

CONSTRUCTING A COMPOSITE GREEN ACCOUNTING INDEX AND ASSESSING ITS NONLINEAR IMPACT ON INSTITUTIONAL QUALITY: A BAYESIAN QUANTILE REGRESSION APPROACH

CONSTRUÇÃO DE UM ÍNDICE COMPOSTO DE CONTABILIDADE VERDE E AVALIAÇÃO DE SEU IMPACTO NÃO LINEAR NA QUALIDADE INSTITUCIONAL: UMA ABORDAGEM DE REGRESSÃO QUANTIL BAYESIANA

Article received on: 9/3/2025

Article accepted on: 11/3/2025

Nguyen Van Hai*

*Faculty of Finance and Accounting, Lac Hong University, Vietnam

Orcid: <https://orcid.org/0009-0003-3836-3085>

nvhai@lhu.edu.vn

The authors declare that there is no conflict of interest

Abstract: Despite growing concerns about environmental issues, we believe the benefits of environmental accounting outweigh the challenges. However, to date, no study has examined the impact of Green Accounting Index (GAI) on Institutional Quality (IQ). This study addresses this gap by investigating the effect of GAI on IQ across 84 countries worldwide during the period 2002–2020. Using a Bayesian Quantile Regression (BQR) model, the results reveal that GAI consistently exerts a positive influence on IQ across all quantiles—0.1, 0.25, 0.5, 0.75, and 0.9. These findings highlight the crucial role of GAI in enhancing institutional quality across different institutional segments. Notably, at the 0.9 quantile, the relationship tends to weaken, which strongly supports the information disclosure theory proposed by Diamond and Verrecchia (1991), suggesting that when a country reaches a stable and robust institutional threshold, the marginal impact of GAI on IQ diminishes. The findings underscore the importance of prioritizing GAI implementation to reduce corruption space and improve institutional quality. GAI provides a more consistent and comprehensive approach to enhancing IQ in diverse environmental contexts.

Keywords: Green Accounting. Institutional Quality. Bayesian Quantile Regression.

Resumo: Apesar das crescentes preocupações com as questões ambientais, acreditamos que os benefícios da contabilidade ambiental superam os desafios. No entanto, até o momento, nenhum estudo examinou o impacto do Índice de Contabilidade Verde (ICA) na Qualidade Institucional (QI). Este estudo busca preencher essa lacuna, investigando o efeito do ICA na QI em 84 países ao redor do mundo durante o período de 2002 a 2020. Utilizando um modelo de Regressão Quantílica Bayesiana (RQB), os resultados revelam que o ICA exerce consistentemente uma influência positiva na QI em todos os quantis — 0,1, 0,25, 0,5, 0,75 e 0,9. Essas descobertas destacam o papel crucial do ICA na melhoria da qualidade institucional em diferentes segmentos institucionais. Notavelmente, no quantil 0,9, a relação tende a enfraquecer, o que corrobora fortemente a teoria da divulgação de informações proposta por Diamond e Verrecchia (1991), sugerindo que, quando um país atinge um limiar institucional estável e robusto, o impacto marginal do ICA na QI diminui. Os resultados destacam a importância de priorizar a implementação da Contabilidade Verde para reduzir o espaço para corrupção e melhorar a qualidade institucional. A Contabilidade Verde oferece uma abordagem mais consistente e abrangente para aprimorar a qualidade institucional em diversos contextos ambientais.

Palavras-chave: Contabilidade Verde. Qualidade Institucional. Regressão Quantílica Bayesiana.



1 INTRODUCTION

The environment is an issue that many countries are concerned about to improve and consolidate to create sustainable value for the economy (Stöver, 2016). However, achieving a green environment and ensuring the accuracy of environmental information requires a transparent and integrated system. Providing transparent environmental information helps countries provide development guidance, control corruption in public institutions, enhance government stability, and enhance accountability (Li et al., 2022). In other words, countries that effectively implement standardized and public environmental reporting systems tend to have more stable institutions because they reduce information costs and improve monitoring effectiveness (Zhang & Kamarudin, 2024). A clean environment and transparent information provide the foundation for sustainable development and long-term economic growth (Appiah et al., 2025). GAI not only provides transparent environmental information but also plays an important role as a tool to improve countries institutional environments. This helps reduce resource misuse, prevents public entities from hiding environmental costs, and increases accountability. As a result, countries can reduce risks from authoritarian policies, improve efficiency, and strengthen government stability on environmental issues. In particular, as environmental degradation worsens and affects the economy (Zheng & Chen, 2024), widespread adoption of transparency-based solutions will lead to profound changes in all aspects of the economy and institutional stability (Diamond & Verrecchia, 1991). Countries with higher levels of GAI implementation tend to have better capacity to publish, monitor and use environmental information effectively. GAI have become one of the key drivers of institutional improvement, sustainable growth and social justice. GAI not only increases the transparency of environmental information but also builds trust in government management through equitable distribution and control of serious environmental problems (Zia et al., 2023). When these concerns are well managed, the economy will improve and create more positive impacts on social welfare (Halдар & Sethi, 2021).

Furthermore, providing accurate information on resource issues such as electricity, remaining forest cover or available fresh water helps people effectively respond to natural hazards such as droughts and floods. This, in turn, will increase public awareness of the government and increase trust in published information, especially in countries with

weaker institutional frameworks. This study aims to address the important question of how GAI affects institutional quality in different contexts. The importance of this issue lies in how environmental information is published transparently across different institutional segments, thereby reducing the risk of resource-related corruption and enhancing social trust. Therefore, this study focuses on two central objectives: (1) to investigate how the impact of GAI on institutional quality varies across institutional quantiles, and (2) to identify which GAI-related policy mechanisms countries should adopt to optimize institutional performance and pursue sustainable development—especially in the face of escalating environmental challenges.

The relationship between the GAI and IQ can be explained through several key theoretical frameworks:

The Environmental Kuznets Curve (EKC) theory, developed by Grossman and Krueger (1991, 1995) based on Kuznets (1955), extends the traditional Kuznets Curve to environmental economics. It emphasizes an inverted U-shaped nonlinear relationship between economic development and environmental or social outcomes. Within this framework, GAI influences institutional quality through the transparency of environmental information. In the early stages of institutional development, when legal and regulatory frameworks are weak, GAI faces challenges in disclosing environmental data. Information disclosure tends to be symbolic rather than substantive, which reduces the effectiveness of governance and may even lower institutional quality. However, as institutions mature and become more robust, GAI evolves into a catalyst for institutional reform. The growing demand for transparency in environmental governance compels governments to publish accurate and verifiable environmental information. This transparency not only enhances public oversight but also reduces corruption, strengthens accountability, and builds social trust in institutions. Thus, within the EKC framework, the relationship between GAI and IQ begins negatively but transitions toward a positive and reinforcing effect once institutional capacity is strong enough to absorb the benefits of environmental disclosure.

