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Exploring the Relationship Between Technological Progress, Human Capital, Political Uncertain, Energy Consumption, and Economic Growth: Evidence from a Panel Data Analysis

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Abstract

This study examines the determinants of economic growth by integrating technological progress, human capital, energy consumption, and monetary policy uncertainty in an extended theoretical model. The empirical investigation covers 18 economies from 2009 to 2019 and applies the Bias-Corrected Estimation (BC) and Generalized Method of Moments (GMM) techniques. The findings reveal that while gross capital formation is a significant growth driver, financial development has no meaningful impact. Notably, intermediate education contributes positively to growth, whereas advanced education surprisingly shows a negative effect. Additionally, the results indicate a direct relationship between renewable energy consumption and growth, with oil consumption having a negative impact. Political instability, measured by the Global Economic Policy Uncertainty (GEPU) index, also hinders growth.

Keywords Endogenous growth model · Human capital · Energy consumption · Political uncertain · Generalized Method of Moments · Bias-Corrected Estimation

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Introduction

The recent economic growth of some sectors and the consequent structural disequilibrium in the various economic activities, as well as an excess of capacity and inadequate productivity, has led to an increase in the research into the determinants associated with the theories of economic growth. In this context, it is undoubtedly of considerable theoretical and practical value to carry out a comprehensive analysis of the key factors that influence the different rates of economic growth.

The models referenced in the literature about economic growth emphasize that human capital, alongside physical capital, are the key factors for economic growth because of their double association with the required advances in technology or technological progress. Most studies, including Wen et al. (2022) and Ifa and Guetat (2022), have addressed the premise that financial development is positively associated with the growth of employment and affluence in an economy. In our proposed model, financial development is a proxy for technological progress, the same decision applied by Ifa and Guetat (2022). The estimation of this elasticity could strengthen the decisions of financial institution decision-makers in supervising financial intermediaries to ensure that they have sound lending practices (Wen et al., 2022). Furthermore, we believe that it is necessary to allocate more credit to high-performing companies that decide to invest in new technologies to guarantee sustainable growth in line with Sustainable Development Goal (SDG) 8.

Regarding the endogenous economic growth approach, it is usual to address the Lucas model and the Romer model. Therefore, we can state that the Lucas (1988) model differs from the Romer (1990) model in terms of how knowledge is generated and transmitted. However, Lucas claims that the transfer of knowledge occurs through human capital, while Romer suggests that it is linked to the involvement of intelligent people. Human capital is the cumulative result of knowledge acquired through formal education or the enhancement of skills through practical experience.

There is a consensus that human capital can be expressed as individuals' knowledge, skills, and abilities, as well as the comprehension they have acquired through their education, training, and work experience over the years. Thus, we reinforce the following premises: (i) education can enhance the human capital inherent in the labour force, which in itself increases labour productivity and therefore economic growth; (ii) education can increase the economy's capacity for innovation, for the development of new technologies, products, and processes and through that association promotes further economic growth; (iii) education can facilitate the dissemination and transmission of the knowledge needed to understand new information and process it to successfully implement new technologies, so once again education promotes economic growth.

There is a consensus that most people with higher levels of education are better able to assume decisive positions for an organization's economy, such as government leaders, decision-making positions in government agencies, and national or foreign private companies, among other positions. For this reason, we consider a labour force with advanced training to be an important input in the production function. In this study, we considered the 3 different levels of education of the employed population, namely basic education, intermediate education, and advanced education, to make an important contribution to the modelling of the integrated model to explain economic growth. Thus, the inclusion of the iterative effect of Education on Employment on economic growth makes it possible to highlight an important contribution to the literature due to its alignment with objective 4 and objective 8 of the Sustainable Development Goals.

The correlation between energy consumption and economic activity has been analyzed for several decades, which is in line with the literature review presented in the following section. However, in our study, considering the extended theoretical modelling of economic growth, the splitting of total energy consumption into its main sources, namely the consumption of gas, oil, coal, as well as renewable energies, allows for a better comprehension of the analysis of the impact of each of the components of the energy source on GDP. The model's use of energy consumption by component promotes economic growth and safeguards the application of directives, particularly in Europe, such as the Renewable Energy Directives (Eurostat 2018a, 2021), the Energy Efficiency Directive (Eurostat 2018b; Commission 2023), and Sustainable Development Goals (SDGs), specifically the 7th, among others.

If we consider the relationship between economic growth and economic policy uncertainty, there is a prevalent assumption that the impact of economic policy uncertainty has a significant influence on exploratory innovation in companies (Gu et al., 2021). However, there are other studies, for example, Feng and Zheng (2022), which have shown the opposite influence on the relationship between economic growth and economic policy uncertainty, whereby an increase in economic policy uncertainty will lead to an increase in credit risk and consequently increased financing restrictions for companies, which will inhibit the progress of relatively high levels of innovation in companies. Thus, the inclusion of this new variable in our integrated economic growth model, whose elasticity is being estimated, will ensure that the sign of the coefficient and its magnitude can be derived for the panel of countries in the sample in such a way as to highlight its effect on economic growth. On the other hand, the greater or lesser strength of this elasticity will help economic policymakers. For example, central banks and regulators of monetary policies, employment policies, and financial regulation policies, among other economic policies, should incorporate global uncertainty as an important part of forecast modelling to predict the evolution of the GDP growth rate. This topic is particularly critical in periods of endogenous crises and post-crises, as in the case of the global sovereign crisis and more recently in the case of the exogenous pandemic crisis and the war crisis, taking into consideration different geographies.

The Human Development Index (HDI) is a composite indicator that assesses human development in three dimensions: health, education, and standard of living (Roser, 2014). The use of this metric in this study is justified by the fact that economic growth should lead, in the most direct sense, to the social and economic development of the population. Thus, analyzing the interaction between HDI and GDP is fundamental for devising effective public policies to promote human development and the SDG goals, namely those listed as goals 3 and 4.

Considering the importance of the drivers selected to integrate a given economic growth model, our main objective was to formulate an integrated theoretical framework for economic growth, notably including technological progress measured by the financial development proxy, gross capital formation, human capital measured by the disaggregation of the employed population by level of education, the disaggregated consumption of non-renewable energy and renewable energy, the economic policy uncertainty index, political stability, and the Human Development Index (HDI) and GDP as a measure of economic growth. As part of the empirical application to validate this theoretical framework, we selected 18 economies, which include Australia, Brazil, Canada, Chile, Colombia, France, Germany, Greece, Ireland, Italy, Korea, Mexico, Netherlands, Russia, Spain, Sweden, the UK, and the USA, considering the period between 2009 and 2019. This period is significant as it encompasses the time between the post-global crisis, the subprime crisis, post-post-subprime crises, and the pre-crisis of the COVID pandemic. In terms of methodology, we used the Bias-Corrected Estimation (BC) and Generalized Method of Moments (GMM) approaches to estimate the two proposed equations. Using both econometric estimation techniques allowed us to focus on dynamic estimators to analyze and validate the theoretical framework model and identify the main relevance and significance of the elasticity effect associated with variables included in the model for measuring economic growth. So, in the contemporary context and how global economies are positioned in the future, where the circulation of goods and capital is the focus of new approaches to new theories that explain economic growth, we regard this study's proposal to analyze and evaluate our extended economic growth model as, on the one hand, an opportunity for research and an important theoretical contribution to the literature on the subject under consideration. On the other hand, the empirical application to a diversified set of economies in different geographies, whose important knowledge will support the policy formulation and implementation aimed at sustainable economic growth, is based on the statistical evidence found in the econometric estimations carried out. In this way, we can state that strategic economic, social, and political decision-making by policymakers and economic agents should be aligned and focused on achieving sustainable economic growth in line with the Sustainable Development Goals (SDGs) referenced in this introductory section.

The "Literature Review" section concisely reviews the relevant literature on the subject, while the "Model Specifications" section outlines the model specifications used in this study. The "Data" section provides details on the data, and the "Methodology" section considers the approaches used in the investigation. The "Results and Discussion" section presents the study's results, findings, and analysis based on the research objectives. Finally, the "Conclusions" section concludes with some closing remarks, limitations of this study, and suggestions for future research.

Literature Review

Relationship Between Economic Growth, Technological Progress, and Human Capital

The relationship between economic growth and human capital has been widely studied, revealing significant findings across various regions. Matousek and Tzeremes (2021) explored the effect of human capital on economic expansion using a sample of 100 countries over 35 years. Their non-parametric and semiparametric analysis revealed that human capital significantly contributes to economic growth, with differences in growth attributed to the quality of human capital. Similarly, Shidong et al. (2022) examined G10 economies, showing that human capital not only drives economic growth but also enhances the impact of renewable energies.

In European regions, Agasisti and Bertoletti (2022) analyzed the impact of higher education systems (HESs) on economic growth across 284 regions over 18 years. Their findings demonstrated that improvements in the quality of research and regional universities positively impacted regional GDP per capita. Similar findings emerged from the USA, where Faggian et al. (2017) showed that education, particularly the retention of a highly educated workforce, plays a crucial role in promoting economic growth. Additionally, Jorgenson and Fraumeni (1992) examined the period from 1948 to 1986, concluding that investment in human capital and education accounted for a substantial proportion of economic growth.

In Asia, Majidi (2017) found that foreign trade and human capital significantly impact economic development, while Fatimah et al. (2021) observed that although human capital positively influences economic growth in Malaysia, Thailand, and Indonesia, innovation capacity was not statistically significant. Similarly, Maitra (2016) showed that while human capital and labour force investment positively affected Singapore's economic growth from 1981 to 2010, the effects of human capital were not immediate.

