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Disaggregated Effects of Energy Use on Growth: A Monte Carlo Algorithm for EMDEs

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ABSTRACT

Bayesian methods are recognized as a promising alternative to address multicollinearity issues inherent in the frequentist framework. This study employs a Bayesian hierarchical regression to investigate the distinct impacts of renewable and non-renewable energy consumption on economic growth in emerging market and developing economies (EMDEs). The findings demonstrate that both types of energy exhibit strong positive effects on economic growth, with non-renewables exerting a more pronounced impact compared to renewables. The limited contribution of renewable energy sources to economic growth can be attributed to inadequate investments in renewable technologies and infrastructure in the developing world. These findings provide robust empirical evidence that can inform policymakers involved in energy transition initiatives.

INTRODUCTION

Energy plays a pivotal role in various aspects of society. Its impact extends beyond conventional outputs and holds significant importance in both development and sustainable economic growth (Wang et al., 2018). Hence, energy not only influences economic growth but also has a profound effect on human well-being. The presence of energy infrastructure is directly linked to the provision of essential services such as modern healthcare facilities, education systems, and social interaction platforms. Conversely, the scarcity of energy resources signifies the absence of adequate healthcare facilities, limited educational and employment opportunities, and the weakened ability of the population to combat poverty (Ouedraogo, 2013). According to projections from the U.S. Department of Energy (2010), there is an anticipated 49% increase in energy demand between 2007 and 2035. Alarmingly, the International Energy Agency (IEA) (2022, p. 43) projects that non-renewable energy sources will account for approximately 75% of global

energy supply by 2030. The heavy reliance on non-renewable energy sources worldwide raises serious concerns regarding potential resource depletion, energy security, and environmental issues. In response to these significant challenges, governments have started prioritizing renewable energy sources and investing in renewable energy technologies. Since 2004, these investments have expanded exponentially, resulting in a rapid decline in the cost of renewable energy technologies (Bulut and Inglesi-Lotz, 2019). Effective management and planning of energy resources have become crucial for achieving economic growth and sustainable development (Ur Rehman et al., 2019).

However, designing a clean energy transition, particularly in emerging market and developing economies (EMDEs), has faced substantial challenges due to a lack of robust empirical foundations. Previous studies examining the energy-growth nexus have struggled to differentiate the individual effects of renewables and non-renewables on economic growth, hindering the formulation of appropriate energy transition policies. The inclusion of both renewable and non-renewable energy variables in the same model can lead to multicollinearity problems when these variables exhibit a high degree of correlation (above 0.8). Multicollinearity occurs when predictor variables in an econometric model are highly correlated, causing estimation issues and undermining the reliability and stability of the estimates. The strong correlation between renewable and non-renewable energy variables increases the likelihood of multicollinearity. Including both variables as independent predictors in a regression analysis becomes challenging due to their interdependence or shared underlying factors, such as overall energy consumption or energy demand, further contributing to high correlation. Addressing multicollinearity is crucial to disentangle the independent effects of renewable and non-renewable variables.

While ordinary least squares (OLS) or other frequentist methods do not directly handle multicollinearity issues, several remedies can mitigate this problem. Bayesian methods, on the other hand, offer more flexibility for addressing multicollinearity. Bayesian regression models can incorporate prior information and utilize techniques like hierarchical modeling to address multicollinearity and estimate coefficients more robustly (Block et al., 2011).

This study aims to contribute to the existing knowledge on the relationship between energy and economic growth by highlighting the advantages of employing a Bayesian approach over traditional frequentist inference when addressing multicollinearity concerns. Through a simulation study using a Bayesian hierarchical approach on a panel dataset of 41 EMDE countries, this research seeks to disentangle the individual effects of renewable and non-renewable energy consumption on economic growth. The findings demonstrate a strong positive association between both types of energy and economic growth, with non-renewable sources exerting a more significant influence compared to renewables. The study is organized as follows: Section 1 provides the research's clear motivation. Section 2 examines empirical investigations regarding the relationship between energy and economic growth. Section 3 introduces the methodology, model, and data employed in the study. The outcomes of Bayesian simulations are presented and interpreted in Section 4. Finally, Section 5 concludes the study and offers recommendations based on the findings.