The Porter Hypothesis, proposed and developed by Porter and van der Linde (1995, 1996), the Porter Hypothesis argues that strict environmental regulations can stimulate innovation and improve long-term economic and social efficiency. In this context, the implementation of standardized GAI regulations requires public agencies and enterprises to disclose detailed information about emissions, resource use, environmental damages,

and environmental costs. Initially, this increases costs and puts pressure on public management units, making information only representative and reducing trust in the organization in the short term. However, in the long run, this negative impact acts as a catalyst for innovation. This requires governments to implement new comprehensive institutional quality reforms to enhance the effectiveness of adopting green transparency reforms.

The Information Disclosure Theory, pioneered by Diamond and Verrecchia (1991) and based on George's (1970) information asymmetry theory, explains that accurate government disclosure of information plays an important role in reducing information asymmetry and enhancing trust in markets and institutions. In this context, GAI provides transparent information on emissions data, energy consumption, environmental costs, resource management, environmental impact and environmental tax compliance. Furthermore, GAI reduces opportunities for rent-seeking and corruption in public administration, improves government accountability and efficiency, and helps improve institutional quality. This shows that GAI has a positive relationship with institutional quality; However, Diamond and Verrecchia note that the effectiveness of this relationship tends to decrease as countries reach a stable threshold of transparency.

Empirical evidence reflects a multidimensional perspective. Stöver (2016) examined the relationship between green accounting, institutional quality and investment decisions, highlighting the macroeconomic implications of analyzing the oil and mining industries. In this study, institutional quality is measured by perceived market risk. The results show that good institutional quality can increase or decrease the rate of resource exploitation depending on the specific context. Kinuthia et al. (2025) explored the moderating role of institutional quality in the relationship between economic growth, financial development and carbon emissions in sub-Saharan Africa. Using a fixed effects regression model, the results indicate that good institutional quality creates positive space for economic growth and financial development to influence carbon emissions. In other words, strong institutions reduce environmental costs and improve the transparency of information about carbon emissions. Additionally, the study highlights the role of institutions in the transition to low-carbon growth. Nuta and Tanasa (2023) analyzed the role of institutional quality in environmental degradation. Through a literature review, the study presents specific findings showing that good institutions help reduce pollution and improve ecological conditions. However, the authors cautioned that even strong

institutional frameworks lose effectiveness if not implemented or supported by concrete policy actions, emphasizing the gap between institutional design and real-world enforcement. Haldar and Sethi (2021) shared findings effect of institutional quality on the negative relationship between energy consumption and CO₂ emissions. Examining 39 developing countries from 1995 to 2017 using multiple econometric approaches (MG, AMG, CCEMG, Dynamic System GMM, Panel Grouped-Mean FMOLS, and PQR), the study concluded that institutional quality plays a decisive role in reducing the adverse environmental impact of energy consumption. Furthermore, their results validated the Environmental Kuznets Curve hypothesis within the institutional framework and revealed a long-term positive relationship between renewable energy use and emission reduction. Expanding the perspective, Appiah et al. (2025) approached environmental issues through the lens of green economic growth (GGDP) and assessed institutional quality based on six key pillars: control of corruption, government effectiveness, political stability, regulatory quality, rule of law, and accountability. The study emphasized that institutional weaknesses are the primary causes of environmental degradation and resource depletion, while institutional improvements enhance effective environmental governance. Employing Bootstrap Quantile Regression and OLS, their findings showed that control of corruption and government effectiveness positively influence GGDP, though rule of law and regulatory quality were statistically insignificant. Likewise, Çitil et al. (2023) investigated the impact of institutional quality on air quality across G20 countries between 2004 and 2020. Utilizing several advanced econometric techniques including Pesaran's (2007) CADF unit root test, the Method of Moments Quantile Regression (MMQR), and causality analysis the study found that institutional quality significantly improves air quality, although the adverse effects of energy consumption remain a major environmental challenge. Finally, Zia et al. (2023) examined the combined effects of energy efficiency (EE), institutional quality (IQ), and green technology (GT) on environmental outcomes in BRICS countries from 1995 to 2019. Applying second-generation econometric methods, the study revealed that EE, IQ, and GT collectively contribute to reducing environmental degradation, highlighting the interconnectedness of governance, innovation, and environmental performance.

Through the literature review, two research gaps can be identified:

First, most existing studies have primarily focused on examining the impact of institutional quality on environmental outcomes such as carbon emissions, natural

resource exploitation, green accounting aspects or the moderating role of institutional indicators on macroeconomic variables affecting the environment. However, there has not yet been any study that develops a comprehensive composite index of GAI. This limitation leaves an important gap in understanding the holistic impact of GAI. More importantly, up to now, there has been no research directly investigating the effect of GAI on the improvement of IQ. The transparent disclosure of information related to resource management, emissions, environmental cost adjustments and compliance with environmental taxation can enhance market confidence, reduce corruption in public administration and ultimately strengthen institutional quality. In addition, this study constructs an Institutional Quality Index based on six key pillars including control of corruption, government effectiveness, political stability, regulatory quality, rule of law and accountability to ensure a more comprehensive assessment of GAI impact compared to using a single institutional indicator.

Second, unlike previous studies that mainly used traditional frequency-based methods, this study aims to evaluate the impact of GAI on institutional quality using a Bayesian quantile regression model. Regression techniques allow researchers to analyze the influence of GAI on different institutional quantiles, thereby clarifying the non-linear relationship between GAI and institutional quality. However, an issue that needs to be addressed is the high correlation between variables, which often leads to multicollinearity. Therefore, Bayesian quantile regression provides a powerful method to address these problems by handling endogeneity and multicollinearity (Benoit & Van den Poel, 2017; Dinh et al., 2024). This approach provides a multidimensional understanding of the interactive effects of GAI in different institutional contexts. Transparency of environmental information reduces opportunities for corruption in public management units and improves social responsibility. This therefore increases social trust and paves the way for strategic policies aimed at improving institutional quality.