In the Middle East and North Africa (MENA) region, Adeleye et al. (2022) emphasized that human capital is a critical driver of economic growth, supported by the research of Turna and Ceylan (2022) in Turkey. Their study demonstrated that human and physical capital asymmetrically affect GDP in both the short and long term, with energy consumption contributing positively to economic growth.

Relationship Between Economic Growth, Energy Consumption, and Human Capital

Human capital's role in driving both economic growth and sustainability is further explored in the context of energy consumption. Ganda (2022) studied BRICS countries, showing that human capital significantly affects environmental quality and sustainability, both in the short and long term. Similarly, Zafar et al. (2019) found that in the USA, increased human capital helps mitigate the environmental degradation caused by energy consumption and economic activity. The combined effects of human capital and renewable energy on economic growth were also explored by Shidong et al. (2022), Ben Jebli et al. (2019), and Balsalobre-Lorente et al. (2018), who found that renewable energy and human capital contribute to reducing CO_2 emissions while supporting economic growth in the EU-5 countries and South and Central America.

In other studies, the relationship between energy consumption and human capital varies by economic development levels. For example, Narayan (2016) found a neutral relationship between energy usage and economic activity in developed countries, while a conservation hypothesis was observed in developing economies. Kablamaci

(2017) also identified various causal relationships between energy consumption and GDP across 91 countries, with renewable energy investment shown to promote sustainable growth in 13 OECD countries by Kamoun et al. (2019).

Li and Ouyang (2019) examined the impact of human capital, economic activity, and financial development on carbon emissions in China. Their results indicated that financial development reduces emissions, though human capital exhibited an N-shaped curve, with long-term per capita earnings leading to emission reductions. The study by Hung (2022) in China further emphasized the bidirectional relationship between GDP and the Human Development Index (HDI), with increasing GDP improving human development.

Relationship Between Economic Growth, Technological Progress, Human Capital, Energy Consumption, Economic Development, and Economic Policy Uncertainty

Studies have increasingly explored how economic growth and human capital interact with technological progress and policy uncertainty. Ngo et al. (2022) hypothesized a reciprocal relationship between financial development, technological progress, and green growth, supported by econometric evidence that both human capital and the Human Development Index (HDI) positively influence sustainable growth. Adewale Alola et al. (2021) also explored the influence of technological innovation on the HDI across 12 Sub-Saharan countries, concluding that economic activity and technological advancements significantly contribute to sustainable development, in line with Romer's growth model.

The relationship between political security, renewable energy, and tourism has also been shown to drive economic activity in Turkey, as studied by Aydin (2022). Still in Turkey, there is evidence that the GEPU shocks negatively influence macroeconomic activity, leading to declines in share prices, investment, employment, consumption, and GDP growth (Daştan et al., 2024). Khan et al. (2022) expanded on these findings, investigating the impact of political stability, economic growth, and financial development on inequality in countries part of the Belt Road Initiative (BRI). They found that increased GDP reduces inequality in developing economies, while financial development and emissions increase it.

Economic policy uncertainty (EPU) has a direct effect on financial markets and, by extension, human capital, and economic growth. Sayar et al. (2020) found that democracy, income, and human capital contribute to reducing inequality in 23 developing economies, though their Financial Kuznets Curve hypothesis was not confirmed. In China, Chen et al. (2019) demonstrated that EPU hurts the economy, whereas oil price shocks positively influence industrial economic growth. Finally, Asafo-Adjei et al. (2021) examined the link between financial markets, GDP, and EPU, finding a two-way causality between financial development and GDP across most countries, with economies like South Africa being particularly vulnerable to external shocks.

Model Specifications

The current study aims to expand upon the models of endogenous growth put forth by Lucas and Romer, which builds upon the model developed by Solow. In Solow's model, economic growth is primarily driven by technological progress, while Romer's model incorporates the concept of technological spillover, where technological advances are widely available. On the other hand, Lucas' model posits that technological progress is strongly linked to human capital, i.e. each person's education and individual skills. Building on these existing frameworks, the present research seeks to incorporate institutional variables into the model, offering a more comprehensive understanding of the factors driving economic growth.

Model Presentation

According to the literature review, we now expose the endogenous growth models in which the present work proposes to expand, and the production equation which will be estimated in this research (Appendix 1).

$$Y_t = A_t^{\beta_1} K_t^{\beta_2} L_t^{\beta_3} EC_t^{\beta_4} EPU_t^{\beta_5} DHI_t^{\beta_6} \mu^e \tag{1}$$

where Y_t is the GDP (Growth Domestic Product), A_t is the technological progress, $L_t^{\beta_3}$ for labour, or human capital, $EC_t^{\beta_4}$ is the energy production,$EPU_t^{\beta_5}$ (Global Economy Policy Uncertain Index) measures the political and economic stability, $DHI_t^{\beta_6}$ is the Development Human Index, and μ^e is the error.

As the work expands the models of Romer and Lucas, we have the variable, which is the technical progress represented by $A_t = FD$, in which FD stands for financial development as a proxy for technological progress, the same strategy applied by Ifa and Guetat (2022). In addition, we divide L_t into three variables to capture the effect of the skilled unskilled (H_1), intermediate skilled (H_2), force, and skilled (H_3) workforce, thus $L_t = (H_1 + H_2 + H_3)$, so we have in these variables the ideas of Lucas's models. Finally, in the decomposition of energy production (EC_t), we consider the consumption of gas (NGC), oil (OC), coal (CC), and renewable energy (RC), so $EC_t = (CC_t + NGC_t + OC_t + RC_t)$. The following Eq. (2) is the expanded endogenous growth model that will be predicted in this work.

$$Y_t = FD_t^{\beta_1} H_{1t}^{\beta_2} H_{2t}^{\beta_3} H_{3t}^{\beta_4} K_t^{\beta_5} CC_t^{\beta_6} NGC_t^{\beta_7} OC_t^{\beta_8} RC_t^{\beta_9} EPU_t^{\beta_{10}} DHI_t^{\beta_{11}} \mu^e \tag{2}$$

To simplify, Eq. (3) is placed in logarithmic form; in this way, it becomes a linear function, as can be seen

$$\begin{aligned} lnY_t = \beta_0 + \beta_1 lnFD_t + \beta_2 lnH_{1t} + \beta_3 lnH_{2t} + \beta_4 lnH_{3t} + \beta_5 lnK_t + \beta_6 lnCC_t \\ + \beta_7 lnNGC_t + \beta_8 lnOC_t + \beta_9 lnRC_t + \beta_{10} lnEPU_t + \beta_{11} lnDHI_t + \varepsilon_t \end{aligned} \tag{3}$$

It is necessary to apply the partial derivation technique to demonstrate the relationship and how model variables impact production. Although the model applied in the estimates has more than three independent variables for simplification, we will use a model with three explanatory variables. So, if f is a function of A, K, and L, its partial derivative is defined by

$$f_A(A,K,L) = \lim_{h\to 0}\frac{f(A+h,K,L) - f(A,K,L)}{h} \tag{4}$$

The resolution is made by keeping K and L constant and deriving $f(A,K,L)$ about A (Stewart, 2008). As said, the model of this work is a production function of endogenous growth

$$Y = FD^{\beta_1}.K^{\beta_2}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8} \tag{5}$$

where Y is the output, A the technological progress, K stands for the capital, and L the workforce are the independent variables or the function's inputs; in this way, we have the function in logarithm form from the Eq. (3). Therefore, the first-order partial derivation formula for the proposed model is

$$\frac{\partial Y}{\partial X_i} = \lim_{h\to 0}\frac{f\left(FD+h,K,H_1,H_2,H_3,EC,EPU,DHI\right) - f(FD,K,H_1,H_2,H_3,EC,EPU,DHI)}{h} \tag{6}$$

The first-order derivative tells us the trend of the function, whether it is an ascending or descending function. In addition, this can be interpreted as the rate of variation. In other words, being $Y = f(FD,K,H_1,H_2,H_3,EC,EPU,DHI)$, so $f_k = \partial Y/\partial K$, it is interpreted as the variation of Y concerning to K if the other independent variables are unchanged (Stewart, 2008), for example.

Applying first-order derivatives partial in Eq. (5), we got the following results:

$$\begin{cases}
\frac{\partial Y}{\partial FD} = \beta_1 FD^{\beta_1-1}.K^{\beta_2}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8} \\
\frac{\partial Y}{\partial K} = \beta_2 K^{\beta_2-1}.FD^{\beta_1}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8} \\
\frac{\partial Y}{\partial H_1} = \left(1-\beta_3\right)H_1^{-\beta_3}.FD^{\beta_1}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8} \\
\frac{\partial Y}{\partial H_2} = \left(1-\beta_4\right)H_2^{-\beta_4}.FD^{\beta_1}.H_1^{1-\beta_3}.H_3^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8} \\
\frac{\partial Y}{\partial H_3} = \left(1-\beta_5\right)H_3^{-\beta_5}.FD^{\beta_1}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8} \\
\frac{\partial Y}{\partial EC} = \beta_6 EC^{\beta_6-1}.FD^{\beta_1}.K^{\beta_2}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}EPU^{\beta_7}.DHI^{\beta_8} \\
\frac{\partial Y}{\partial EPU} = \beta_7 EPU^{\beta_7-1}.FD^{\beta_1}.K^{\beta_2}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EC^{\beta_6}.DHI^{\beta_8} \\
\frac{\partial Y}{\partial DHI} = \beta_8 DHI^{\beta_8-1}.FD^{\beta_1}.K^{\beta_2}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.
\end{cases} \tag{7}$$