1. REVIEW OF LITERATURE

The study of Kraft and Kraft (1978) marked the beginning of the literature on energy and economic growth. Their research aimed to examine the relationship between total energy consumption and economic growth in the United States from 1947 to 1974 using Granger causality tests. The study proposed four hypotheses: growth, conservation, feedback, and neutrality. Each hypothesis offered a different perspective on the causal relationship between energy consumption and economic growth, as well as the impact of energy-saving policies. The growth hypothesis posits a one-way causality running from energy consumption to economic growth, suggesting that policies promoting energy savings could have negative effects on economic activities. In contrast, the conservation hypothesis suggests a one-way causality from economic growth to energy consumption, assuming that energy-saving policies do not hinder economic activities. The feedback hypothesis proposes a two-way causal relationship between energy consumption and economic growth, emphasizing the mutual interaction between energy consumption and economic policies. Lastly,

the neutrality hypothesis argues that there is no causal relationship between energy consumption and economic growth, and energy-saving policies have no significant impact on economic growth.

Initially, early empirical studies focused on aggregated analyses to explore the causal relationship between total energy consumption and economic growth. Over time, research on energy-growth relationships diversified into two main approaches. The first approach examined the separate effects of renewable and non-renewable energy consumption using distinct models. Numerous studies followed this approach, investigating the individual impacts of energy types on economic growth. Some examples include the works of Ouedraogo (2013), Lin and Moubarak (2014), Shahbaz et al. (2014), Ozturk and AlMulali (2015), Inglesi-Lotz (2016), Paramati et al. (2017), Koçak and Şarkgüneşi (2017), Ntanos et al. (2018), Ozcan and Ozturk (2019), and Dabboussi and Abid (2022), among others. In contrast, the second approach focused on studying the effects of both renewable and non-renewable energy consumption within a single model. This approach aimed to provide a comprehensive understanding of the relationship between energy consumption and economic growth. Several studies adopted this approach, including the works of Apergis and Payne (2011), Tugcu et al. (2012), Jebli et al. (2015), Bhattacharya et al. (2016), Aydin (2019), Okumus et al. (2021), and Ozturk et al. (2022), among others.

Considering the specific focus of our study, we align with the second approach, concentrating on relevant research conducted in EMDEs. Compared to the first approach, studies within this second direction are relatively scarce, making our research particularly valuable and insightful. Below, the author analyzes the featured studies. Apergis and Payne (2011) conducted a study on the relationship between renewable and nonrenewable energy consumption and economic growth, focusing on both developed and developing countries from 1990 to 2007. Using heterogeneous panel cointegration procedures, they found a long-run equilibrium relationship with positive and statistically significant coefficient estimates for real GDP, renewable energy consumption, non-renewable energy consumption, real gross fixed capital formation, and the labor force in both country panels. In a similar vein, Apergis and Payne (2012) examined the relationship between renewable and non-renewable energy consumption and economic growth for 80 countries using a multivariate panel framework from 1990 to 2007. Their study, employing the Pedroni heterogeneous panel cointegration test, revealed a long-run equilibrium relationship with positive and statistically significant coefficient estimates for real GDP, renewable energy consumption, non-renewable energy consumption, real gross fixed capital formation, and the labor force. Al-Mulati et al. (2014) explored the impact of renewable and non-renewable electricity consumption on economic growth in 18 Latin American countries. Their results indicated that renewable electricity consumption had a more significant effect on promoting economic growth in the long run and the short run compared to nonrenewable electricity consumption. Jebli et al. (2015) employed various techniques, including long-run OLS, fully modified OLS, and dynamic OLS, to investigate 69 countries between 1980 and 2010.

They concluded that both renewable and non-renewable energy consumption, along with trade, had positive effects on economic growth. Similarly, Kahia et al. (2017), using the panel Error Correction Model, found positive significant elasticities among real GDP, renewable energy consumption, non-renewable energy consumption, real fixed investment, and the labor force in a sample of eleven MENA net oil-importing countries (NOICs) from 1980 to 2012. Bebonchu and Chelsea (2018) conducted a GMM regression analysis to examine the impact of electricity generation on economic growth across a panel of 174 countries from 1980 to 2012. Their results indicated a strong positive and statistically significant relationship between both renewable and non-renewable electricity generation and economic growth. Shahbaz et al. (2019) analyzed a panel of 38 renewable-energy-consuming countries from 1990 to 2018 and identified the positive effects of renewable energy, non-renewable energy, capital, and labor on economic growth using dynamic OLS, fully modified OLS, and heterogeneous non-causality approaches. Asif et al. (2021) investigated the impact of non-renewable and renewable energy consumption on economic growth using a panel of 99 countries worldwide. Their findings showed a significantly positive impact of both non-renewable and renewable energy consumption on economic growth. In Wang et al. (2022), the empirical results indicated that linear terms of fossil fuel energy consumption and electricity production from oil sources significantly enhanced economic growth, while the squared terms of both had a detrimental effect on economic growth in Pakistan, both in the long run and the short run. This suggested an inverted U-shaped influence of fossil fuel on output per person in Pakistan.

