The Potential Of Human Capital In The Economy: A Macroeconomic Analysis For The Economic Growth Chain

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ABSTRACT
This article investigates the impact of human capital on economic growth, emphasizing the importance of education as a key factor in increasing worker productivity and promoting economic development. The analysis explores various theories, including neoclassical and endogenous growth models, highlighting the positive externalities associated with the accumulation of human capital. Using panel data for the 26 Brazilian states and the Federal District between 2012 and 2020, the study examines the relationship between the proportion of people with secondary education, energy consumption, schooling, internet access and GDP. The results highlight the importance of education and access to services as critical drivers of sustainable economic growth. The fixed effects panel model, chosen as the most appropriate, reveals a positive and significant impact of secondary education and energy consumption on GDP. The findings suggest that investments in human capital, particularly in education and innovation, are essential for long-term economic development.

KEYWORDS: Human Capital; Economic Growth; Education; Panel Data; Endogenous Growth Models; Brazil.

ABBREVIATIONS: R&D: Research and Development; GDP: Gross Domestic Product; IBGE: Brazilian Institute of Geography and Statistics; PNAD: National Household Sample Survey; INEP: National Institute of Studies and Research; ANATEL: National Telecommunications Agency; EPE: Energy Research Company.

1. INTRODUCTION

The issue of human capital and its impact on economic growth have been the subject of intense research and debate in recent decades. The importance of human capital as a fundamental element of economic and social development is increasingly recognized. The complex relationships between education, its competencies, health, and productivity in the context of the 21st-century globalized economy are also becoming more apparent, and it is essential to understand these interactions [1].

According to Altbach [2], since the 1990s, there have been major changes in world economic dynamics, mainly due to rapid technological evolution, globalization and changes in labor market requirements. In this context, intellectual capital, made up of citizens' knowledge, skills, experience and health, has become one of the most valuable assets of any country. Access to quality education, vocational training and health services plays a key role in building this capital.

In this context, Heckman [3] points out that the relationship between intellectual stock and economic growth is bidirectional. On the one hand, better-educated and healthier people are generally more productive and innovative, contributing to increased production and economic efficiency. On the other hand, sustainable economic growth provides resources that can be reinvested in the development of human capital, creating a virtuous cycle.

In addition, intellectual capital plays a key role in helping economies adapt to change. In the age of automation, artificial intelligence and changing industries, skills, and the ability to learn continuously are essential. Societies that invest in the education and training of their citizens are better equipped to adapt to these changes and continue to grow economically [4].

From this context, we can see the potential of human capital as a key driver of economic growth and investment in society's individual and collective capacities. As society evolves, it understands and maximizes the potential of this capital, which will be fundamental for countries seeking long-term prosperity and well-being [5].

In short, the potential of human capital is a critical element for economic growth in an ever-changing world. Understanding these dynamics and investing strategically in the education of the population is essential if countries are to achieve sustainable economic growth while promoting well-being and social justice. This article, therefore, analyzes the relationship between human capital and economic growth, examining the 26 Brazilian states, plus the Federal District, from 2012 to 2020.

The article is divided into five sections, the first being the introduction, followed by the theoretical framework in which the Human Capital Theory and Endogenous Growth Models are discussed. The third section contains the methodology, the fourth presents the results and discussions, and finally, the final considerations.

2. THEORETICAL BACKGROUND

2.1 HUMAN CAPITAL THEORY

In economic literature, human capital is recognized as a key factor in economic growth. According to the neoclassical approach, human capital should be seen as an additional factor of production in the production process. Thus, the process of economic growth is explained by its accumulation. The importance of education in economic growth is allied to the theory of human capital, emphasizing that investment in the professional qualification of workers will increase their productive capacity and thus promote economic progress [6].

Mincer [5] pointed out *a priori* that there is a correlation between investment in vocational training and the distribution of personal income. In this way, workers' individual rational choices in the allocation of qualifications, training and time to acquire new knowledge will determine their level of human capital and individual income. Therefore, the more an individual invests in education, the greater the return and the higher the productivity, which has a positive effect on the economy.

On the other hand, Schultz [6] emphasized that spending on education is heterogeneous among individuals with different incomes. The skills that workers acquire, therefore, depend on the relationship between additional income and the cost of acquiring these skills. For the author, the education of the population, in addition to increasing the productivity of the workforce, will also promote social welfare, especially for the poorest workers. In this context, improving the quality and professionalization of the population through investment in education will increase the productivity of the workforce and increase company profits.