By dividing the first-order derivative by the production function $\left(\frac{\frac{\partial Y}{\partial FD}}{Y}\right)$, we have

$$\frac{\frac{\partial Y}{\partial FD}}{Y}=\frac{\left(\beta_1 FD^{\beta_1-1}.K^{\beta_2}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8}\right)xFD}{FD^{\beta_1}.K^{\beta_2}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8}}\rightarrow\frac{\frac{\partial Y}{\partial FD}}{Y}=\frac{\left(\beta_1 FD^{\beta_1-1}\right)xFD}{FD^{\beta_1}}\rightarrow\frac{\frac{\partial Y}{\partial FD}}{Y}=\beta_1 \tag{8}$$

The results of Eq. (8) show us the degree of variation of the product (Y) about the variables considered (FD). For example, keeping all the variables constant, if FD increases by 1%, the product (Y) will vary in β_1 intensity, so we have the marginal productivity of the financial development. The same relationship can be expanded to the other variables. Thus, the linear link between the explanatory and dependent variables is demonstrated, as in Eq. (8).

$$\begin{cases}
\frac{\frac{\partial Y}{\partial FD}}{Y}=\frac{\left(\beta_1 FD^{\beta_1-1}.K^{\beta_2}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8}\right)xFD}{FD^{\beta_1}.K^{\beta_2}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8}}\rightarrow\frac{\frac{\partial Y}{\partial FD}}{Y}=\frac{(\beta_1 FD^{\beta_1-1})xFD}{FD^{\beta_1}}\rightarrow\frac{\frac{\partial Y}{\partial FD}}{Y}=\beta_1\\
\frac{\frac{\partial Y}{\partial K}}{Y}=\frac{\left(\beta_2 K^{\beta_2-1}.FD^{\beta_1}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8}\right)xK}{FD^{\beta_1}.K^{\beta_2}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8}}\rightarrow\frac{\frac{\partial Y}{\partial K}}{Y}=\frac{(\beta_2 K^{\beta_2-1})xK}{K^{\beta_2}}\rightarrow\frac{\frac{\partial Y}{\partial K}}{Y}=\beta_2\\
\frac{\frac{\partial Y}{\partial H_1}}{Y}=\frac{\left[(1-\beta_3)H_1^{-\beta_3}.FD^{\beta_1}.K^{\beta_2}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8}\right]xH_1}{FD^{\beta_1}.K^{\beta_2}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8}}\rightarrow\frac{\frac{\partial Y}{\partial H_1}}{Y}=\frac{(1-\beta_3)H_1^{1-\beta_3}}{H_1^{1-\beta_3}}\rightarrow\frac{\frac{\partial Y}{\partial H_1}}{Y}=\left(1-\beta_3\right)\\
\frac{\frac{\partial Y}{\partial H_2}}{Y}=\frac{\left[(1-\beta_4)H_2^{-\beta_4}.FD^{\beta_1}.K^{\beta_2}.H_1^{1-\beta_3}.H_3^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8}\right]xH_2}{FD^{\beta_1}.K^{\beta_2}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8}}\rightarrow\frac{\frac{\partial Y}{\partial H_2}}{Y}=\frac{(1-\beta_4)H_2^{1-\beta_4}}{H_2^{1-\beta_4}}\rightarrow\frac{\frac{\partial Y}{\partial H_2}}{Y}=\left(1-\beta_4\right)\\
\frac{\frac{\partial Y}{\partial H_3}}{Y}=\frac{\left[(1-\beta_5)H_3^{-\beta_4}.FD^{\beta_1}.K^{\beta_2}.H_1^{1-\beta_3}.H_2^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8}\right]xH_3}{FD^{\beta_1}.K^{\beta_2}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8}}\rightarrow\frac{\frac{\partial Y}{\partial H_3}}{Y}=\frac{(1-\beta_5)H_3^{1-\beta_5}}{H_3^{1-\beta_5}}\rightarrow\frac{\frac{\partial Y}{\partial H_3}}{Y}=\left(1-\beta_5\right)\\
\frac{\frac{\partial Y}{\partial EC}}{Y}=\frac{\left(\beta_6 EC^{\beta_6-1}.FD^{\beta_1}.K^{\beta_2}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EPU^{\beta_7}.DHI^{\beta_8}\right)xEC}{FD^{\beta_1}.K^{\beta_2}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8}}\rightarrow\frac{\frac{\partial Y}{\partial EC}}{Y}=\frac{(\beta_6 EC^{\beta_6-1})xEC}{EC^{\beta_6}}\rightarrow\frac{\frac{\partial Y}{\partial EC}}{Y}=\beta_6\\
\frac{\frac{\partial Y}{\partial EPU}}{Y}=\frac{\left(\beta_7 EPU^{\beta_7-1}.FD^{\beta_1}.K^{\beta_2}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EC^{\beta_6}.DHI^{\beta_8}\right)xEPU}{FD^{\beta_1}.K^{\beta_2}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8}}\rightarrow\frac{\frac{\partial Y}{\partial EPU}}{Y}=\frac{(\beta_7 EPU^{\beta_7-1})xEPU}{EPU^{\beta_7}}\rightarrow\frac{\frac{\partial Y}{\partial EPU}}{Y}=\beta_7\\
\frac{\frac{\partial Y}{\partial DHI}}{Y}=\frac{\left(\beta_8 DHI^{\beta_8-1}.FD^{\beta_1}.K^{\beta_2}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EPU^{\beta_7}\right)xDHI}{FD^{\beta_1}.K^{\beta_2}.H_1^{1-\beta_3}.H_2^{1-\beta_4}.H_3^{1-\beta_5}.EC^{\beta_6}.EPU^{\beta_7}.DHI^{\beta_8}}\rightarrow\frac{\frac{\partial Y}{\partial DHI}}{Y}=\frac{(\beta_8 DHI^{\beta_8-1})xDHI}{DHI^{\beta_8}}\rightarrow\frac{\frac{\partial Y}{\partial DHI}}{Y}=\beta_8
\end{cases} \tag{9}$$

Therefore, predicting the causal relationship between the model's variables is possible.

Data

The present study focuses on investigating the economic behaviour of 18 countries, namely Australia, Brazil, Canada, Chile, Colombia, France, Germany, Greece, Ireland, Italy, Korea, Mexico, the Netherlands, Russia, Spain, Sweden, the UK, and the USA, from 2009 and 2019. This timeframe was deliberately chosen to examine the economic trends between the two global crises, namely the 2008 subprime crisis, which resulted from the collapse of the American real estate market, and the ongoing COVID-19 pandemic, which emerged in early 2020. Studying the economic patterns during this period aims to comprehensively understand how the global economy has fared in the intervening years.

This research aims to assess the impact of certain variables, specifically the $GEPU_t$ indicator of Political and Economic Stability, on the Gross Domestic Product. Consequently, the dataset used in this study is restricted to countries included in the indicator.

The data used to estimate the results was taken from secondary sources. Gross Domestic Product (Y_t) and Gross Capital Formation (K_t), both in dollars constant in 2015 values, and Labour force with basic education (H_{1t}), Labour force with intermediate education (H_{2t}), and Labour force with advanced education (H_{3t}) were obtained from the World Development Indicators (WDI). FD_t represents financial development, used as a proxy for technological progress, and we used the Financial Development Index, computed by the International Monetary Fund (IMF). Metric for measuring energy consumption (Coal Consumption (CC_t), Natural Gas (NGC), Oil (OC_t), and Renewable Energy (RC_t)) are available in the database of British Petroleum (BP). Finally, the variable that captures economic development is represented by the Human Development Index (DHI_t).

Although the countries China, India, and Japan are included in the GEPU database, which served as the foundation for our sample, they were excluded from the analysis due to missing values in the other variables used to estimate the results.

The variables under consideration were transformed into logarithmic forms as the production function is exponential. This approach provides an alternative to linearizing the equation and enables the interpretation of the coefficients through the concept of elasticities in the estimation results.

Methodology

Generalized Method of Moments (GMM)

The issue of heteroscedasticity is a common challenge encountered by researchers, necessitating effective handling strategies. Currently, a prevalent approach to address heteroscedasticity of unknown form is the utilization of the Generalized Method of Moments (GMM) as outlined by Baum et al. (2003). This method relies on orthogonality conditions, enabling efficient estimation in the presence of such heteroscedasticity. Moreover, GMM estimation is widely employed for models with endogenous variables, particularly lagged dependent variables, especially in situations with limited time horizons (Kripfganz, 2019).

The efficiency of GMM is advantageous for ensuring consistency even in the presence of arbitrary heteroscedasticity. However, this advantage is counterbalanced by the potential for suboptimal performance in finite sample sizes (Baum et al., 2003). Given the trade-off involving the risk of consistency loss, the current study incorporates alternative methodologies beyond the efficient Generalized Method of Moments.

The foundational principle of GMM lies in the assumption that the instruments Z are exogenous, denoted by $E\left(Z_i u_i\right) = 0$. The set of L instruments provides L

moments, forming the basis for the estimation within the GMM framework (Kripfganz, 2019).

$$g_i\left(\hat{\beta}\right) = Z_i'\hat{u}_i = Z_i'\left(y_i - X_i\hat{\beta}\right) \tag{10}$$

$Lx1$ is g_i. The exogenity shows the existence of L moments conditions, and this condition is satisfied by the function, $E\{g_i(\beta)\} = 0$, the actual value of β (Baum et al., 2003). A sample moment corresponds to each of the L moment equations (Baum et al., 2003), and can be written as follows:

$$\overline{g}_i\left(\hat{\beta}\right) = \frac{1}{n}\sum_{i=1}^{n}\overline{g}_i\left(\hat{\beta}\right) = \frac{1}{n}\sum_{i=1}^{n}Z_i'\left(y_i - X_i\hat{\beta}\right) = \frac{1}{n}Z'\hat{u} \tag{11}$$

The idea behind GMM (Generalized Method of Moments) is to select an estimator for β by finding a solution to the equation $\overline{g}\left(\hat{\beta}\right) = 0$ (Baum et al., 2003). The GMM estimator aims to minimize a quadratic form through the equation

$$\hat{\theta} = arg\ \min_{\theta}\left(\sum_{i=1}^{N}m_i\right)' W\left(\sum_{i=1}^{N}m_i(\theta)\right) \tag{12}$$

If in the equation that will be estimated $L = K$, it is possible to assume that many equations exist (L moments conditions) as the K coefficients in $\left(\hat{\beta}\right)$. If $\overline{g}\left(\hat{\beta}\right) = 0$ can be solved in this scenario. The resulting GMM method estimator is essentially the same as the IV estimator (Baum et al., 2003).