While most of the studies reviewed above collectively demonstrate the positive effects of renewable and non-renewable energy consumption on economic growth, there are some contrasting findings. For example, Destek (2016), Abbassi et al. (2020), and Asiedu et al. (2021) found evidence supporting a positive effect of renewable energy consumption and a negative effect of non-renewable energy consumption on economic growth. Similarly, Destek and Aslan (2017), utilizing bootstrap panel causality for a panel of 17 emerging economies between 1980 and 2012, found no causality between renewable energy consumption and economic growth for 12 emerging economies, while no significant relationship was observed between non-renewable energy consumption and economic growth in nine emerging economies. Ummalla and Samal (2019), focusing on China and India, employed Granger causality, autoregressive distributed lag bounds testing, and vector error correction model (VECM) techniques. They found a positive impact of renewable energy consumption on economic growth in India but no causality for China. Furthermore, they found a positive impact of natural gas consumption on economic growth in China but no causality for India.

Previous studies using conventional frequentist methods encountered challenges due to the strong correlation between renewable and non-renewable energy variables, leading to inconsistent and conflicting results. To address this collinearity issue, we adopt a Bayesian approach, which offers a flexible framework. By employing a Bayesian hierarchical approach in our analysis, we are able to draw meaningful conclusions. Firstly, we find that both renewable and non-renewable energy sources have a positive impact on economic growth. Secondly, our use of Bayesian statistics demonstrates its superiority over the frequentist framework in effectively addressing multicollinearity issues.

2. BAYESIAN HIERARCHICAL PERSPECTIVE

Given the growing concerns and limitations associated with standard frequentist statistics, the Bayesian approach has gained significant traction in the behavioral and social sciences over the past three decades. This shift has been facilitated by the remarkable advancements in computational tools. In this study, we employ a two-level mixed-effects method within a Bayesian hierarchical framework to account for the variability of energy consumption across 41 EMDEs. This approach enhances the precision of our estimates by capturing the inherent differences in energy consumption among these countries. Mixed-effects models, also known as multilevel models, offer the advantage of incorporating both fixed effects and random effects. The fixed effects, similar to the regression coefficients in frequentist statistics, are estimated directly. Conversely, the random effects are summarized based on their estimated variances and covariances. These random effects can be in the form of either random intercepts or random coefficients, while the data's grouping structure may include multiple levels of nested groups. In our analysis, we specifically focus on random intercepts, assuming that energy usage varies across the studied countries. Meanwhile, we consider the effects of physical capital, human capital, and labor to be the same across these countries.

Several empirical studies exploring the relationship between energy and economic growth have employed various model specifications. However, a commonly observed specification can be found in studies conducted by Apergis and Payne (2011), Al-Mulali (2014), Kahia et al. (2017), Ummalla and Samal (2019), Ozturk et al. (2022), and Thach (2023). Following the approach of these studies, we adopt a similar model specification in our analysis. In our model, we consider real GDP as the dependent variable, representing the economic growth. The independent variables include renewable energy, nonrenewable energy, physical capital, human capital, and labor. The variables of primary interest in our model are renewables and non-renewables, as we aim to investigate their effects on economic growth. Additionally, we include physical capital, labor, and human capital as control variables, accounting for their potential influence on the relationship between energy and economic growth.

To operationalize this approach, we specify a Bayesian random-effects model as follows:

$$Y_{i,t} = a_0 + a_1.RE_{i,t} + a_2.NRE_{i,t} + a_3.K_{i,t} + a_4.L_{i,t} + a_5.H_{i,t} + \alpha.u + \varepsilon_{i,t}.$$

In our analysis, we consider a sample of 41 EMDEs, denoted by the index i. The time period of our dataset spans from 1965 to 2019, with some transition economies having data available from 1985 (Azerbaijan, Belarus, Kazakhstan, Russia, Turkmenistan, Ukraine, and Uzbekistan) onwards. Within this panel dataset, we include several variables to examine the relationship between energy and economic growth.