For Becker [7], workers acquire productive capacity through the accumulation of general and specific human capital. Thus, an individual's choice to acquire more specialized skills is part of the *trade-off* between higher current income and higher future income, i.e., investing resources and time in education now for higher returns later. This is the opportunity cost that workers face when they decide to allocate their time to jobs with a lower stock of human capital and lower pay, or to dedicate themselves to learning and potentially earning higher wages in the future. However, it should be noted that workers' productivity is not only determined by their skills and educational expenditure; other factors are also important, such as motivation and the quality of the working environment.

The human capital theory argues that the demand for qualified professionals is a condition for a return on investment in improving a company's productivity by increasing its stock of human capital, which in turn includes the stock of individual capital acquired through the acquisition of knowledge and skills. Thus, the impact of the theory can be seen through the behavior of the labor market, affecting the availability/scarcity of qualified professionals. In this sense, when professionals seek qualifications, they can enjoy the privilege of internal or external mobility, the latter with a greater risk of return on investment, as the professional may not return to the organization [7,8]

With regard to the accumulation of human capital, the effort an individual makes to acquire training and qualifications depends on their personal characteristics and the intrinsic factors of what they learn, i.e., each worker is educated in a different way, which is one of the reasons for the accumulation of human capital that explains the different levels of worker productivity [7,8].

In this case, when the stock of human capital increases, the returns on the capital stock grow due to the expansion of investment in the educational structure, until equilibrium is reached, i.e., until per capita income increases, as there is a direct relationship between education and the economy [9]. Also noteworthy is the positive effect and repercussion of the accumulation of individual human capital, which facilitates intergenerational educational processes between economic agents, with positive effects on the economy over time. To this end, a growing number of economies invest in education and professional training in order to obtain a positive return on the economy's capital stock.

It can therefore be concluded that the direct and indirect effects of human capital on per capita income growth mainly affect technological progress [10]. Human capital is thus a fundamental input in the process of creating, acquiring and diffusing technology in the medium and long term, and one of the determinants of economic growth, as shown by Romer in 1990.

2.2 GROWTH MODELS

The first studies to explain growth through the positive externalities of human capital and knowledge accumulation were Romer [11] and Lucas Jr. [12]. These articles develop the so-called endogenous growth theory, according to which per capita income growth is determined endogenously by excluding the argument of the diminishing marginal returns of the capital factor. In other words, in traditional neoclassical growth models, such as Solow [13], technological change and population growth are treated exogenously, while in the new ones, these variables are treated endogenously and take into account the variation of income in growth between countries.

Lucas Jr. [12] noted that human capital, as measured by education and on-the-job learning, is the primary determinant of capital accumulation. In his model, variable investments in human capital generate positive externalities that raise the level of technology. Human capital variables are cumulative factors and sources of economic growth.

Romer [11] considered positive externalities and assumed that technological knowledge or research capital were the only appropriate forms of capital. He argues that research capital or technological knowledge leads to diminishing returns on a large scale, but that, due to innovation, they should be considered purely public goods and that the creation of new knowledge by companies has externalities for others. They are looking for new production opportunities.

The effects of these positive externalities increase the returns on the production of consumer goods, thus offsetting the effects of diminishing returns on research capital and positively affecting long-term growth. Romer [11] showed that education also plays an important role in economic growth, as it allows people to research and develop new products and processes.

Romer [11] investigates how technological innovations, derived internally from economic activities, drive economic growth without depending on external influences. In this study, he challenges traditional growth theories by arguing that technological progress can be the direct result of companies' investment decisions and the accumulation of knowledge within an economy. To this end, the author proposes that knowledge, as an input in the production process, has characteristics of non-rivalry and partial exclusion, which allow for increasing returns to scale and foster sustainable economic growth. The theoretical model developed in the paper incorporates technology as an endogenous variable and thus analyzes how business decisions on investments in R&D and human capital affect the rate of technological innovation and, in turn, economic growth.

The results of the study indicate that policies that encourage R&D and education can have a profound impact on economic growth, since the accumulation of technological knowledge and human capital are crucial drivers of change and innovation. Romer [11] also discusses the implications for public policy, suggesting that support for education and research can lead to a virtuous cycle of growth and innovation.

Barro and Lee [14], on the other hand, examine the determinants of economic growth in an analysis of 98 countries over the period from 1960 to 1985. The main objective of his work is to explore the influence of human capital and other macroeconomic factors on the economic growth of these nations.