If $L > K$, there are more equations than unknown. In this scenario, it is not possible to find a $\hat{\beta}$ that will ensure that all L sample moment conditions are precisely zero. Typically, the model is characterized by a high degree of overidentification, where the number of moment conditions (L) greatly exceeds the number of parameters to be estimated (K) (Kripfganz, 2019). A large number of instruments compared to the size of the cross-sectional sample can lead to biased estimates of coefficients and standard errors and reduce the power of specification tests (Roodman, 2009b). To solve this problem, a LxL weighting matrix W is applied and utilized to build a quadratic form within the moment conditions (Baum et al., 2003). An asymptotically efficient estimator necessitates the use of an optimal weighting matrix, which is essentially a consistent estimate of the inverse of the asymptotic covariance matrix $m(\hat{\theta})$ (Kripfganz, 2019).

$$W\left(\hat{\theta}\right) = \left(\frac{1}{N}\sum_{i=1}^{N}m_i\left(\hat{\theta}\right)m_i\left(\hat{\theta}\right)'\right)^{-1} \tag{13}$$

The weight matrix, $W\left(\hat{\theta}\right)$, can be derived from an inefficient initial GMM estimator, which results from selecting a suboptimal W during the estimation process (Kripfganz, 2019). Thus, give the GMM function:

$$J\left(\hat{\beta}\right) = n\overline{g}\left(\hat{\beta}\right)' W\overline{g}\left(\hat{\beta}\right) \tag{14}$$

The optimal value for $\widehat{\beta}$, which minimizes $J\left(\widehat{\beta}\right)$, can be estimated using a GMM estimator. The GMM estimator that achieves maximum efficiency is the one that employs an optimal weighting matrix W, which minimizes the estimator's asymptotic variance (Baum et al., 2003). The one-step difference generalized method of moments (diff-GMM) approach is computationally efficient, but it requires a strong assumption of homoscedasticity to ensure its validity. In contrast, the one-step system GMM (sys-GMM) approach may lead to inefficiencies even under homoscedasticity (Kripfganz, 2020). The feasible efficient GMM estimator, which is a two-step procedure, can be expressed as follows (Kripfganz, 2019):

$$\widehat{\widehat{\theta}} = arg\ \min_{\beta} \left(\frac{1}{N}\sum_{i=1}^{N} m_i(\beta)\right)' W\left(\widehat{\theta}\right)\left(\frac{1}{N}\sum_{i=1}^{N} m_i(\beta)\right) \tag{15}$$

The one-step Generalized Method of Moments (GMM) estimator exhibits heteroscedasticity consistency but loses its efficiency property (Kripfganz, 2019). The two-step estimator exhibits asymptotic efficiency, conditional on a specified set of instruments. However, in the context of finite samples, estimating the optimal weighting matrix may be susceptible to variations that stem from the arbitrary selection of an initial weighting matrix (Kripfganz, 2020).

The GMM presents a computationally efficient method for obtaining consistent and asymptotically distributed estimators of statistical model parameters (Salkind, 2013). Compared to the maximum likelihood (ML) estimator, which is typically regarded as the optimal estimator in classical statistical paradigms, the GMM may provide a more suitable alternative in scenarios where dependence on the probability distribution exists. This fact is because the GMM is founded on the population moment condition, which allows for estimating the model coefficients based on information derived from the model (Salkind, 2013).

In general, it can be observed that the variable, denoted as $y_{i,t-1}$, exhibits a correlation with the fixed effects in the error term. This correlation leads to the emergence of what is commonly known as "dynamic panel bias" (Nickell, 1981). The abovementioned relationship can produce biased estimators if an appropriate methodology is not employed. Specifically, the estimated coefficients may be overestimated due to the incorrect attribution of predictive power to the relationship, which pertains to the fixed effects (Roodman, 2009a). Concerning the sample size of the current study, the value of $T = 11$. A larger sample size would likely lead to a reduced impact of each year on the others and potential mitigation of the endogeneity problem. An approach to tackle this issue involves the use of instrumental variables for $y_{i,t-1}$, and other endogenous variables that are hypothesized to be uncorrelated with the fixed effects. This strategy is integrated within the System GMM methodology (Roodman, 2009a).

The difference and system GMM estimators are commonly used techniques for estimating parameters in panel data settings with "small T, large N" dimensions, where the number of time periods is limited and there are many individuals. These methods prove particularly useful when the independent variables are not strictly exogenous and when they are correlated with past and current error terms. Moreover, they can handle fixed effects, heteroscedasticity, and autocorrelation within individuals (Roodman, 2009a).

Bias-corrected Estimation

When analyzing panel data models that include a lagged dependent variable and unobserved group-specific heterogeneity, the conventional "fixed effects" (FE) and "random effects" (RE) estimators may produce biased results if the time horizon is limited. This means that the estimates obtained from these models may not accurately reflect the true relationship between the variables being studied. Therefore, it is important to carefully consider the choice of the estimator and the length of the time horizon when conducting panel data analysis (Nickell, 1981).

Quasi–maximum likelihood (QML) can be an alternative approach to the panel-data scenario in which the time horizon is not extensive. In this context, the ordinary least square (OLS) is usually applied or the generalized least square (GLS) for random or fixed effects because, according to Kripfganz (2016), the use of initial observations to condition estimates may result in bias due to the correlation between the lagged dependent variable and the combined error term. Quantile maximum likelihood (QML) estimators can exhibit significantly higher efficiency if all the regressors are strictly exogenous; however, this entails additional assumptions concerning the initial observations (Kripfganz & Breitung, 2022).

Given that the analytical nature of the bias is established, the bias-corrected (BC) estimator can rectify it directly at the origin by adapting the corresponding moment conditions. In addition, the fixed-effects/random-effects (FE/RE) estimators maintain their characteristic property of low variance. The bias-corrected (BC) estimator can handle higher-order autoregressive models and offers both FE and RE variations. Additionally, the BC estimator is a moment-based estimator with a well-defined asymptotic distribution, facilitating the straightforward computation of standard errors. Furthermore, standard errors can be adapted to account for cross-sectional dependence by applying robust techniques (Kripfganz & Breitung, 2022).

A generic dynamic panel-data model can be described as:

$$y_{it} = \sum_{j=1}^{p} \lambda y_{i,t-1} + x_{it}'\beta + \varepsilon_{it} \;\; \varepsilon_{it} = u_i + \alpha_{it} \tag{16}$$

In which, $x_{it}\prime$ is a vector of time-varying variables (Kripfganz, 2016). In dealing with panel-data estimation, it is necessary to address whether the fixed or random effects will be applied; this decision is taken through the interpretation of Hausman's test.

The fundamental assumptions of the model are as follows: (High-order) autoregressive model, given only minimal regularity conditions on the initial observations, it is possible to model the dependent variable with p lags. The regressors are assumed to be strictly exogenous x_{it}; regarding the idiosyncratic error term, the following assumptions are made: $E\left[x_{it}u_{is}\right] = 0$ for all t and s. There exist unobserved group-specific factors in the model, FE, $E\left[x_{it}\alpha_i\right] \neq 0$, or for RE $E\left[x_{it}\alpha_i\right] = 0$. The model assumes that the idiosyncratic errors are serially uncorrelated, such that the expected value of their product is zero for all periods t and s. However, the errors may exhibit heteroscedasticity, such that the expected value of the square of the error term is σ_i (Kripfganz & Breitung, 2022).

To simplify the model, it is assumed that $p = 1$ and $\theta = (\lambda_1 \beta\prime)\prime$. The estimator known as the fixed effects and bias-corrected estimator with just identification solves the following:

$$\hat{\theta} = arg \ \min_{\theta} \left(\sum_{i=1}^{N} m_i(\theta) \right)' \left(\sum_{i=1}^{N} m_i(\theta) \right) \tag{17}$$

While the estimator, referred to as the random effects and bias-corrected estimator with over-identification, solves the following:

$$\hat{\theta}^{(j)} = arg \ \min_{\theta} \left(\sum_{i=1}^{N} m_i(\theta) \right)' W \left(\sum_{i=1}^{N} m_i(\theta) \right) \tag{18}$$

In the context of finite element analysis, we employed an adjusted profile likelihood estimator for our BC estimation. This estimator is designed to handle scenarios where the dependent variable exhibits a sole lag. In addition to the aforementioned benefits, it should be noted that the BC estimator in question does not necessitate a preliminary consistent estimator (Kripfganz & Breitung, 2022).