The variable RE represents the share of renewable energy in total primary energy consumption, while NRE represents the share of non-renewable energy sources. These energy variables are available for each country i and year t. To capture the influence of physical capital, we include the variable K as a proxy for the stock of physical capital. Human capital is represented by the variable H, which is derived from average years of schooling and returns to education based on the Mincer equation. The number of people engaged in the economy is denoted by L. The GDP variable (Y) and the physical capital variable (K) are measured at constant 2017 national prices, while the number of people engaged in the economy (L) is measured in million people. To ensure data consistency and facilitate analysis, we take logarithms of Y, L, and K. In our model, we account for random effects with the term u, which captures unobserved heterogeneity across countries. Additionally, the random error term ε represents other unexplained factors.

To collect the necessary data, we rely on reputable sources. The data for renewable energy (RE) and non-renewable energy (NRE) are sourced from Our World in Data, which draws from reliable sources such as the BP Statistical Review of World Energy, IEA, and World Bank. The data for other variables, including the human capital index (H), are gathered from the Penn World Table version 10.01. Prior specification is a crucial step in Bayesian analysis, and careful consideration should be given to this aspect.

Priors represent the initial beliefs or background knowledge about the model parameters before observing the data. There are different approaches to specifying priors, and one classification proposed by Smid et al. (2019) categorizes them into three main types: naïve, thoughtful, and data-based. Another common classification distinguishes between informative and non-informative priors (Hox et al., 2012). In our study, we adopt Smid's classification as it encompasses non-informative and data-based priors as thoughtful under certain circumstances.

When prior knowledge about the model parameters is absent or insufficiently informative, specifying data-based priors is acceptable. This perspective has been supported by researchers such as Wasserman (2000), Darnieder (2011), Van de Schoot et al. (2015), and Martin & Walker (2019). The work of van Erp et al. (2018) and Thach (2023) has demonstrated the advantages of utilizing data-based prior distributions in Bayesian analysis compared to frequentist and naïve Bayesian estimation approaches.

In the context of linear modeling, it is common to assign a normal prior distribution to the structural parameters, while an inverse gamma distribution is often specified for the variance terms (Van de Schoot et al., 2015). In our analysis, we employ normal priors for the two main parameters of interest, RE and NRE, with their prior means drawn from the standard mixed-effects regression. These priors are used in conjunction with Markov Chain Monte Carlo (MCMC) simulations to estimate the model parameters.

3. BAYESIAN OUTCOMES AND DISCUSSION

3.1 Sensitivity analysis

First, we conduct a comparison of three mixed-effects models: simple mixed-effects, random effects, and full mixed-effects. To assess the model fit and determine the most appropriate model for further inference, we utilize the Deviance Information Criterion (DIC) as a measure of model performance (Table 1). The random-effects model yields the lowest DIC values among the three models, indicating superior fit and capturing the underlying patterns in the data more effectively. Therefore, we select the randomeffects model for subsequent analysis and inference.

Table 1. Model comparison using DIC

Candidate model	DIC
Full mixed-effects	38855.01
Random effects	-679.5649
Simple mixed-effects	2781.207

Source: Calculation by the author

Second, the subsequent sensitivity analysis aims to examine how different prior variance specifications of the normal distribution for the two independent variables of interest, RE and NRE, affect the posterior distributions. To conduct this analysis, the author varied the value of the prior variance within a range from non-informative to informative, ranging from 10,000 to 1. The results indicate that varying the information levels of the priors does not significantly impact the posterior distributions, as shown in Figure 1. This suggests that the posterior estimation results remain robust and valid across different specifications of the prior variance. Furthermore, the analysis reveals an interesting trend: as the prior variance becomes more informative (i.e., narrower), the model fits the data better. This is evident from the increase in the log marginal likelihood as the prior variance becomes narrower, as shown in Figure 1. A higher log marginal likelihood indicates a better fit of the model to the observed data. Therefore, incorporating more informative prior variance, which provides more specific information about the parameters, leads to an improved model fit. It suggests that the inclusion of prior knowledge can enhance the model's performance and capture the underlying relationship between the independent variables and the dependent variable more accurately.