Additionally, unlike traditional quantile regression or bootstrap quantile regression, information is often expressed as a single value, such as the mean or percentile, which does not fully reflect the uncertainty of the estimates. This framework may lead to misleading results, which may be inconsistent with actual variations in the factors that influence improvements in institutional quality. On the other hand, in Bayesian quantile regression, each estimated parameter is represented by a probability distribution (Le Quoc D, 2024; Dinh, 2025a; Dinh 2025b; Dinh, 2025c; Quoc & Le Quoc, 2025). This allows

researchers to not only measure parameter values but also describe the uncertainty of the relationship. Particularly in the context of institutional modeling, the measurement of relevant information can be disrupted by unobserved factors. Bayesian quantile regression is a powerful method that allows researchers to estimate probability distributions by updating estimates over time (Benoit & Van den Poel, 2017). This approach not only provides a better understanding of the impact of green transparency on trust in government, but also provides highly accurate estimates, helping policymakers design more country-tailored strategies.

The dataset were compiled from 84 countries around the world from 2002 to 2020. Bayesian quantile regression results show that GAI has a positive impact on institutional quality at all quantiles. This implies that GAI plays an important role in improving the institutional quality of countries by publishing information on environment, costs, emissions and tax compliance. As a result, it reduces the opportunities for corruption in public services and improves the stability and efficiency of government. Furthermore, this study makes a significant contribution to the scholarly literature in several ways. First, the study clarifies the impact of GAI on institutional quality by applying a Bayesian quantile regression model, providing a multidimensional perspective on how GAI affects different institutional segments. Second, this study provides policy-relevant insights in promoting GAI, especially in the context of highly impacted environmental conditions. This aims to improve institutional quality in countries around the world.

2 METHOD

2.1 Data and sample

The study sample includes 84 countries worldwide, selected based on available data from 2002 to 2020. Data on institutional quality are constructed from six key pillars using the World Governance Indicators (WGI). GAI is collected from two main sources: (1) the Global Development Index published by the World Bank and data from the Organization for Economic Co-operation and Development (OECD), based on 15 individual indicators and aggregated into a composite measure using principal component analysis (PCA). Definition and measurement of variables are presented in *Appendix 1*.

2.2 Variable justification

Institutional Quality (IQ) reflects the degree of efficiency, transparency, and fairness of political, legal, and administrative institutions in maintaining economic stability. IQ is an appropriate and widely accepted measure in previous studies, such as Nuta & Tanasa (2023), Haldar & Sethi (2021), Zia et al. (2023), Tuyet & Dinh (2025), and Van et al. (2025). In this study, to comprehensively evaluate the impact of GAI on IQ, we constructed a composite IQ index that reflects all aspects of national institutions based on six core indicators: Control of Corruption (CC), Regulatory Quality (RQ), Rule of Law (RL), Political Stability (PS), Voice and Accountability (VA), and Government Effectiveness (GE).

$$IQ = W_1CC + W_2RQ + W_3RL + W_4PS + W_5VA + W_6GE \quad (1)$$

Principal Component Analysis (PCA) is a powerful tool that helps reduce the multidimensionality of data (Jackson, 2005; Huy & Loan, 2022; Khoi & Dinh, 2025; Le Quoc et al., 2025; Nguyen Quoc et al., 2025; Quoc et al., 2025a; Quoc et al., 2025c). The objective of this technique is to extract closely related components into fewer factors by transforming the original data (Oanh & Dinh, 2024a, Oanh & Dinh, 2025b; Huy & Dinh, 2025a; Huy & Dinh, 2025b). The results in Table 1 and Table 2 illustrate the PCA results for 84 countries, summarizing the main findings. As shown in Table 1, the total variance explained by the first and second principal components is 93.09%, with eigenvalues of 5.2148 and 0.3706, respectively. However, since the eigenvalue of the second and subsequent components is below the threshold of 1, only the first principal component was retained to construct the composite IQ index. The PCA results highlight that the weights of RQ, GE, and CC are relatively high, which implies that these variables contribute significantly to the construction of IQ. The variable RL has the highest loading (0.4290), reflecting trust in transparent and effective institutions and representing an important indicator for most countries. This finding strongly supports a comprehensive and effective GAI, or in other words, an effective GAI promotes IQ.

Table 1

Probability contribution of the variables of IQ

Dim	Eigenvalue	Proportion	Comulative
Dim 1	5.21486	0.8691	0.8691
Dim 2	0.37069	0.0618	0.9309
Dim 3	0.24791	0.0413	0.9722
Dim 4	0.08571	0.0143	0.9865

Source: Calculations by the authors

Table 2 - PCA results for the 6 variables with positive weights (W) are presented. And the overall IQ scores for 84 countries are calculated using the formula below:

$$IQ = 0.4229CC + 0.4212RQ + 0.4290RL + 0.3609PS + 0.3895VA + 0.4215GE$$

Table 2

PCA result of IQ

IQ	CC	RQ	RL	PV	VA	GE
	0.4229	0.4212	0.4290	0.3609	0.3895	0.4215

Source: Calculations by the authors

Based on previous literature, the measurement of GAI is quite diverse. However, these measures generally indicate that GAI cannot be captured by a single variable. GAI needs to be constructed from multiple factors, such as emission pollution, energy resources, and the genuine savings index adjusted for environmental costs (ANS) (Wang et al., 2024; Zheng & Chen, 2024; Appiah et al., 2025). A novel contribution of this study compared to previous research is the addition of an important measure, environmental tax (TAX). This measure reflects national policies and efforts to internalize environmental costs, thereby enhancing the comprehensiveness of the GAI construction. In this study, GAI is constructed from 15 component variables: (1) Renewable energy (FEC); (2) Renewable electricity (ELC); (3) Fossil fuel energy (COMM); (4) Forest area (FRST); (5) Total natural resource rents (TOTL); (6) Freshwater extraction (H2O); (7) Energy intensity (PIMW); (8) Resource depletion damage (DRES); (9) Damage from particulate matter pollution (DPEM); (10) Net deforestation (DFOR); (11) CO₂ emission damage (DCO₂); (12) Energy resource depletion (DNGY); (13) Mineral depletion (DMIN); (14) Total greenhouse gas emissions (GHG); and (15) Environmental tax (TAX). These indicators play a crucial role in constructing a comprehensive composite GAI that fully represents the environmental accounting capacity of each country.

To construct the GAI, we used a PCA technique on the 15 component variables to condense them into a single composite measure. Table 3 presents the PCA results of the 15 component variables, summarizing the main information. The component variables were reduced to 5 principal components with eigenvalues greater than 1, explaining 73.72% of the variance of the indices. Eigenvalues and eigenvectors provide detailed information about the importance of each metric. If the variance explained by the first principal component exceeded 70%, PC1 was used to calculate the composite index. If multiple principal components are generated, a composite index is calculated using the weighted sum of the PCs, with the explained variance serving as the weight (Kurniawan et al., 2025). In this study, choosing only the first principal component (PC1) would lose a large part of the information. We therefore decided to combine several key components to construct a single composite index, preserving most of the explanatory information while providing a comprehensive measure of GAI. The threshold was determined by applying a threshold of explained variance greater than 70% and eigenvalue greater than 1.