Results and Discussions

This study proposed estimating two distinct models: Model 1, represented by Eq. 19, and Model 2, represented by Eq. 20. The main difference between these models lies in their treatment of the labour force. While Model 1 considers the total labour force, Model 2 considers the level of education (basic, intermediate, and advanced) to capture its interaction with economic growth.

$$\begin{aligned} Y_t = \beta_0 + \beta_1 FD_t + \beta_2 HT_{1t} + \beta_3 K_t + \beta_4 CC_t + \beta_5 NGC_t \\ + \beta_6 OC_t + \beta_7 RC_t + \beta_8 lnEPU_t + \beta_9 DHI_t + \varepsilon_t \end{aligned} \tag{19}$$

$$\begin{aligned} Y_t = \beta_0 + \beta_1 FD_t + \beta_2 H_{1t} + \beta_3 H_{2t} + \beta_4 H_{3t} + \beta_5 K_t + \beta_6 CC_t + \beta_7 NGC_t \\ + \beta_8 OC_t + \beta_9 RC_t + \beta_{10} EPU_t + \beta_{11} DHI_t + \varepsilon_t \end{aligned} \tag{20}$$

which is the technical progress represented by $A_t = FD$, in which FD stands for financial development as a proxy for technological progress, the same strategy applied by Ifa and Guetat (2022). In addition, we divided HT_t into three variables to capture the effect of basic education (H_1), intermediate education (H_2), and advanced education (H_3), thus $HT = (H_1 + H_2 + H_3)$, so we have in these variables the ideas of Lucas's models. Finally, in the decomposition of energy production (EC_t), we considered the consumption of gas (NGC), oil (OC), coal (CC), and renewable energy (RC).

It has been determined that converting the equations into log–log form will facilitate interpreting the results. This approach allows for direct analysis of the concept of elasticity, thereby simplifying the overall interpretation process.

Based on the economic growth models examined in this study and specific characteristics of the GMM approach, the technical progress (FD), the labour force

$(HT_{1t}, H_{1t}, H_{2t}, H_{3t})$, and capital (K_t) are regarded as endogenous variables. That said, all other variables are considered exogenous.

The methodologies were chosen considering the characteristics of the sample examined in this study, which has a relatively short time frame. Moreover, the GMM methodology produces robust estimators when heteroscedasticity is present, a condition addressed in this dataset.

Cross-sectional independence tests, specifically the Pesaran, Frees, and Friedman tests, were utilized to evaluate the association among the error terms in the sample. The null hypothesis assumes cross-sectional independence. The outcomes of the tests are inconclusive, as the Pesaran and Frees tests suggest the presence of cross-sectional dependence for the Model 1 fixed effects and random effects, and for the Model 2 for fixed effects, whereas the Pesaran test suggests otherwise for the random effects in Model 2. The Wooldridge test was employed to check the hypothesis of no autocorrelation in panel data. The findings suggest that, at a 1% significance level, there is insufficient evidence to reject the null hypothesis, thereby indicating the absence of autocorrelation in the sample.

Furthermore, the modified Wald test was employed to investigate heteroscedasticity. The results reveal that, at a 1% confidence level, the null hypothesis cannot be rejected, implying that the sample exhibits constant variance. The outcomes of the tests are presented in Table 1.

Due to the non-normal distribution of errors, which implies the presence of heteroscedasticity, diagnostic tests were conducted to confirm this observation. To address this issue, the Generalized Method of Moments (GMM) was chosen as the preferred estimation technique. The main advantage of the GMM is its ability to provide consistent estimates even in the presence of heteroscedasticity.

Table 2 presents an expanded model incorporating variables previously treated as exogenous, aligning with the framework proposed by Lucas and Romer.

Table 1 Diagnostic tests

Model 1	Fixed effects	Random effects
Pesaran's test of cross-sectional independence	−0.201	−0.021
Frees' test of cross-sectional independence	0.895	1.444
Friedman's test of cross-sectional independence	9.333	11.051
Average absolute value of the off-diagonal elements	0.321	0.349
Modified Wald test for groupwise heteroskedasticity	2260.54***	
Wooldridge test for autocorrelation in panel data	10.658***	
Model 2	Fixed effects	Random effects
Pesaran's test of cross-sectional independence	0.074	2.327**
Frees' test of cross-sectional independence	0.87	1.379
Friedman's test of cross-sectional independence	10.01	16.98
Average absolute value of the off-diagonal elements	0.312	0.361
Modified Wald test for groupwise heteroskedasticity	2655.78***	
Wooldridge test for autocorrelation in panel data	11.546***	

Significance level at 1%***, 5%**, and 10%* to evaluate the results. Source: Author's conception, based on Stata 15 software

Table 2 Bias-corrected estimation model 1

Variables	Bias-Corrected Estimation FE robust	Bias-Corrected Estimation RE robust	Bias-Corrected Estimation FE Lag(1)	Bias-Corrected Estimation RE Lag(1)
Gross Domestic Product				
L1	0.4440***	0.9160***	0.4633***	0.8607***
Financial Development	0.0129	0.0394	0.0117	0.0139
Total Labour Force	– 0.1505	– 0.0678**	– 0.1945**	– 0.0751
Gross Fixed Capital Formation	0.1661***	0.0671***	0.1591***	0.0861
GEPU (×4)	– 0.0192**	– 0.0089**	– 0.0176***	– 0.0065
Natural Gas Consumption	– 0.0027	0.0118**	– 0.0107	0.0121*
Oil Consumption	0.04805*	– 0.0226**	0.0544**	– 0.0230
Coal Consumption	– 0.0016	0.0016	0.0018	– 0.0064
Renewable Consumption	0.01920**	0.0047	0.0125	0.0080***
DHI	0.7404824**	0.0277	0.4957	0.5340
Constant	4.033113**	0.3423	4.7064***	0.6136
Hansen test of the overidentifying restrictions	13.2732*		2.589	
Generalized Hausman test	192.2839***		3637.8831***	
Arellano-Bond test for autocorrelation of the first-differenced residuals				
H0: no autocorrelation of order 1:	– 0.9702		– 0.4879	
H0: no autocorrelation of order 2:	– 1.4867		– 0.0568	
Variables	Bias-Corrected Estimation FE Lag(2)	Bias-Corrected Estimation RE Lag(2)	Bias-Corrected Estimation FE Lag(3)	Bias-Corrected Estimation RE Lag(3)
Gross Domestic Product				
L1	0.6890***	1.2435	0.7836***	1.1596***
L2	– 0.1585*	– 0.3428***	– 0.1102	– 0.2627
L3			– 0.0151	0.0136
Financial Development	– 0.0012	0.0254	0.0079	0.0417
Total Labour Force	– 0.14627	– 0.0482*	– 0.1614	– 0.0505
Gross Fixed Capital Formation	0.1258***	0.0527**	0.0867***	0.0508
GEPU	– 0.0160**	– 0.0093*	– 0.0185*	– 0.0129
Natural Gas Consumption	– 0.0243*	0.0103**	– 0.0360*	0.0112**
Oil Consumption	0.04756*	– 0.0138*	0.0509*	– 0.0151
Coal Consumption	0.0005	– 0.0065	0.0001	– 0.0040
Renewable Consumption	0.0072	0.0063***	– 0.0019	0.0050***
DHI	0.6258*	0.4052	0.6643	0.2624
Constant	4.0864**	0.5678	4.0702***	0.5665

Table 2 (continued)

Variables	Bias-Corrected Estimation FE robust	Bias-Corrected Estimation RE robust	Bias-Corrected Estimation FE Lag(1)	Bias-Corrected Estimation RE Lag(1)
Hansen test of the overidentifying restrictions	3.2943		6.4125	
Generalized Hausman test	1014.6526***		715.8827***	
Arellano-Bond test for autocorrelation of the first-differenced residuals				
H0: no autocorrelation of order 1:	– 1.0975		– 1.1029	
H0: no autocorrelation of order 2:	– 1.0417		– 1.1486	
H0: no autocorrelation of order 3:			1.4657	

Significance level at 1%***, 5%**, and 10%* to evaluate the results. Source: Author's conception, based on Stata 15 software

Although the labour force variable lacks statistical significance, it shows an inverse relationship with economic activity, suggesting a detrimental effect on economic growth. On the other hand, gross capital formation demonstrates both economic significance and the anticipated directional relationship, aligning with SDG 8 (Decent Work and Economic Growth). Specifically, this aligns with target 8.1, which promotes sustained per capita economic growth. The GEPU variable, representing political instability, shows an inverse association with GDP, implying that rising uncertainty negatively influences economic growth. This finding, supported by prior research from Feng (1997), Uddin et al. (2017), Aydin (2022), Asafo-Adjei et al. (2021), and Daştan et al., 2024, reinforces the importance of political stability for achieving the goals of SDG 8, particularly in fostering productive employment and economic resilience in less developed economies.

Energy consumption variables reveal mixed results. Natural gas consumption positively correlates with economic growth, while oil consumption has an inverse relationship. More importantly, the positive correlation between renewable energy consumption and economic growth, as seen in studies by Ben Jebli et al. (2019), Ben Mbarek et al. (2018), Balsalobre-Lorente et al. (2018), Aydin (2022), and Kamoun et al. (2019), highlights a shift toward sustainable energy sources. This supports SDG 7 (Affordable and Clean Energy), particularly target 7.2, which emphasizes increasing the share of renewable energy in the global energy mix. The shift toward renewables not only promotes cleaner, sustainable energy but also contributes indirectly to SDG 3 (Good Health and Well-Being) by reducing pollution, which improves public health outcomes.