The author proposes the hypothesis that there is a positive correlation between economic growth and initial human capital, measured by school enrollment rates in 1960, while a negative correlation is expected with the initial level of GDP per capita. The methodology employed includes robust econometric analysis, using education data as a proxy for human capital and evaluating its relationship with per capita GDP growth. In addition, Barro [15] analyzes the impact of factors such as physical investment, fertility rates and the proportion of government consumption in GDP.

The results of the study reveal that per capita GDP growth is strongly associated with human capital and physical investment, suggesting that policies that promote education and investment may be crucial to stimulating economic growth. The results also show that growth is negatively affected by the initial level of GDP per capita and by the proportion of government consumption in GDP, thus suggesting the need for government efficiency and measures to raise initial income levels in economic development processes.

Taking a more qualitative approach to this same analysis, Nakabashi and Figueiredo [10] explore the interactions between education and economic development, with a particular focus on the importance of the quality of human capital in economic growth. They propose that not only the quantity, but above all, the quality of human capital is crucial to boosting economic development in a sustainable way. This argument is reinforced in more recent work, which continues to investigate the nuances of this relationship.

The main objective of Nakabashi and Figueiredo [10] is to understand how the quality of the education system and the formation of human capital impact the rate of economic growth. The authors defend the hypothesis that qualitative improvements in human capital, rather than simple quantitative increases in education, are capable of accelerating economic growth. This hypothesis is examined through econometric models that incorporate proxies for human capital reflecting its quality, adjusting these variables to capture differences in educational quality between regions or over time. The findings of these studies indicate a positive relationship between the quality of human capital and the rate of economic growth. The results suggest that policies aimed at improving the quality of education can offer much higher returns in terms of economic growth than policies that only increase years of schooling without attention to quality.

Cravo and Soukiazis [16] confirm and complement the observations of Nakabashi and Figueiredo [10], indicating that the influence of human capital on economic growth is more significant when quality variables are taken into account than when quantitative variables are considered alone. Therefore, the work of Nakabashi and Figueiredo [10] highlights how the quality of human capital is a crucial determinant of economic growth. They argue that investments in qualitative improvements in education are more effective in promoting economic development than strategies focused exclusively on increasing the quantity of education.

Also in this context, Pelinescu *et al.* [17] investigate the connection between human capital, innovation and economic growth in European Union countries, showing that human capital is crucial to fostering innovation capacity and, consequently, economic growth. This study uses indicators such as research and development spending to demonstrate how human capital can boost innovation and drive sustainable economic development.

In another paper, Prasetyo [18] analyzes the importance of human capital as the main determinant of regional economic growth, stressing that investments in education and training are fundamental to sustaining economic growth. This research highlights that human capital not only positively influences growth but also modulates the relationship between innovation and economic development.

These studies corroborate and expand on previous observations by Nakabashi and Figueiredo [10], showing that not only the quantity, but especially the quality of human capital, is decisive for economic growth. Such research underlines the need for educational policies that not only increase the number of years of schooling but also significantly improve the quality of teaching, thus preparing a more capable and innovative workforce.

3. METHODOLOGY

The empirical research conducted in this study involved collecting quantitative data from a representative sample of the target population. The data was obtained through a survey of PNAD and IBGE data carried out in 2012 and 2021.

3.1 PANEL MODELS

Data analysis is fundamental to decision making in various fields, including economics, administration and medicine, among others [19]. In this context, panel models have emerged as an essential tool for analyzing data sets that contain repeated information over time or between different individuals. These models are especially valued for their ability to take into account heterogeneity between individuals and the time effect, providing more reliable and accurate results [20].

Panels, also known as longitudinal data or panel data, are a specific way of organizing data that allows individual and/or temporal variations to be tracked. Each individual in a panel dataset is followed over time, represented by a unique combination of identification and time. This two-dimensional structure is used for the estimation of models that can differentiate between fixed effects, which capture unchanged characteristics over time within an individual, and random effects, which assume that variations between individuals are random [20].

Exploring these different types of dashboard models and understanding how they use this data structure to uncover complex patterns is the focus of this paper, highlighting their applicability and importance in various professional and academic fields.

3.2 FIXED-EFFECT PANEL DATA

The fixed effects panel data methodology is a statistical approach for analyzing longitudinal data sets in which the same individual units are observed over time. This method is particularly useful for controlling for certain unobservable characteristics over time that can affect the dependent variable [20].

The main advantage of using fixed effects in panel models is the ability to control for unobservable unit-specific characteristics, providing a more robust approach to analyzing longitudinal data. This helps to reduce endogeneity problems and improve the internal validity of the estimates. However, it is important to consider possible heterogeneity that is not captured by fixed effects. In some cases, you can consider a random effects model to solve this problem [21].