Table 3

Probability contribution of the variables of GAI

Dim	Eigenvalue	Proportion	Comulative
Dim 1	4.26419	0.2843	0.2843
Dim 2	2.72747	0.1818	0.4661
Dim 3	1.74458	0.1163	0.5824
Dim 4	1.23923	0.0826	0.6650
Dim 5	1.08191	0.0721	0.7372
Dim 6	0.92419	0.0616	0.7988

Source: Calculations by the authors

The results in Table 3, we proceeded to synthesize the PCs into a single GAI measurement index, based on the weight of the explained variance ratio. This method helps retain most of the information from the component variables and has been widely applied in previous studies, such as Fernandez & Martos (2020), Zheng & Chen (2024), and Chao & Wu (2017). However, to ensure the PCs before aggregation, the orientation of the PCs in the good dimension is very necessary (Jain & Mohapatra, 2023). This method reflects positive aspects of the environment and institutions, where higher PCs increase trust and improve institutional quality. Boudt et al. (2022) emphasized that reorienting the PCs according to an important variable or a positive policy variable will

make the composite index easier to interpret while maintaining the statistical meaning of PCA. From this, the general formula is formed as follows:

$$CI = \sum_{i=1}^k \pi_i Y_i \quad (2)$$

Including:

CI: Composite Index.

π_i : Proportion of PC_i .

k : Number of principal components retained.

Y_i : Principal component PC_i .

Based on the above reasoning, the GAI score is calculated using the following formula:

$$GAI = 0.2843 PC_1 + 0.1818PC_2 + 0.1163PC_3 + 0.0826PC_4 + 0.0721PC_5 \quad (3)$$

From these arguments, we propose the following hypothesis:

Hypothesis H1: Green Accounting index (GAI) increases Institutional Quality (IQ).

In addition to the main variables, this study also includes six control variables. These variables play a particularly important role in reducing errors and increasing model durability, including: gross domestic product (GDP), foreign direct investment (FDI), urbanization rate (UR), trade openness (TRADE), inflation rate (INF), and unemployment rate (UNE). These variables enhance the impact of GAI in improving IQ.

2.3 Research methodology

The baseline model illustrating the interaction of GAI on IQ is constructed as follows:

$$IQ_{i,t} = \beta_0 + \beta_1 GAI_{i,t} + \beta_2 X_{i,t} + \varepsilon_{i,t} \quad (4)$$

Concerns in model (1) need to be considered and resolved to minimize errors and increase the reliability of results. First, multicollinearity between variables can lead to

biased results and reduce the accuracy of the estimated parameters. Second, endogeneity between the independent variable and the errors $\varepsilon_{i,t}$ can pose serious problems regarding the consistency of model estimates.

To address these issues, this study uses a BQR model. This is a powerful method that allows researchers to examine the impact of GAI across different institutional quantiles, thereby providing precise estimates, especially when the relationships between variables vary across the distribution. Based on a probabilistic approach, BQR incorporates additional information through prior distributions, thereby improving the accuracy and validity of parameter estimates. Additionally, this model effectively handles endogeneity by using a conditional prior distribution, thereby increasing reliability and reducing errors in the model. Therefore, BQR is a powerful and flexible tool for exploring the complex structure of data while improving the robustness of quantitative analysis (Benoit & Van den Poel, 2017).

The baseline model to analyze the relationship between the independent variable GAI and the dependent variable IQ is established as follows:

$$IQ_i = GAI_i^T \beta_1 + \varepsilon_i \quad (5)$$

In this context, the regression model can be generalized to quantile regression, where we minimize the loss function for each quantile:

$$\widehat{\beta}_\tau = \underset{\beta \in R^k}{\operatorname{argmin}} \sum_{i=1}^n \rho_\tau(IQ_i - GAI_i^T \beta_1) \quad (6)$$

Here, ρ_τ is the control function corresponding to the quantile of interest, measuring the difference between the observed value and the predicted value at different points of the distribution. By applying these methods, we are able to evaluate the impact of GAI on institutional quality across multiple quantiles. This helps provide a general and comprehensive understanding of how GAI affects different segments of national organizations.

Additionally, Bayesian inference updates prior distributions with observed data to determine posterior distributions, thereby allowing model estimation while accounting for uncertainty (Van & Le Quoc, 2024; Van et al., 2024; Quoc et al., 2025b; Quoc &

Quoc, 2025, Oanh & Ha, 2025). The choice of quantiles plays an important role in quantile regression because it affects the smoothness of the estimates and the accuracy of the results. Higher quantiles can reduce variance but increase bias, while lower quantiles improve accuracy but increase variance. Therefore, in this study, we use five quantiles: 0.1, 0.25, 0.5, 0.75, and 0.9. These values are especially important to improve the reliability of results as well as the accuracy of parameter estimates.

By using multiple quantiles, we gain deeper insights into the model's behavior and the influence of parameters on the results. To estimate the posterior distribution, we use the MCMC technique by running 8000 iterations. These methods ensure more accurate and reliable estimates, providing deeper and more detailed information on the impact of GAI on institutional quality.

3 RESULTS

3.1 Overview of descriptive statistics

Descriptive statistics of the variables are presented in full in Table 4. The results showed that IQ had a mean value of 0.053 with a standard deviation of 1.26, indicating significant variation in IQ within the sample. IQ ranges from -2.5 (lowest institutional quality) to 2.5 (highest institutional quality). This range is standardized according to the World Bank. Some countries still have relatively low IQ, while many others achieve very high IQ. This reflects the diversity of the sample, which included underdeveloped, developed, and developed countries. The average GAI value was 0.74 with a standard deviation of 0.16, reflecting the variability of the data. GAI ranges from 0 (indicating no GAI), representing countries in the early stages of GAI implementation, to approximately 1 (representing complete GAI), representing countries that do a good job of disclosing GAI information.

In particular, Table 4 highlights three key questions that need to be considered and clarified. First, there is the concern about cross-sectional dependence (CD test), which is an important issue to check before proceeding with panel data analysis. Ignoring this aspect can lead to misleading model results and meaningless solutions. To address this issue, this study uses Pesaran's (2021) cross-sectional dependence test. The results show that all variables are statistically significant ($p < 0.01$), implying cross-sectional

dependence. Next is to check the normality of the data set using the Jarque-Bera technique. The results showed that no variables followed a normal distribution ($p < 0.01$). This reflects skewness or kurtosis in the data, meaning the distribution is skewed and may contain outliers or heavy tails. Therefore, a robust research model is needed to address this issue. Finally, testing for slope heterogeneity showed that the Delta and adjusted Delta coefficients (Pesaran & Yamagata, 2008) were statistically significant ($p < 0.01$), highlighting the presence of slope heterogeneity. Based on these considerations, it is important to choose an appropriate model to solve these problems. Models such as OLS, FEM or SEM can lead to misleading research results. Therefore, this study uses a BQR model, which represents inferences based on specific quantiles. Additionally, Bayesian inference allows to estimate the model through prior distributions, thereby improving the accuracy of the search results.