The Human Development Index (HDI) plays a significant role in this analysis. The positive correlation between HDI and economic growth is consistent with the findings of Hung (2022), Adewale Alola et al. (2021), Kaewnern et al. (2023), Ponce et al. (2021), and Khan et al. (2022), and accentuates the importance of human development in fostering economic progress. This is closely tied to SDG 4 (Quality Education), as higher HDI scores reflect better access to education, which equips the

Table 3 Bias-corrected estimation model 2

Variables	Bias-Corrected Estimation FE robust	Bias-Corrected Estimation RE robust	Bias-Corrected Estimation FE Lag(1)	Bias-Corrected Estimation RE Lag(1)
Gross Domestic Product				
L1	0.4223***	0.9254***	0.4245***	0.9035***
Financial Development	− 0.0068	0.0763***	− 0.0158	0.0568
Advanced Education	− 0.1716	0.1513	− 0.1897	0.1032
Basic Education	− 0.0300	− 0.0104	− 0.0333	− 0.0095
Intermediate Education	0.0626	− 0.1419*	0.1211	− 0.0734
Gross Fixed Formation	0.1698***	0.0411***	0.1658***	0.0552
GEPU	− 0.0162**	− 0.0216***	− 0.0153**	− 0.0223**
Natural Gas Consumption	− 0.0178	0.0099*	− 0.0270	0.0067
Oil Consumption	0.0550**	− 0.0498***	0.0585***	− 0.0496
Coal Consumption	− 0.0025	− 0.0011	− 3.61E − 06	− 0.0060
Renewable Consumption	0.0081	− 0.0061	0.0029	− 0.0047
DHI	0.6753**	0.3917*	0.5525	0.6173
Constant	2.1611***	− 0.1061	2.0573***	− 0.2966
Hansen test of the overidentifying restrictions	9.0352*		3.3147	
Generalized Hausman test	940.099***		1355.9515	
Arellano-Bond test for autocorrelation of the first-differenced residuals				
H0: no autocorrelation of order 1:	− 1.0319		− 1.0618	
H0: no autocorrelation of order 2:	− 1.5394		− 0.9976	
Variables	Bias-Corrected Estimation FE Lag(2)	Bias-Corrected Estimation RE Lag(2)	Bias-Corrected Estimation FE Lag(3)	Bias-Corrected Estimation RE Lag(3)
Gross Domestic Product				
L1	0.6615***	1.2681***	0.7409***	1.1565***
L2	− 0.1659**	− 0.3617	− 0.0903	− 0.2304
L3			− 0.0457*	− 0.0203
Financial Development	− 0.0191	0.0672	0.00007	0.0939
Advanced Education	− 0.1737*	0.1439	− 0.0894	0.1768
Basic Education	− 0.0323	− 0.0109	− 0.0186	− 0.0163
Intermediate Education	0.1349*	− 0.0666	0.0653	− 0.0925
Gross Fixed Formation	0.1317***	0.0390	0.0952***	0.0397
GEPU	− 0.0147**	− 0.0192	− 0.0183*	− 0.0212**
Natural Gas Consumption	− 0.0375**	0.0040	− 0.0411**	0.0036
Oil Consumption	0.0537**	− 0.0313*	0.0595**	− 0.0348
Coal Consumption	− 0.0007	− 0.0045	− 0.0008	− 0.0021
Renewable Consumption	0.0004	− 0.00257	− 0.0043	− 0.0051
DHI	0.7021**	0.5582	0.7749*	0.4804
Constant	2.1112***	− 0.1384	1.8514***	− 0.17033

Table 3 (continued)

Hansen test of the overidentifying restrictions	2.2777	0.967
Generalized Hausman test	359.2819***	376.3888***
Arellano-Bond test for autocorrelation of the first-differenced residuals		
H0: no autocorrelation of order 1:	− 1.2631	− 1.094
H0: no autocorrelation of order 2:	− 0.3409	− 1.8324*
H0: no autocorrelation of order 3:		1.9300**

Significance level at 1%***, 5%**, and 10%* to evaluate the results. Source: Author's conception, based on Stata 15 software

workforce with the skills necessary to drive economic growth (supporting SDG 8, target 8.2). Moreover, improvements in education and human development enhance societal well-being, indirectly contributing to better health outcomes (SDG 3).

The estimated results of Model 2 aim to capture the impact of educational level on the economy. The results can be seen in Table 3.

Surprisingly, the findings reveal that workers with advanced education negatively impact the economy, which contradicts the expected relationship. However, the positive relationship and statistical significance observed for intermediate education suggest that economic growth may be more strongly linked to the promotion and facilitation of technical and vocational courses. This finding is particularly relevant to SDG 4 (Quality Education), which stresses the need for inclusive and equitable education. It aligns with target 4.4, which aims to substantially increase the number of youths and adults with relevant skills for employment, decent jobs, and entrepreneurship. The results emphasize the importance of aligning education with labour market demands to foster economic development, as also emphasized by SDG 8 (Decent Work and Economic Growth).

The HDI, used as a proxy for social development, holds significant importance. The positive association between HDI and economic growth is consistent with prior research by Hung (2022), Adewale Alola et al. (2021), Kaewnern et al. (2023), Ponce et al. (2021), and Khan et al. (2022), and underlines the role of improved education, health, and living standards in driving economic growth. This relationship highlights the interconnectedness of SDG 3 (Good Health and Well-Being), SDG 4, and SDG 8, as improved human development fosters a healthier, more educated, and more productive workforce. Economic and political stability also mitigate inequality, which is crucial for promoting inclusive growth as part of SDG 8.

The GEPU variable negatively affects GDP, indicating that increased uncertainty or political instability hinders economic growth. This finding echoes those of prior studies and reinforces the importance of stable political environments for economic development, as envisioned in SDG 8.

Regarding energy consumption, the results are once again mixed. In this model, oil consumption exhibits a positive relationship with economic growth, while natural gas consumption shows a negative association. The positive association between oil consumption and economic growth could raise concerns about the sustainability of growth, but it also highlights the ongoing dependency on traditional energy sources. However, the shift away from natural gas may signal an evolving energy consumption profile, which has implications for SDG 7 (Affordable and Clean Energy). As the global energy mix shifts toward more sustainable forms, the transition away from fossil fuels is crucial for achieving long-term economic and environmental goals.

Conclusions

In this study, we have presented the results of two distinct models, Model 1 and Model 2, which aimed to investigate the relationship between technological progress, represented here by the financial development, labour force, gross fixed formation, the GEPU as a proxy for political stability, energy consumption, human development, and economic growth. The main difference between these models lies in their treatment of the labour force, with Model 2 considering the level of education to capture its interaction with economic growth.

The results obtained from Model 1 through the GMM approach indicate that the financial development variable is non-significant for economic growth. On the other hand, gross capital formation displays both economic significance and the expected signal, consistent with prevailing macroeconomic theories, while the labour force displays a negative relationship. Additionally, the GEPU variable, which measures political stability, exhibits an inverse association with GDP, suggesting that instability or political uncertainty would likely negatively affect economic growth. Furthermore, the direct relationship observed between renewable energy consumption and the inverse relationship for oil consumption may indicate a shift in the energy consumption and production profile towards sustainable growth that is less harmful to the environment.

The findings from Model 2, which aimed to isolate the effect of the workforce on economic growth based on different educational levels, reveal that intermediate and advanced education are statistically significant. Surprisingly, workers with advanced education harm the economy, which contradicts the anticipated relationship. However, the positive relationship and statistical significance observed for intermediate education suggest that economic growth may be linked to the promotion and facilitation of technical courses tailored to the labour market's needs.

With regard to future studies, it is recommended to investigate, analyze, and, if possible, determine the reasons for the occurrence of unexpected results, in particular, why basic and higher education are not directly related to economic growth since the majority of the population has at least a basic education, and to assess whether these are in line with the prevailing academic discourse. This further research may involve investigating whether such outcomes can be attributed to specific features of the database or whether a discernible pattern of change in the economic landscape may be driving these results.

The results obtained from both models suggest that aligning education with the demands of the labour market to foster economic development is crucial. In conclusion, our study highlights the significance of various economic factors in driving economic growth and calls for policymakers to consider these factors when formulating policies to promote sustainable economic development.

This study faces significant limitations due to using an index as the primary analytical tool. While indices are commonly employed in academic research, they may not comprehensively represent real-world situations' complex and multifaceted nature, as previously noted by Foster et al. (2012) about a different indicator. Additionally, the sampling period utilized in this study may be deemed insufficient to enable rigorous, long-term statistical inference. This could account for the disparities observed compared to previous investigations, particularly concerning the outcomes resulting from modifications to institutional metrics.

Appendix 1. Classical Endogenous Growth Models

The AK Model

In 1956, Solow introduced a neoclassical economic growth model that is widely recognized. This model considers three primary factors influencing economic growth, specifically physical capital ($K_{(t)}$), the labour force ($L_{(t)}$), and knowledge ($A_{(t)}$). As a result, the output function ($Y_{(t)}$) can be articulated as follows.

$$Y_{(t)} = F\left[K_t, L_t, A_t\right] \tag{21}$$

In this context, $K_{(t)}$ symbolizes durable production goods, including machinery.$L_{(t)}$ represents the aggregate contribution of the human workforce to economic growth, a variable subject to temporal fluctuations influenced by the population growth rate. Lastly, $A_{(t)}$ signifies knowledge, alternatively referred to as technology (Barro & Sala-i-Martin, 2000).

Nevertheless, the Solow neoclassical economic growth model proved inadequate in elucidating long-term growth dynamics. As posited by Barro and Sala-i-Martin (2000), the model's assumption of constant technological progress results in the economy reaching a steady state. In this state, alterations in variables cease to translate into changes in the overall economic landscape. Moreover, the model assumes constant knowledge (A), leading to diminishing returns on capital over time. This, in turn, dissuades new investments and acts as a deterrent to sustained economic growth. In response to these limitations, the AK model emerged as a modified version of the Solow model. A notable characteristic of the AK model is the absence of diminishing returns on capital (Barro & Sala-i-Martin, 2000). The *AK* function can be expressed as follows.

$$Y = AK \tag{22}$$

According to the model proposed by (Barro & Sala-i-Martin, 2000), a positive constant denoted as A signifies the level of technology, with the variable K having a broader interpretation that encompasses human capital. In this framework, the constancy of the return on capital is maintained, contingent upon A being greater than zero.