In order to estimate the influence of human capital on GDP growth in Brazil in the years 2012 and 2012, the fixed effects panel data methodology is used. The most appropriate model is chosen using the following tests: *F-test* for the choice of fixed effects and pooled regression (stacked data), Lagrange multiplier test by Breusch and Pagan for random effects and the Hausman test to choose between the fixed or random effects panel.

3.3 RANDOM-EFFECT PANEL DATA

Random effects panel models offer a powerful approach for analyzing longitudinal data, where heterogeneity between individuals is modeled as random components. This type of model is particularly useful in economic, sociological and health studies, where data on the same individuals or entities is collected over several units of time [22].

Unlike fixed effects models, which assume that unobserved individual differences are fixed parameters to be estimated, random effects models consider these differences to be random variables coming from a common distribution. This assumption allows random effects to capture intra-individual variations and provide estimates that are generalizable to a larger population [21].

The application of these models is vast. For example, in economics, they can be used to study the impact of policies over time in different regions or countries, assuming that regional or national differences follow a random distribution around a global average [20]. In public health, random effects are used to analyze how medical interventions affect different subgroups of patients, taking into account random variations between these subgroups [20].

The challenges in applying random effects panel models include the need for a large amount of data to obtain accurate estimates and the complexity in correctly specifying the model, which must justify the choice of random effects over fixed effects, especially when the independent variables are correlated with unobserved effects [21].

3.4 EMPIRICAL MODEL AND DESCRIPTION OF VARIABLES

The empirical model to be estimated is a production function with an emphasis on human capital, with additional variables, proportion of people with secondary education, electricity consumption and proportion of schools per population of the municipality, in the Cobb-Douglas log-linear format, assuming the following equation for random effects:

$$lnpib_{it}^{5} = \beta 0_{it} + \beta 1_{it}(lnmédio_{it}) + \beta 2_{it}(lnk_{it}) + +\beta 3_{it}(lninternet)$$

Where *pib* is the value of total GDP collected from the IBGE; $\beta 0$, $\beta 1$, $\beta 2$, $\beta 3$ are the parameters of the model; *médio* refers to the proportion of people who have completed secondary school taken from the PNAD; *k* refers to energy consumption in kilowatts per hour (kW/h) with its data from the EPE; *escola_pop* refers to the population in relation to the number of schools (i.e. on a scale it would be 1 school for *x* number of people) with data collected from IBGE and INEP; *i* refers to the states and finally *t* refers to time.

Each of the variables chosen was intended to make the empirical model more robust. The variable *k* (energy consumption in kilowatts per hour) was chosen because of a literature review of various articles, such as Monteiro and Silva [22]. Internet access (*lninternet*), quantifies internet access points, with data provided by ANATEL. The hypothesis is that greater connectivity facilitates business and services, as well as boosting innovation and information and finally, secondary education (*lnmédio*) indicates the proportion of individuals who have completed secondary education. Data like this usually comes from the PNAD, and the expectation is that a higher proportion of education is positively correlated with GDP, indicating that education raises productive capacity. The other model for fixed effects:

$$lnpib_{it} = \beta 0_{it} + \beta 1_{it}(lnmédio_{it}) + \beta 2_{it}(lnk_{it}) + +\beta 3_{it}(lninternet)$$

For the fixed effects model, only the variable *lninternet* was added, which in this case is between access points in relation to the population.

The database used is made up of 26 states and 1 Federal District, covering the period from 2012 to 2020. The independent variables were selected based on previous literature reviews and specific hypotheses related to the study's object. The independent variables included (*lnmédio*, *lnk*, *escola_pop*), which were used to explain the dependent variable (*lnpib*).

The data was obtained from official sources such as the IBGE, the EPE, the ANATEL, the INEP and, finally, the PNAD.

Table 1: Description of the variables in the econometric model.

Variable	Description	Source	Expected Signal	Treatment
pib_{it}	Total GDP	IBGE	.	Natural logarithm
$\beta 0$, $\beta 1$, $\beta 2$, $\beta 3$, $\beta 4$	Model parameters	.	.	
average ln	Refers to the proportion of people who have completed high school	PNAD	+	Natural logarithm
lnk	Energy consumption in Kwatts/hour	EPE	+	Natural logarithm
lninternet	Number of Internet access points, by Federative Unit	ANATEL	+	Natural logarithm

Source: Prepared by the Authors.