Table 4

Overview of descriptive statistics

Variables	Mean	Std. Dev.	Minimum	Maximum	Pesaran CD Test	Jarque-Bera Test
IQ	0.053038	1.260922	-2.50000	2.50000	3.0590***	803.74***
GAI	0.742914	0.169496	0.00000	1.00000	42.068***	235.09***
GDP	3.333926	4.035379	-17.8212	34.4662	128.80***	185.67***
FDI	5.693480	21.65113	-296.013	431.789	27.635***	739.16***
UR	62.13918	20.55826	15.6260	100.000	23.861***	77.690***
TRADE	83.95548	48.65128	20.4471	437.327	43.175***	772.32***
UNE	7.670726	5.319935	0.31600	32.9440	21.613***	367.85***
INF	4.750169	6.386381	-18.8992	85.3533	43.151***	675.71***
Slope heterogeneity						
Delta	15.493***					
Adj.	21.355***					

Notes: *** indicates significance level of 1%.

Source: Calculations by the authors

3.2 BQR Results

Bayesian quantile regression (BQR) results of the impact of GAI on IQ for 84 countries over the period 2002 to 2020 are detailed in Table 5, summarizing the main findings. In this study, we used five quantiles: 0.1, 0.25, 0.5, 0.75, and 0.9. As shown, GAI has a positive impact on IQ across all quantiles. This suggests that GAI contributes to improving institutional quality in these countries by improving IQ at any given institutional quantile. The results show that transparent disclosure of environmental

information helps reduce corruption, increase stability and accountability, thereby improving IQ.

Table 5*BQR result*

Variables	Quantile: 0.1			Quantile: 0.25			Quantile: 0.5		
	Mean	Lower	Upper	Mean	Lower	Upper	Mean	Lower	Upper
GAI	0.809385	0.093853	1.54248	0.90705	0.2742246	1.56128	1.94272	1.269595	2.64105
GDP	-0.000774	-0.024589	0.02337	-0.00586	-0.0258032	0.01286	-0.01785	-0.040978	0.00360
FDI	0.002566	-0.004950	0.00782	0.00357	-0.0020180	0.00760	0.00117	-0.002061	0.00418
UR	0.003124	-0.002184	0.00834	0.00391	0.0000249	0.00783	0.00237	-0.004222	0.00868
TRADE	0.002194	-0.000258	0.00394	0.00212	0.0008950	0.00339	0.00240	0.000226	0.00509
UNE	0.038750	0.022360	0.05440	0.04007	0.0232704	0.06102	0.05859	0.042077	0.07477
INF	0.007029	-0.005429	0.01825	0.00162	-0.0082507	0.01114	-0.00676	-0.019721	0.00766
C	-2.661663	-3.259239	-2.09229	-2.34965	-2.7936157	-1.92987	-2.25570	-2.679130	-1.81674
Variables	Quantile: 0.75			Quantile: 0.9					
	Mean	Lower	Upper	Mean	Lower	Upper			
GAI	2.77276	2.10201	3.45159	2.289228	1.55058	3.008760			
GDP	-0.01576	-0.04329	0.01268	0.004790	-0.02910	0.037176			
FDI	-0.00131	-0.00444	0.00282	-0.000425	-0.00465	0.006173			
UR	-0.00164	-0.00741	0.00425	0.001985	-0.00417	0.007470			
TRADE	0.00163	-0.00150	0.00458	-0.003875	-0.00654	-0.000629			
UNE	0.02579	0.01055	0.04156	0.006977	-0.01526	0.031690			
INF	-0.00760	-0.02544	0.01393	-0.007202	-0.03034	0.016056			
C	-1.17889	-1.83703	-0.51181	0.228123	-0.66510	1.197264			

Source: Calculations by the authors

4 DISCUSSION

The study results presented in Table 5 show the impact of GAI on IQ in 84 countries in different quantum contexts. Using five quantiles including 0.1, 0.25, 0.5, 0.75, and 0.9, the study provides a comprehensive view of the impact of GAI across institutional segments. The results show that GAI and IQ have a clear and consistent positive relationship, with GAI influencing IQ across all quantiles. This implies that GAI plays an important role in improving institutional quality globally, as it increases IQ regardless of the specific percentile, thus emphasizing its importance for each country. The consistent effect in institutional allocation shows the positive impact of GAI, especially in the disclosure of information on emissions, energy resources, real savings adjusted for environmental costs and transparent environmental taxes. In addition, it also helps reduce corruption in environmental management units and enhance accountability in current environmental issues. Therefore, it improves and enhances IQ efficiency, thereby contributing to sustainable development. These results extend and strengthen the existing literature on GAI, especially compared to previous studies such as Stöver (2016), Kinuthia et al. (2025), Nuta and Tanasa (2023), Kinuthia et al. (2025), Appiah et al. (2025), and Zia et al. (2023), who examined the role of institutions in environmental outcomes. Previous studies have addressed this issue by using institutions as an intermediary variable to assess the impact of macroeconomic factors on the environment. This study focuses on exploring the transparent disclosure aspect of environmental management, providing deeper insights into how GAI addresses institutional quality issues such as reducing corruption, improving efficiency, and enhancing the stability of national governance systems. This study shifts the focus to GAI, which addresses the accurate and transparent disclosure of environmental information, by providing a more comprehensive and contemporary perspective on the role of environmental information verification in enhancing accountability and improving IQ. This is especially important in the current context, when environmental quality and environmental information are becoming a major concern of many countries. The results strongly support hypothesis H1, which shows that GAI has a positive impact on IQ. Furthermore, these results are consistent with previously established theories, including the Environmental Kuznets Curve (EKC) Theory (Grossman & Krueger, 1995), the Porter Hypothesis (Porter & Linde, 1991; 1995), and the Information Disclosure Theory (Diamond & Verrecchia,

1991). In these theoretical frameworks, transparent publication of environmental indicators is shown to increase trust in institutions and reduce corruption in public entities that make false claims for private gain. Notably, this result strongly supports the information disclosure theory. Within this framework, Diamond and Verrecchia note that when a stable level of transparency is achieved, increasing institutional quality may gradually weaken and reduce the positive relationship between GAI and IQ. This is shown in the BQR results table. At the 0.1, 0.25, 0.5, and 0.75 quantiles, the effect of GAI on IQ increases significantly, while at the 0.9 quantile, the effect gradually decreases. This implies that at higher institutional quantiles, the relationship tends to weaken. This shows that GAI not only provides accurate information on the environment, emissions, energy and actual savings after taking into account environmental costs, but also enhances accountability through strict environmental regulations. Therefore, it improves and ensures the quality of institutions, especially in the current context of countries emphasizing the transparency of information related to the environment.