The *AK* model posits that a single equation can describe both short-term and long-term economic growth and that model parameter changes can affect variable levels and growth rates (Barro & Sala-i-Martin, 2000). Technological progress, represented by the variable A, is a key factor in economic growth, as it raises the marginal and ordinary products of capital, leading to increased economic expansion and alterations in the savings rate (Barro & Sala-i-Martin, 2000). It is worth noting that technological progress can vary over time and may differ between countries, which could help to explain the differences observed between economies. In this way, technological progress has been identified as a means for economies to avoid the return of decreasing capital in the long run (Barro & Sala-i-Martin, 2000).

Solow (1956) introduced a simplified growth model that incorporates only three variables. The ensuing equation encapsulates the essence of the model.

$$Y = A \times L^{(1-\alpha)} \times K^{\alpha} \tag{23}$$

All variables constituting the model are deemed endogenous, leading to the nomenclature of an endogenous growth model (Appendix 2). The contributions of physical capital (K) and labour (L) to economic growth (Y) exhibit diminishing returns, whereas technology (A) is held constant (Kasim, 2017). However, according to the innovation model proposed by Barro and Sala-i-Martin (2000), technological advancements stand as the singular avenue through which an economy can avert a decline in returns in the long run.

The Lucas Model

Lucas' model explores the possibility that human and physical capital production relies on different technologies. In this model, only human capital serves as an input in the educational sector, creating an imbalance in the economic expansion rate between human capital and physical capital due to an asymmetry resulting from the positive relationship between the two factors (Barro & Sala-i-Martin, 2000). This asymmetry can be observed in the real wage per unit of human capital, leading to an opportunity cost of dedicating human capital to education (Barro & Sala-i-Martin, 2000).

However, this asymmetry also leads to the relaxation of the restriction of decreasing scale returns, creating opportunities for long-term economic expansion even in the absence of exogenous technological advancement. Human capital is considered a potential technological improvement for long-term economic growth (Barro & Sala-i-Martin, 2000).

Human capital is defined as individuals' individual skills, talents, and education and is considered a rival commodity—meaning that multiple firms cannot simultaneously use it. This contrasts with Romer's proposal that knowledge is a non-rival good. Nevertheless, the concept of spillover remains relevant to this assumption.

Mathematically, the model can be described as follows.

$$Y = AK^{\alpha}H^{1-\alpha} \tag{24}$$

In this particular model, denoted by $0 \leq \alpha \leq 1$, the variable H represents the product of the number of workers, commonly referred to as L in other models, and the quality of labour, denoted by h. The inclusion of this specification in the model ensures that treating L as a constant will not lead to decreasing returns of scale. This is due to the dual effect on output resulting from h and K, with the growth in productivity of H being driven by h, which represents the increased capacitation of workers. As such, the model accounts for the cumulative effect of education workers receive, which is treated as a multiplier of labour. This serves to signify the role played by education as a contributing factor to economic growth.

In agreement with Barro and Sala-i-Martin (2000), the Y may be spent for consumption (C) or invested in human (I_h) or physical capital (I_K), so we can rewrite the model as follows

$$Y = AK^{\alpha}H^{1-\alpha} = C + I_h + I_K \tag{25}$$

whereas physical and human capital have the same rate of depreciation (δ), the slump of human and physical capital is given by the equations, $H = I_h - \delta_h$, and $K = I_k - \delta_k$, respectively.

According to Mankiw et al. (1992), a higher level of savings or a lower rate of population growth tends to lead to greater compensation and a more advanced level of human capital for a certain amount of human capital accumulation. This implies that the impact of physical capital emulation and population expansion on earnings is more significant when considering human capital. Additionally, human capital is found to be positively correlated with the percentage of savings and population expansion. Therefore, neglecting the role of human capital can result in biased estimates.

The proposals of the model reveal that there are divergences in Romer's model, as the elasticity of income concerning the stock of physical capital does not differ significantly from the portion of the capital derived from income. Even without externalities, the accumulation of physical capital and population expansion has a greater effect on earnings than the Solow model (Mankiw et al., 1992).

Overall, the Solow model recognizes the significance of both human and physical capital. However, the expanded Solow model proposed by Lucas (1988) shows that differences in savings, education, and population growth rate can explain the per capita income variations among countries.

The Romer Model

The AK model of endogenous growth is based on the assumption that diminishing returns do not exist because factors of production can be accumulated and replicated. This premise has been extensively analyzed by several economists, such as Lucas (1988) and Romer (1990), who expanded upon Solow's initial model. However, in their models of endogenous growth, the role of spillover effects is crucial (Barro & Sala-i-Martin, 2000), a factor that Solow did not consider.

Lucas' model differs from the model proposed by Romer in how knowledge is created and transmitted; for Lucas, this occurs through the human capital. In this model, spillover is related to the involvement of intelligent people. Lucas assumes that human capital rather than physical capital is what generates the non-rival and non-excludable scenario (Romer, 1990). Human capital (H) is a measurement of the accumulative outcome of knowledge, whether acquired through formal education or enhancement of skills by practice. The model proposed by Romer separates the rival component of knowledge, the human capital ($H = H_Y + H_A$), from the non-rival, technological component, (A) (Romer, 1990).

Romer proposed a solution to address the issue of diminishing returns associated with descending scales by positing that knowledge creation was a byproduct of investment (Barro & Sala-i-Martin, 2000). Specifically, he argued that as a firm increases its physical capital, it becomes more efficient in production, leading to a phenomenon he termed "learning by doing" (Barro & Sala-i-Martin, 2000).

The production function of this endogenous growth model may be expressed in the following manner, as demonstrated.

$$Y_i = AL_i^{1-\alpha} . \sum_{j=1}^{N} (X_{ij})^{\alpha} \tag{26}$$

As variables L_i and K_i continually represent the previously mentioned inputs, A_i is the knowledge available, X_{ij} is the use of j type of a specific type of intermediate merchandise, and N is the number of varieties of intermediates to the firm i. The technology factor is a job enhancer; thus, the steady state occurs only when A_i grows at a steady rate (Barro & Sala-i-Martin, 2000).

The model proposed by Romer is reasoned on three assumptions. The first is technology changes, which tend to improve since technological change is a way to continue capital accumulation, and these two added factors contribute to the increase in workers' productivity (Romer, 1990).

The second is that technological change, most of the time, of intentional agents' actions in response to market demands. This makes technological change endogenous to the growth model (Romer, 1990), which differs from the model proposed by Solow, in which technology is considered an exogenous factor.

Finally, the third premise lies in the costs of elaborating new production instructions, and this would only have the initial cost for the creation later; these new instructions can be used repeatedly at zero cost. This premise is taken as the definitive feature of technology (Romer, 1990). After creating the new knowledge, this knowledge "spills" promptly for the country's entire economy. This assumption tells us that a technological change in the firms corresponds to the general learning of the economy and the proportional change in the stock of capital (Barro & Sala-i-Martin, 2000).

These premises have features of Rivalry and Excludability. Rivalry is a purely technological characteristic. A rival is characterized by the fact that only one agent can use, in a way, all can use a non-rival good without impediment. Excludability is the junction of the technological sector and the legal system. A product is Excludability if the intellectual property proprietor can prevent others from using its creation (Romer, 1990). In this context, the economic growth model uses goods which are non-rivalrous but excludable. The first premise can be considered non-rival and partially excludable since it assumes that accumulation is a fundamental part of growth. The second assumption is that technological progress occurs through actions (investment decisions of the agents), so the interest for that decision tends to get benefits, so we can consider a partially excludable characteristic. The third premise assumes that technology is non-rival (Romer, 1990).

For Romer, non-rivalry has two characteristics of high importance for growth theory, merchandise characterized as non-rival can be accumulated without limits at the per capita level. The second is to treat knowledge as a non-rival commodity, in this way, the spillover of knowledge becomes a reality (Romer, 1990).

The essence of the model Romer is learning by doing and knowledge spillovers; this way, it is possible to replace A_i with K in the production function; thus, the production function of the firms (i) can be rewritten $Y_i = F(K_i, KL)$. K and L being constant companies face descending scale returns, but, if each firm expands K_i, it is expected that K increases and occurs spillovers; according to Romer's premises, it would increase the productivity of taking the companies and consequently the economy (Barro & Sala-i-Martin, 2000). In addition, if K_i and K increase with a fixed L, this continuity will promote endogenous growth (Barro & Sala-i-Martin, 2000).

Romer considers that a new product demands η labour unit, so an expansion of N, which improves output and labour productivity, tends to raise wages. In addition, it is assumed that the cost of developing a new product reduces as long as society accumulates new ideas, and the number of products is represented by N (Barro & Sala-i-Martin, 2000). Part of the work is supposed to be applied in production (λ) and another in research and development (R&D) $(1 - \lambda)$, so the changes in N depends on the amount of work dedicated to R&D. So the technological change can be written as $N/N = (1 - \lambda)L/\eta$. To sum up, the cost of developing a new product remains constant in terms of commodities (Barro & Sala-i-Martin, 2000).

Exposed to Romer's arguments, we can mathematically describe his model as follows

$$Y_i = AL_i^{1-\alpha} NX_i^{\alpha} = AL_i^{1-\alpha}.(NX_i)^{\alpha}.N^{1-\alpha} \tag{27}$$

It should be noted that technological progress occurs with the increase of N. Variable A turns out to be a multiplier, a productivity parameter (Barro & Sala-i-Martin, 2000).

In Eq. (7), it is understood that the product has constant scale returns in L_i and NX_i (total amount of inputs), for a given N.

