gases' emissions under institutional influence. Technological Forecasting and Social Change, 161, 120321.
Tsionas, E.G. (2003), Combining DEA and stochastic frontier models: An empirical Bayes approach. European Journal of Operational Research, 147(3), 499-510.
Vlachos, I., Zervopoulos, P.D., Cheng, G. (2024), Supply chain performance evaluation using a network data envelopment analysis model with bias-corrected estimates. Annals of Operations Research, 337(1), 343-395.
Wirtz, B.W., Weyerer, J.C., Geyer, C. (2019), Artificial intelligence and the public sector-applications and challenges. International Journal of Public Administration, 42(7), 596-615.
World Health Organization (WHO). (2010), The World Health Report: Health Systems Financing: The Path to Universal Coverage. Geneva: WHO Press.
Xu, M., Bao, C. (2022), Quantifying the spatiotemporal characteristics of China's energy efficiency and its driving factors: A Super-RSBM and Geodetector analysis. Journal of Cleaner Production, 356, 131867.
Zacharias, C., Zervopoulos, P.D., Emrouznejad, A., Triantis, K., Cheng, G. (2024), A kernel Bayesian data envelopment analysis approach for bias correction of efficiencies. In: Lecture Notes in Operations Research. Berlin: Springer. p175-185.
Zervopoulos, P.D. (2012), Dealing with Small Samples and Dimensionality Issues in Data Envelopment Analysis. MPRA Paper 39226. Available from: https://mpra.ub.uni-muenchen.de/39226
Zervopoulos, P.D. (2014), Measuring the performance of service organizations and the effects of downsizing on performance: Evidence from the Greek citizen service centers. In: International Series in Operations Research and Management Science. Berlin: Springer. p127-154.
Zervopoulos, P.D., Brisimi, T.S., Emrouznejad, A., Cheng, G. (2016), Performance measurement with multiple interrelated variables and threshold target levels: Evidence from retail firms in the US. European Journal of Operational Research, 250(1), 262-272.
Zervopoulos, P.D., Kanas, A., Emrouznejad, A., Molyneux, P. (2024), Can super-efficiencies improve bias correction? A Bayesian data envelopment analysis approach. In: Lecture Notes in Operations Research. Berlin: Springer. p21-31.
Zervopoulos, P.D., Palaskas, T. (2010), Performance-Effectiveness-Efficiency Measurement Methods in Public Sector: International and Greek Experience. MPRA Paper 30936. Available from: https://mpra.ub.uni-muenchen.de/30936
Zervopoulos, P.D., Sklavos, S., Kanas, A., Cheng, G. (2019), A multi-parametric method for bias correction of DEA efficiency estimators. Journal of the Operational Research Society, 70(4), 655-674.
Zervopoulos, P.D., Triantis, K., Sklavos, S., Kanas, A. (2023), An alternative Bayesian data envelopment analysis approach for correcting bias of efficiency estimators. Journal of the Operational Research Society, 74(4), 1021-1041.

Zhang, L., Cheng, G., Song, S., Yuan, B., Zhu, W., He, L., Ma, X., Meng, Q. (2017), Efficiency performance of China's health care delivery system. The International Journal of Health Planning and Management, 32(3), 254-263.

Zheng, D., Gong, J., Zhang, C. (2019), Efficiency of medical service systems in the rural areas of Mainland China: A comparative study from 2013 to 2017. Public Health, 171, 139-147.

Zurano-Cervelló, P., Pozo, C., Mateo-Sanz, J.M., Jiménez, L., Guillén-Gosálbez, G. (2019), Sustainability efficiency assessment of the electricity mix of the 28 EU member countries combining data envelopment analysis and optimized projections. Energy Policy, 134, 110921.

APPENDIX

Table A1: Average environmental performance

Classification	2012	2013	2014	2015	2016	2017	2018	2019	2020
All	0.376	0.393	0.389	0.355	0.363	0.362	0.356	0.343	0.327
Developed	0.525	0.534	0.534	0.475	0.492	0.495	0.495	0.477	0.447
Developing	0.329	0.349	0.345	0.318	0.323	0.321	0.313	0.301	0.290

Table A2: Average health efficiencies

Classification	2012	2013	2014	2015	2016	2017	2018	2019	2020
All	0.831	0.835	0.839	0.848	0.850	0.847	0.846	0.846	0.829
Developed	0.921	0.924	0.927	0.924	0.924	0.924	0.923	0.926	0.910
Developing	0.803	0.808	0.812	0.825	0.827	0.823	0.821	0.821	0.803