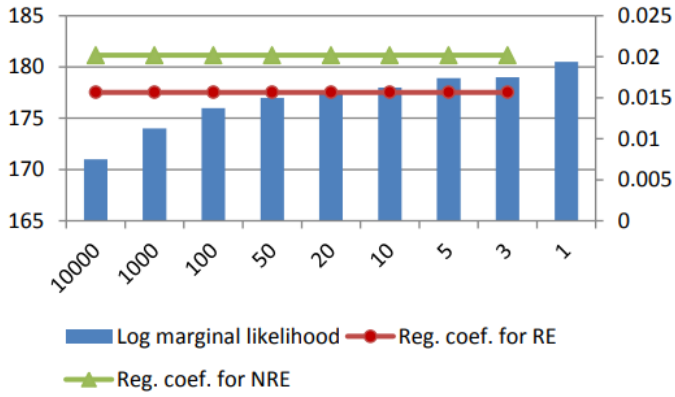

Figure 1. Log marginal likelihood and regression coefficients for RE, NRE across a range of prior variances from 10000 to1

Note: The prior variance values are represented on the X-axis, the logarithm of the marginal likelihood on the right Y-axis, and the mean coefficient estimates on the left Y-axis.

Source: Calculation by the author

3.2 MCMC convergence checks

Ensuring convergence is a crucial aspect of any MCMC simulation. The validity of Bayesian inference relies on the convergence of the Markov chain and the assurance that the sampled values are drawn from the desired posterior distribution. It is imperative to thoroughly examine the convergence of all model parameters. A graphical assessment of the MCMC samples reveals no apparent issues. Figure 2 illustrates the posterior distribution of the structural parameters, demonstrating a normal shape. Additionally, the histogram plots of the variance components exhibit characteristics consistent with an expected inversegamma distribution. These visual summaries provide initial evidence of convergence and align with the expected distributional assumptions for the model parameters. However, further diagnostic tests will be conducted to ensure the convergence of the Markov chain and validate the reliability of the posterior estimates.

Furthermore, cusum plots serve as another visual tool for assessing MCMC convergence. In our analysis, the cusum lines exhibit a jagged pattern rather than smooth, indicating convergence of the MCMC algorithm (Figure 3). This observation provides additional support for the convergence of the Markov chain and the reliability of the posterior estimates.