For certain amounts of L_i, X_i, and Y_i, the variable N increases as the reason for the term $N^{1-\alpha}$ (Barro & Sala-i-Martin, 2000). Therefore, the effect of technological progress is captured. According to Barro and Sala-i-Martin (2000), it is a reflection of straight out the intermediate goods (NX_i) in an extensive N. There is an increase due to decreasing returns for each X_{ij}. Considering constant L_i, Eq. (7) assumes that the NX_i increase will have decreasing scale returns if this increase is a consequence of an expansion in X_i, to a given N. If there is an increase in NX_i from the expansion of N to a given X_i, there are no decreasing returns. Thus, there is a technological change in n expansion, but circumvent the downward trend of returns; this characteristic face is the basis for endogenous growth (Barro & Sala-i-Martin, 2000).

In agreement with Romer, research is precisely associated with the accessibility of human capital in an economy. This also depends on the inventory of knowledge available for an individual to do as a researcher (Romer, 1990). Knowing the non-rival characteristic, possible from the assumption that any individual acting in the research sector would have free access to all stock of knowledge, $A = \mu H_A A$, where μ is a productivity parameter and H_A the interpretation of the total human capital working with the investigation (Romer, 1990). It is believed that more people dedicated to research expect greater productivity. In addition, the greater the knowledge available, the greater the productivity (Romer, 1990). So it gets clear that the marginal product of human capital (H), people who work in the manufacturing sector, expands in dimension to technology (A) (Romer, 1990).

The inclusion of technical progress in the model of Romer fills a gap in the model developed by Solow, which he considered an exogenous variable. So, the greater the knowledge available, the greater the productivity (Romer, 1990). So it gets clear that the marginal product of human capital (H), people who work in the manufacture sector, stretches in magnitude to technology (A) (Romer, 1990). In addition, Romer proposes that free foreign commerce can boost economic growth due to the relationship between countries with different technological levels.

Appendix 2. Classical Endogenous Growth Model Estimations and Discussion

Table 4 presents the outcomes of the Classical Model estimates obtained through the dynamic panel-data estimation approach.

The dynamic models exhibit satisfactory specification as evidenced by the rejection of the null hypothesis for the absence of second-order autocorrelation. Results indicate that financial development and gross fixed capital formation, when statistically significant, display a positive relationship with economic growth, contributing to a growth rate increase of 0.5% and 0.05%, respectively, for every 1% expansion. Conversely, the labour force exerts a negative impact on economic growth, with a 1% increase in the labour force tending to reduce growth by approximately 0.05%. Table 5 presents the outcomes of Model 1 estimates obtained through the Generalized Method of Moments (GMM) approach.

The analysis of GMM reveals the significance of two variables, workforce and gross fixed capital formation, which are considered fundamental for growth models proposed by Lucas (1988) and Romer (1990). Moreover, the labour force variable demonstrates an inverse relationship with economic activity, indicating its negative impact on economic growth, in the event of a 1% increase in the labour force, a corresponding reduction in GDP by approximately 0.02% is anticipated. In contrast, gross capital formation exhibits both economic significance and the expected signal, consistent with prevailing macroeconomic theories; to illustrate, a 1% increase in capital formation is expected to result in a corresponding economic growth of approximately 0.02%. The lack of statistical significance regarding financial development, used as a proxy for technical progress, aligns with the finding reported by Fatimah et al. (2021). Table 6 presents the estimates obtained from the Classical

Table 4 Dynamic panel-data estimations of the classical model

Variables	Dynamic panel-data estimation, one-step system GMM	Dynamic panel-data estimation, two-step system GMM	Dynamic panel-data estimation, one-step difference GMM	Dynamic panel-data estimation, two-step difference GMM
Gross Domestic Product				
L1	0.9852***	0.9549***	0.8485***	0.9950***
Financial Development	−0.0206	−0.0151	0.4455*	0.5273**
Total Labour Force	−0.0227	−0.0498*	0.3740	0.1828
Gross Fixed Capital Formation	0.0206	0.0498*	−0.1600	−0.2108
Arellano-Bond test for AR(1) in levels:	1.9**	2.53***	−1.41	−1.45
Arellano-Bond test for AR(2) in levels:	0.85	1.51	0.43	0.39

Significance level at 1%***, 5%**, and 10%* to evaluate the results. Source: Author's own conception, based on Stata 15 software

Table 5 Generalized methods of moments estimations classical model

Variables	Generalized method of moments estimation Lag(1)	Generalized method of moments estimation Lag(1)	Generalized method of moments estimation Lag(2)	Generalized method of moments estimation Lag(2)
Gross Domestic Product				
L1	0.4364***	0.9504***	0.667***	1.3704***
L2			−0.2041	−0.3906***
Financial Development	−0.0860	-0.005	−0.0632	−0.0036
Total Labour Force	0.1822***	−0.0526***	0.2355***	−0.0240***
Gross Fixed Capital Formation	0.1843***	0.0515***	0.1628***	0.0222***
Constant		0.0540		0.0354

Significance level at 1%***, 5%**, and 10%* to evaluate the results. Source: Author's own conception, based on Stata 15 software

Table 6 Dynamic panel-data estimation classical model with decomposed labour force

Variables	Dynamic panel-data estimation, one-step system GMM	Dynamic panel-data estimation, two-step system GMM	Dynamic panel-data estimation, one-step difference GMM	Dynamic panel-data estimation, two-step difference GMM
Gross Domestic Product				
L1	1.0259***	1.0248***	0.6662	0.7805
Financial Development	−0.0697*	−0.0645*	0.3605	0.2713
Advanced Education	−0.0959	−0.1092	−1.0167	−0.4321
Basic Education	0.0181	0.0216	−0.2073	−0.0947
Intermediate Education	0.0195	0.0354	0.3658	0.2605
Gross Fixed Formation	−0.0003	−0.0006	−0.0371	−0.0886
Arellano-Bond test for AR(1) in levels:	2.22**	2.5***	−1.16	−0.68
Arellano-Bond test for AR(2) in levels:	1.43	1.9**	−0.47	0.13

Significance level at 1%***, 5%**, and 10%* to evaluate the results. Source: Author's own conception, based on Stata 15 software

Table 7 Generalized methods of moments estimations classical model with decomposed labour force

Variables	Generalized method of moments estimation Lag(1)	Generalized method of moments estimation Lag(1)	Generalized method of moments estimation Lag(2)	Generalized method of moments estimation Lag(2)
Gross Domestic Product				
L1	0.4878***	1.0127***	0.6220***	1.4967***
L2			−0.1132	−0.4919***
Financial Development	−0.0119	−0.0330**	−0.0111	−0.008
Advanced Education	−0.2980	−0.0568	−0.2807*	−0.0078
Basic Education	−0.0722	0.0052	−0.0602	−0.0037
Intermediate Education	0.0282	0.0331	0.0006	−0.0021
Gross Fixed Formation	0.1777***	0.0014	0.1650***	−0.0010
Constant		−0.07881		0.03861

Significance level at 1%***, 5%**, and 10%* to evaluate the results. Source: Author’s own conception, based on Stata 15 software

Model, which aimed to isolate the effect of the workforce on economic growth based on different educational levels, namely basic, intermediate, and advanced.

The results of Model 2 regarding the decomposed workforce reveal a lack of statistical significance for the education metrics among the variables considered in the endogenous growth models, with only technological progress (represented by financial development in this study) displaying a negative relationship. Specifically, a 1% decrease in technological progress is projected to correspond to a 0.06% increase in GDP growth. Similar to Model 1, Model 2 demonstrates satisfactory specification, as evidenced by the absence of second-order autocorrelation. Table 7 presents the GMM estimates obtained for the Classical Model, as said before this model difference is the metrics for education.

Similar findings were observed in the estimates based on disaggregated labour force data, albeit without statistical significance, except for advanced education. While the results did not align with initial expectations, they were partially consistent with prior research conducted by Bowen and Qian (2017), and contrary to the findings reported by Clarke et al. (2013), the results indicate the opposite relationship. The unexpected outcome concerning education prompts a desire to investigate the underlying reasons. It is possible that the limited representation of individuals with advanced education within the population and the high costs associated with training this particular workforce could account for this phenomenon. The model also indicates a significant negative effect on financial development. These findings challenge the conventional notion that technological advancements contribute positively to economic growth, and this conclusion contradicts the results reported by previous studies such as Ponce et al. (2021) and Asafo-Adjei et al. (2021).

Similar findings were observed in the estimates based on disaggregated labour force data, albeit without statistical significance, except for advanced education. While the results did not align with initial expectations, they were partially consistent with prior research conducted by Bowen and Qian (2017). Contrary to the findings reported by Clarke et al. (2013), the results indicate the opposite relationship.

The unexpected outcome concerning education raises important questions about SDG 4 (Quality Education). It highlights a potential issue related to the limited representation of individuals with advanced education within the population, which could be a key factor. This situation suggests that access to advanced education remains unequal, a barrier to achieving the goal of inclusive and equitable quality education for all. Additionally, the high costs associated with training a specialized workforce may further limit educational accessibility and effectiveness, impacting the broader goal of improving educational outcomes and labour market readiness.
The model also indicates a significant negative effect on financial development. This challenges conventional assumptions that technological advancements always contribute positively to economic growth, as suggested by studies such as Ponce et al. (2021) and Asafo-Adjei et al. (2021). While not directly related to SDG 8 (Decent Work and Economic Growth), this finding emphasizes the complexity of fostering sustainable economic growth through innovation. It suggests that policy measures must account for the varied impacts of technological change on different sectors of the economy, ensuring that such advancements lead to more inclusive growth and decent work opportunities.

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