5 CONCLUSION

This study aims to evaluate the impact of GAI on IQ in 84 countries around the world from 2002 to 2020. Using BQR, we find that GAI systematically increases IQ across all quantiles, including 0.1, 0.25, 0.5, 0.75, and 0.9. This finding extends a multidimensional perspective on how GAI contributes to improving institutional quality, with a persistent positive impact on different institutional segments. This highlights the importance of GAI in improving global IQ, focusing on improving transparency in institutional environments through accurate disclosure of environmental information, promoting government efficiency and reducing space for corruption.

However, at higher institutional segments (0.9 quantile), this positive relationship tends to decrease. This implies that as countries reach a stable institutional threshold, GAI continues to increase transparency, but the magnitude of its impact on improving the institutional environment decreases. This study provides valuable insights into how GAI affects institutional quality. This study highlights the importance of implementing policies that maximize the benefits of GAI, while being cautious in countries with high levels of institutional stability. This finding adds to the ongoing environmental debate on how GAI, through transparent disclosure, can be integrated into institutional frameworks

to improve government effectiveness. By addressing these questions, the study not only provides a deeper understanding of how GAI affects IQ but also expands the empirical evidence that transparent disclosure improves institutional environments. It provides useful information for policymakers to design policies that enhance IQ and promote sustainable economic development. Based on these findings, we recommend that countries focus on improving transparency and providing complete and accurate environmental information to improve efficiency, stability and reduce corruption. Especially in countries with high institutional thresholds, there is a need to move from expanding GAI to perfecting it. This means that countries with high IQ can move from building new legal frameworks to strengthening enforcement capacity and improving the quality of green policy supervision. In addition, applying AI technology to information disclosure helps reduce marginal costs as well as information distortion. In such cases, expanding and strengthening GAI becomes a more effective strategy to address institutional challenges and promote sustainable development.

It is important to note that no specific policy is suitable for every country or every stage of development. Instead, developing the most appropriate policies must be based on a thorough understanding of how GAI affects IQ. By implementing flexible and targeted policies, countries can create opportunities for development and international integration. A limitation of this study is that the construction of the GAI index could be expanded by enhancing other relevant variables such as strict environmental indicators. In future studies, the authors plan to evaluate a broader range of GAI or apply alternative approaches, with the aim of recommending policies appropriate to the current context.

REFERENCES

- Appiah, M., Onifade, S. T., & Gyamfi, B. A. (2025). Pathways to sustainability in sub-Saharan Africa: Are institutional quality levels subservient in achieving green GDP growth? *Journal of the Knowledge Economy*, 16(1), 2366–2390. <https://doi.org/10.1007/s13132-024-01774-7>
- Benoit, D. F., & Van den Poel, D. (2017). bayesQR: A Bayesian approach to quantile regression. *Journal of Statistical Software*, 76(7), 1–32. <https://doi.org/10.18637/jss.v076.i07>
- Boudt, K., d’Errico, M., Luu, H. A., & Pietrelli, R. (2022). Interpretability of composite indicators based on principal components. *Journal of Probability and Statistics*, 2022(1), 4155384. <https://doi.org/10.1155/2022/4155384>
- Çitil, M., İlbasmış, M., Olanrewaju, V. O., Barut, A., Karaoğlan, S., & Ali, M. (2023). Does green finance and institutional quality play an important role in air quality?

- Environmental Science and Pollution Research, 30(18), 53962–53976. <https://doi.org/10.1007/s11356-023-26016-2>
- Chao, Y. S., & Wu, C. J. (2017). Principal component-based weighted indices and a framework to evaluate indices: Results from the Medical Expenditure Panel Survey 1996 to 2011. *PLoS One*, 12(9), e0183997. <https://doi.org/10.1371/journal.pone.0183997>
- Diamond, D. W., & Verrecchia, R. E. (1991). Disclosure, liquidity, and the cost of capital. *Journal of Finance*, 46(4), 1325–1359. <https://doi.org/10.1111/j.1540-6261.1991.tb04620.x>
- Dinh, L. Q., Oanh, T. T. K., & Ha, N. T. H. (2024). Financial stability and sustainable development: perspectives from fiscal and monetary policy. *International Journal of Finance & Economics*, 30(2), 1724-1741. <https://doi.org/10.1002/ijfe.2981>
- Dinh L.Q. (2025a). “The Impact of Digital Financial Inclusion on Income Inequality Amid Economic Complexity: A GMM and Bayesian Regression Approach”. *Social Responsibility Journal*, 21(7), 1383–1400. <https://doi.org/10.1108/SRJ-10-2024-0727>
- Dinh, L. Q. (2025b). The optimal inflation threshold in digital financial inclusion: a key to sustainable development. *SN Business & Economics*, 5(5), 1-20. <https://doi.org/10.1007/s43546-025-00810-1>
- Dinh, L. Q. (2025c). Reassessing the Impact of Foreign Direct Investment on Environmental Quality in 112 Countries: A Bayesian Quantile Regression Approach. *International Social Science Journal*. 75(257), 641-659. <https://doi.org/10.1111/issj.12577>
- Dinh L.Q (2025d). Is There a Trade-Off Between Sustainable Development Goals Achievement and Banking Profitability? Evidence From Combined Non-Parametric Methods. *Natural Resources Forum*. <https://doi.org/10.1111/1477-8947.70036>
- Fernandez, E. J., & Martos, M. J. R. (2020). Review of some statistical methods for constructing composite indicators. *Studies of Applied Economics*, 38(1). <https://doi.org/10.25115/eea.v38i1.3002>
- George, A. (1970). The market for “lemons”: Quality uncertainty and the market mechanism. *Quarterly Journal of Economics*, 84(3), 488–500.
- Grossman, G. M., & Krueger, A. B. (1991). Environmental impacts of a North American Free Trade Agreement (NBER Working Paper No. 3914). National Bureau of Economic Research. <https://doi.org/10.3386/w3914>
- Grossman, G. M., & Krueger, A. B. (1995). Economic growth and the environment. *Quarterly Journal of Economics*, 110(2), 353–377. <https://doi.org/10.2307/2118443>
- Haldar, A., & Sethi, N. (2021). Effect of institutional quality and renewable energy consumption on CO2 emissions– an empirical investigation for developing countries. *Environmental Science and Pollution Research*, 28(12), 15485–15503.
- Huy, N. Q., Dong, N. V. H., & Dinh, L. Q. (2025). Examining the roles of monetary and fiscal policies in Vietnam’s economic growth amid global challenges: A Bayesian VAR and wavelet coherence approach. *International Journal of Innovative Research and Scientific Studies*, 8(2), 2758–2769. <https://doi.org/10.53894/ijriss.v8i2.5791>
- Huy, N. Q., & Dinh, L. Q. (2025a). Balancing Bank Profits With Sustainable Development Goals: Examining the Pivotal Role of Financial Stability. *Sustainable Development*, 33(S1), 1182-1199. <https://doi.org/10.1002/sd.70057>
- Huy, N. Q., & Dinh, L. Q. (2025b). The Financial Inclusion-SDGS Nexus: Evidence from ASEAN. *International Journal of Sustainable Development and Planning*, 20(9), 4051-4061. <https://doi.org/10.18280/ijstdp.200934>