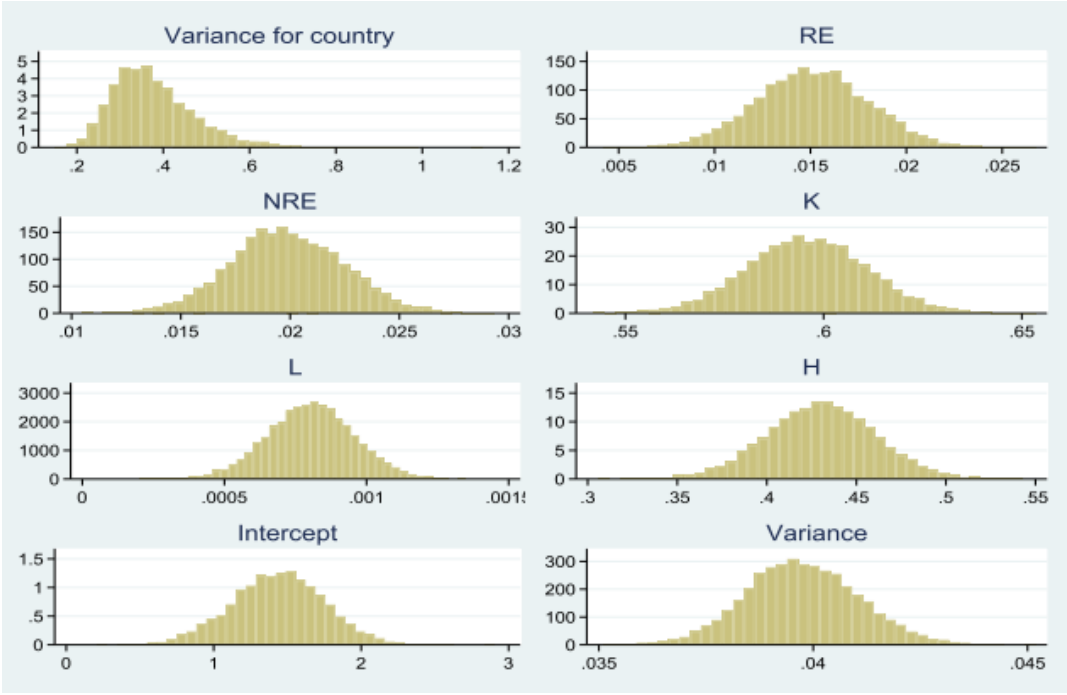

Figure 2. Histogram plots

Source: Calculation by the author

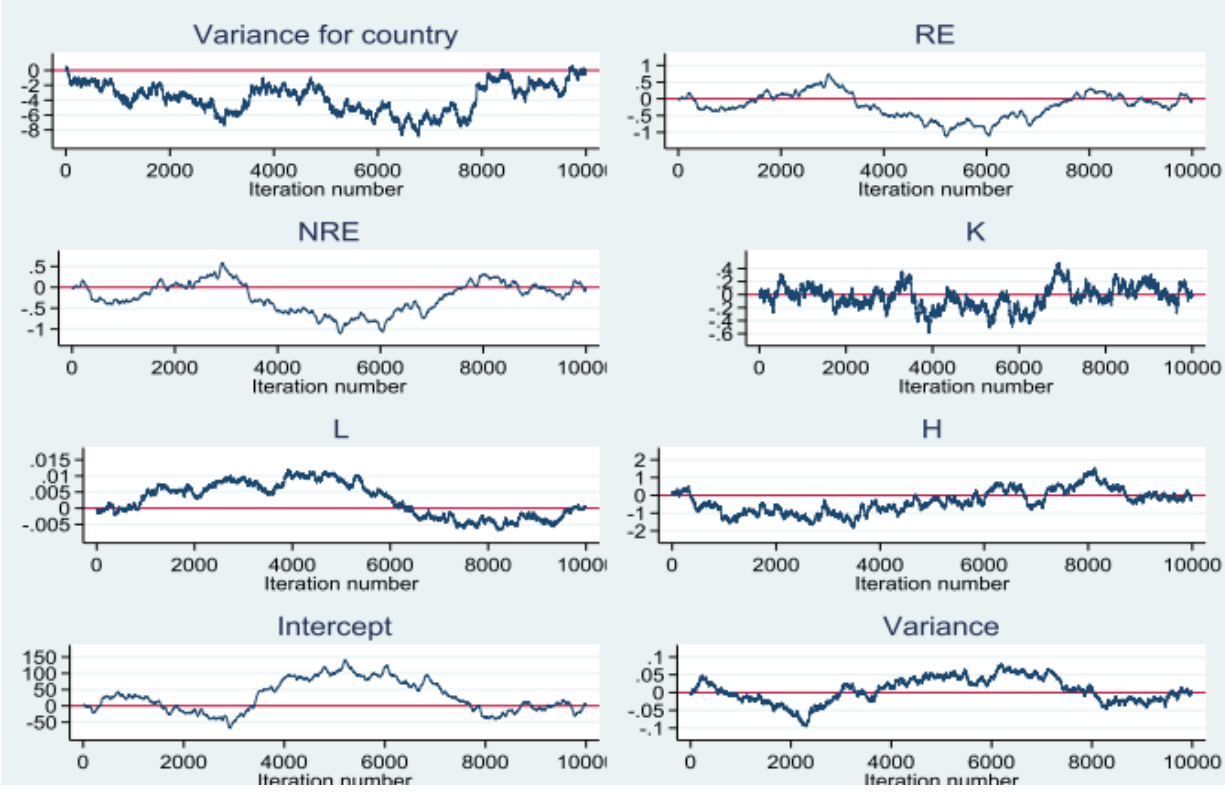

Figure 3. CUSUMS

Source: Calculation by the author

In addition to visual inspection, formal tests, such as the effective sample size (ESS), can be employed to evaluate convergence (Table 2). An efficiency greater than one is considered satisfactory, indicating that the samples effectively capture information from the posterior distribution. The results presented in Table 2 confirm the absence of non-convergence issues, as all model parameters exhibit efficiencies exceeding 3. Furthermore, the highest correlation time, measured by the number of lags, is found to be around 26, indicating that the autocorrelation in the MCMC samples diminishes within a reasonable lag range. These findings provide further assurance of the convergence of the Markov chain.

Table 2. ESS test

Parameter	ESS	Corr. time	Efficiency
Response variable: Y			
RE	438.35	22.81	0.0438
NRE	372.53	26.84	0.0373
K	9022.49	1.11	0.9022
L	9773.35	1.02	0.9773
H	8034.07	1.24	0.8034
Intercept	434.69	23.00	0.0435

Source: Calculation by the author

3.3 Results and discussion

The results presented in Table 3 reveal the posterior estimates of the model parameters, with Monte Carlo standard errors (SE) close to one. This level of standard error is within the expected range for an MCMC algorithm. Notably, all regression coefficients exhibit strongly positive signs with a 1% probability. In Bayesian analysis, point estimates indicate the central tendency and help assess the effect size. Of particular interest are the regression coefficients for RE and NRE. The coefficients for RE and NRE are 0.015 and 0.020, respectively, indicating that the impact of NRE on the response variable (Y) is larger than that of RE.

In summary, based on our analysis, all independent variables show a robust positive correlation with the response variable, with NRE exerting a stronger influence compared to RE. This suggests that nonrenewable energy sources make a more significant contribution to economic growth compared to renewables. These findings align with previous studies conducted by Apergis and Payne (2011), Apergis and Payne (2012), Al-Mulati et al. (2014), Jebli et al. (2015), Kahia et al. (2017), Bebonchu and Chelsea (2018), Shahbaz et al. (2019), Asif et al. (2021), and Wang et al. (2022). These studies also observed positive effects of both renewables and non-renewables on economic growth in the context of some EMDEs, providing support for the growth hypothesis. It is worth noting that our findings differ from those of Destek (2016), Abbassi et al. (2020), and Asiedu et al. (2021), who found evidence of a positive effect of renewable energy consumption and a negative effect of non-renewable energy consumption on economic growth. Additionally, our results contrast with those of Destek and Aslan (2017) and Ummalla and Samal (2019), who obtained mixed results. The use of a Bayesian hierarchical approach in our analysis allowed for insights into the individual impacts of renewable and non-renewable energy consumption on economic growth, leading to these interesting findings. The Bayesian results support our theoretical expectations. These outcomes can be attributed to various factors that hinder significant investments in renewable technologies in EMDEs (IEA, 2022). These factors may include issues related to high costs of renewable technologies, intermittency, expensive storage costs, and supply chain limitations. Consequently, these factors contribute to the relatively higher growth performance of nonrenewables compared to renewables.

Table 3. Output of chosen Bayesian hierarchical model

Parameter	Reg. coef.	Std. dev.	Monte Carlo SE	Probability of impacts being more than zero	Credibility interval	
					Lower bound	Upper bound
Response variable: Y						
RE	0.0150877	0.0029435	0.000141	1	0.0093123	0.0208449
NRE	0.01984	0.0025779	0.000134	1	0.0147912	0.024914
K	0.5958194	0.015079	0.000159	1	0.5662965	0.6253338
L	0.0008031	0.0001506	1.5e-06	1	0.0005044	0.0010975
H	0.430271	0.0302925	0.000338	1	0.3703503	0.4898238
Intercept	1.434051	0.3143187	0.015076	1	0.8043888	2.043877

Source: Calculation by the author

CONCLUSION AND RECOMMENDATION

Conventional frequentist methods often encounter challenges related to multicollinearity when analyzing the impact of renewables and non-renewables on economic growth, due to their high correlation. Both commonly used frequentist approaches, which involve analyzing each variable separately or including both variables in a single model, fail to differentiate their individual effects. To overcome these limitations, Bayesian analysis offers a viable alternative. In our study, we employed a Bayesian hierarchical model using panel data from 41 EMDEs. The results revealed a positive relationship between both renewable and non-renewable energy sources and economic growth, with nonrenewables exerting a stronger influence. These findings align with our theoretical expectations, emphasizing the significant role of non-renewable energy sources in driving economic growth in the developing world. This outcome can be attributed to challenges such as the high costs of renewable technologies, expensive storage solutions, supply chain limitations, and intermittency.

The substantial positive impact of non-renewables on economic growth, as evidenced in our analysis, underscores the importance of considering both non-renewables and renewables, along with fundamental factors such as capital and labor, as primary drivers of economic growth. It emphasizes the need for countries worldwide to prioritize the utilization of both renewable and non-renewable energy sources in order to achieve their economic growth objectives. In the long term, governments should actively encourage increased investments in renewable energy infrastructure and technologies to facilitate a smoother transition towards clean energy.

A key limitation of our study is the specification of data-dependent prior distributions for the structural parameters. For future investigations, we recommend the use of informative priors to further enhance the robustness of the analysis results.

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