- Huy, N. Q., & Loan, N. T. (2022). Factors affecting green credit development at commercial banks in Vietnam. *International Transaction Journal of Engineering, Management, & Applied Sciences & Technologies* Vol 13 (12).
- Jackson, J. E. (2005). *A user's guide to principal components*. John Wiley & Sons.
- Jain, N., & Mohapatra, G. (2023). A comparative assessment of composite environmental sustainability index for emerging economies: A multidimensional approach. *Management of Environmental Quality: An International Journal*, 34(5), 1314–1331. <https://doi.org/10.1108/MEQ-12-2022-0330>
- Kinuthia, P., Onyango, J., & Adaramola, M. S. (2025). Economic growth, financial development and carbon emissions: Does institutional quality matter? *The Journal of Financial, Accounting, and Economics*, 2(2), 63–79. <https://doi.org/10.58857/JFAE.2025.v02.i02.p01>
- Kurniawan, R. D., Riza, H., Wardhani, S. S. W., Ba'Abdullah, F., & Kusumaningrum, D. (2025). Advancing country-level research benchmarking: A bibliometric multistage principal component analysis-based composite index approach. *Journal of Scientometric Research*, 14(1), 16–31. <https://doi.org/10.5530/jscires.20251297>
- Kuznets, S. (1955). Economic growth and income inequality. *The American Economic Review*, 45(1), 1–28.
- Khoi, N.T, & Dinh, L.Q (2025). Digital Financial Inclusion and Sustainable Development in ASEAN: Insights from Monte Carlo Simulations. *Economic Papers: A journal of applied economics and policy*. <https://doi.org/10.1111/1759-3441.70002>
- Le Quoc, D. (2024). The relationship between digital financial inclusion, gender inequality, and economic growth: Dynamics from financial development. *Journal of Business and Socio-economic Development*. <https://doi.org/10.1108/JBSED-12-2023-0101>
- Le Quoc, D., Nguyen Quoc, H., & Nguyen Van, H. (2025). Evaluating the influence of digital financial inclusion on financial crises and economic cycles: a Bayesian logistic regression insight. 33(2), 280-301. *Journal of Financial Regulation and Compliance*. <https://doi.org/10.1108/JFRC-10-2024-0206>
- Li, D., Bai, Y., Yu, P., Meo, M. S., Anees, A., & Rahman, S. U. (2022). Does institutional quality matter for environmental sustainability? *Frontiers in Environmental Science*, 10, 966762. <https://doi.org/10.3389/fenvs.2022.966762>
- Nuta, A. C., & Tanasa, F. (2023). Informality and the moral perception of paying fair payroll taxes – a perspective on institutional quality influence. *The Journal of Accounting and Management*, 13(3), 45–54.
- Oanh, T. T. K., & Dinh, L. Q. (2024a). Digital financial inclusion, financial stability, and sustainable development: Evidence from a quantile-on-quantile regression and wavelet coherence. *Sustainable Development*, 1–15. <https://doi.org/10.1002/sd.3021>
- Oanh, T. T. K., & Dinh, L. Q. (2024b). Exploring the influence of digital financial inclusion and technological progress on renewable energy consumption: A Bayesian quantile regression analysis. *Environment, Development and Sustainability*, 1–30. <https://doi.org/10.1007/s10668-024-05675-2>
- Oanh T.T.K, Ha. N.T.H (2025). Enhancing Green Growth: Exploring the Influence of Fiscal Spending and Green Finance. *Studia Universitatis „Vasile Goldiș” Arad – Economics Series*, 35(3), 69-91. <https://doi.org/10.2478/sues-2025-0013>
- Pesaran, M. H. (2021). General diagnostic tests for cross-sectional dependence in panels. *Empirical Economics*, 60(1), 13–50. <https://doi.org/10.1007/s00181-020-01875-7>

- Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics*, 142(1), 50–93. <https://doi.org/10.1016/j.jeconom.2007.05.010>
- Porter, M. (1996). America's green strategy. *Business and the Environment: A Reader*, 33, 1072.
- Porter, M. E., & van der Linde, C. (1995). Toward a new conception of the environment–competitiveness relationship. *Journal of Economic Perspectives*, 9(4), 97–118. <https://doi.org/10.1257/jep.9.4.97>
- Quoc, H. N., Le Quoc, D., & Van, H. N. (2025a). Assessing digital financial inclusion and financial crises: The role of financial development in shielding against shocks. *Heliyon*, 11(1), e41231. <https://doi.org/10.1016/j.heliyon.2024.e41231>
- Quoc, H. N., Van, H. N., & Le Quoc, D. (2025b). Unraveling the Nexus between Sustainable Development, Bank Profitability, and Loan Loss Provisions in Vietnam: A Bayesian Vector Autoregression Perspective. *Research on World Agricultural Economy*, 6(2), 123–139. <https://doi.org/10.36956/rwae.v6i2.1444>
- Quoc, H. N., Van, H. N., & Le Quoc, D. (2025c). Financial Inclusion in the Digital Era and Its Impact on Sustainable Development in ASEAN Nations: Key Findings from the Combined Non-parametric Methods. Preprint. <https://doi.org/10.21203/rs.3.rs-7596012/v1>
- Quoc, H.N., Quoc, D.L. (2025). Linkages Between Primary Sector Value Added, Financial Development, and Economic Growth: Evidence from Vanuatu. *Research on World Agricultural Economy*. 6(4): 610-626. DOI: <https://doi.org/10.36956/rwae.v6i4.2643>
- Quoc, H. N., & Le Quoc, D. (2025). Revisiting Fiscal Policy and Income Inequality in the Context of Economic Complexity. Preprint. <https://doi.org/10.21203/rs.3.rs-7611309/v1>
- Stöver, J. (2016). Green accounting, institutional quality and investment decisions: Macroeconomic implications from an analysis of the oil and mining sector (No. 171). *HWWI Research Paper*. <https://hdl.handle.net/10419/127426>
- Tuyet, N.T.B., Dinh, L.Q. (2025). The role of economic freedom and institutional quality in driving sustainable development: Comparative evidence from developed and developing economies. *International Journal of Sustainable Development and Planning*, 20(7), 2963-2972. <https://doi.org/10.18280/ijstdp.200720>
- Van, H. N., & Le Quoc, D. (2024). Assessing the impact of digital financial inclusion on sustainable development goals: Analyzing differences by financial development levels across countries. *Journal of the Knowledge Economy*, 1-24. <https://doi.org/10.1007/s13132-024-02515-6>
- Van, H. N., Quoc, H. N., & Le Quoc, D. (2024). The role of green credit in promoting sustainable development in vietnam: evidence from quantile-ON-quantile regression. *Research on World Agricultural Economy*, 6(1), 88–99. <https://doi.org/10.36956/rwae.v6i1.1399>
- Van, H. N., Quoc, H. N., & Le Quoc, D. (2025). Towards Sustainable Development: Drivers From Financial and Institutional Development. *Journal of Public Affairs*, 25(3), e70073. <https://doi.org/10.1002/pa.70073>
- Wang, N., Zhao, Y., Li, J., & Cai, G. (2024). Enhancing China's green GDP accounting through blockchain and artificial neural networks (ANNs) and machine learning (ML) modeling. *Scientific Reports*, 14(1), 29235. <https://doi.org/10.1038/s41598-024-75994-x>

Zhang, Y., Ong, T., & Kamarudin, F. (2024). Environmental regulation and corporate environmental performance: A bibliometric analysis. *Journal of Infrastructure, Policy and Development*, 8(4), 3149. <https://doi.org/10.24294/jipd.v8i4.3149>

Zheng, X., & Chen, Y. (2024). A better strategy: Using green GDP to measure economic health. *Frontiers in Environmental Science*, 12, 1459764. <https://doi.org/10.3389/fenvs.2024.1459764>

Zia, Z., Shuming, L., Akbar, M. W., & Ahmed, T. (2023). Environmental sustainability and green technologies across BRICS countries: The role of institutional quality. *Environmental Science and Pollution Research*, 30(11), 30155–30166.

APPENDIX

Appendix 1

Variable description and source

Symbol	Indicator	Measurement	Source
Dependent variable			
IQ	Institutional quality	The IQ index is constructed from six core institutional pillars (each variable is measured on a scale from -2.5 to 2.5), using Principal Component Analysis (PCA).	Authors
1. VA	Accountability	The degree of democratic governance and transparency of information.	WGI
2. RL	Rule of Law	The extent of public trust in and compliance with the legal framework.	WGI
3. RQ	Regulatory Quality	The government’s ability to formulate and effectively implement sound regulations.	WGI
4. GE	Government Effectiveness	Quality of public services and the degree of independence of government from political pressures.	WGI
5. CC	Control of Corruption	The prevalence of corruption and abuse of power in the public sector.	WGI
6. PS	Political Stability	The level of political risk facing the country.	WGI
Independent variables			
GAI	Green Accounting Index	In this study, we apply the Principal Component Analysis (PCA) technique to measure the GAI. (All component variables are standardized prior to the PCA).	Authors
1. FEC	Renewable energy	The share of renewable energy in total energy consumption (%).	WDI
2. ELC	Renewable electricity	The proportion of renewable electricity in total electricity production (%).	WDI
3. COMM	Fossil fuel energy	The share of fossil fuel consumption in total energy use (%).	WDI
4. FRST	Forest area	The proportion of natural and planted forest area to the country’s total land area (%).	WDI
5. TOTL	Total natural resource rents	Total resource rent as a percentage of GDP.	WDI
6. H2O	Freshwater extraction	Annual freshwater withdrawal as a percentage of total internal water resources (%).	WDI
7. PRIW	Energy intensity	The amount of primary energy used to produce one unit of GDP.	WDI
8. DCO2	CO ₂ emission damage	The monetary value of damage caused by CO ₂ emissions (% of GNI).	WDI

9. DRES	Resource depletion damage	The depreciation value of natural resources, including energy, minerals, and forest resources (% of GNI).	WDI
10. DPEM	Damage from particulate matter pollution	The monetary value of health damage caused by fine particulate (PM2.5) air pollution (% of GNI).	WDI
11. DFOR	Net deforestation	The monetary loss due to deforestation (% of GNI).	WDI
12. DNGY	Energy resource depletion	The monetary value of extraction of energy resources (oil, natural gas, coal) beyond sustainable levels (% of GNI).	WDI
13. DMIN	Mineral depletion	The monetary value of mineral extraction (% of GNI).	WDI
14. GHG	Total greenhouse gas emissions	Total greenhouse gas emissions (Mt CO ₂ e), including CO ₂ , CH ₄ , N ₂ O, and F-gases, divided by total population to obtain per capita emissions.	WDI
15. TAX	Environmental tax	The ratio of environmental tax revenue to GDP (%).	OECD
Control variables			
UNE	Unemployment rate	Represents the percentage (%) of the total labor force that is unemployed and actively seeking employment.	WB
TRADE	Trade Openness	Measures the extent of a country's participation in international trade relative to its GDP (% of GDP).	WB
UR	Urban Population	Urban population as a percentage of the total population (% of total population).	WB
FDI	Foreign Direct Investment	Net inflows of foreign direct investment as a percentage of GDP (% of GDP).	WB
INF	Inflation	The annual CPI growth rate (%) refers to the year-on-year percentage change in the Consumer Price Index (CPI).	WB
GDP	Economic Growth	Annual growth rate of GDP per capita (%).	WB

Authors' Contribution

Both authors contributed equally to the development of this article.

Data availability

All datasets relevant to this study's findings are fully available within the article.

How to cite this article (APA)

Hai, N. V. CONSTRUCTING A COMPOSITE GREEN ACCOUNTING INDEX AND ASSESSING ITS NONLINEAR IMPACT ON INSTITUTIONAL QUALITY: A BAYESIAN QUANTILE REGRESSION APPROACH. *Veredas Do Direito*, e223809. <https://doi.org/10.18623/rvd.v22.n5.3809>