4. RESULTS AND DISCUSSION

The results of the analysis of three different models for economic data—pooled data, fixed effects, and random effects—are presented in Table 1 and offer *insights* into the impact of variables such as education and energy consumption on GDP. The pooled data model reveals that, without adjusting for heterogeneities, average education does not show a significant effect on GDP, while energy consumption stands out as a strong indicator of economic activity. However, this model does not capture individual or temporal particularities, which are essential for a more precise analysis.

Table 2: Panel estimation results (between *lnpib* and *lnmedio*, *lnk*).

	Pooled data	Fixed effects	Random effects
lnmedium	1,033556	0,3449524	0,3526036
	(0,6288515)	(0,0694823)***	(0,0700201)
lnk	1,854576	0,1594452	0,1709551
	(0,2422091)***	(0,056539)***	(0,0568622)***
Constant	15,65351	25,05109	24,9909
	(1,840292)***	(0,3191358)***	(0,3876786)***

Coefficient of determination (R²)	0,2390	0,2065	0,2093
Chow test (F)			2982,30***
Breusch-Pagan Lagrange multiplier test			940,88***
Hausman test			6,24**

Source: Authors' elaboration.
Note: *** 1% significance level;
** 5% significance level;
* 10% significance level.

In the fixed and random effects models, which adjust for unobserved heterogeneities, both show that the proportion of people with secondary education and energy consumption have a positive and significant impact on GDP. The coefficients found in these models are lower than in the pooled data model, suggesting a more realistic assessment of the variables by excluding unobserved constant influences. The statistical significance of these results is reinforced by the Chow and Breusch-Pagan tests, which confirm the validity of these models for the analysis.

The Hausman test, which also showed significance, indicates a preference for the fixed effects model over the random effects model. This result suggests that the unchanged characteristics of each unit, which do not vary over time, are crucial to understanding the impact of the variables studied on GDP. Thus, the fixed effects model is considered the most appropriate for this study, offering a robust framework for exploring how education and energy consumption contribute to economic growth.

In short, this analysis highlights the importance of well-specified economic models that take into account both heterogeneity between units and time effects in order to accurately capture the true impacts of economic variables on GDP. The results not only highlight the relevance of education and energy as pillars of economic development, but also guide public policies by pointing to the need for investment in these sectors.

Table 2 presents the analysis of three different models for economic data—pooled data, fixed effects, and random effects—offering insights into the impact of variables such as education, energy consumption, and access to schools on GDP. This table is similar to Table 1, but incorporates an additional variable, access to school, broadening the analysis and providing a more comprehensive view of the factors that influence GDP.

Table 3: Panel estimation results (between *lnpib* and *lnmedio*, *lnk*, *lnescola*).

	Pooled data	**Fixed effects**	**Random effects**
lnmedium	0,5800665	0,3613038	0,5615612
	(0,3495784)*	(0,0846115)***	(0,0846726)***
lnk	1,755797	0,1608901	0,2111667
	(0,1345012)***	(0,0568152)***	(0,0610451)***
lnescola	0,8887397	0,0358462	0,427246
	(0,038243)***	(0,1053934)	(0,0856739)***
Constant	8,023432	24,75263	21,31188
	(1,072895)***	(0,9339753)***	(0,8003913)***
Coefficient of determination (R²)	0,7665	0,5187	0,6749
Chow test (F)			905,45***
Breusch-Pagan Lagrange multiplier test			862,02***
Hausman test			39,58***

Source: Authors' elaboration.
Note: *** 1% significance level;
** 5% significance level;
* 10% significance level.

The results derived from the three different models for the data—pooled data, fixed effects, and random effects—offer a comprehensive view of the impact of education and energy consumption on GDP. In the pooled data model, it can be seen that both average education, energy consumption and access to school have a significant positive impact on GDP.

Moving on to the fixed effects model, which adjusts for unobserved individual heterogeneities, all the coefficients are smaller in magnitude, suggesting a more accurate assessment of the variables, excluding external influences. This model also reveals a significant negative constant, which may indicate factors not captured by the model that negatively affect GDP.

In the random effects model, which assumes that variations between individuals are random, the coefficients for the same variables indicate a positive impact on GDP. The constant is positive and statistically significant, suggesting that factors inherent to individuals positively influence GDP.

The coefficient of determination, which measures the proportion of the variation in the dependent variable explained by the model, is higher in the pooled data model, indicating that although this model captures more variation, it may not be the most accurate due to the lack of adjustments for fixed or random effects.

The statistical tests for model validation, such as the Chow test, which checks the adequacy of the fixed effects, and the Breusch-Pagan Lagrange multiplier test, which tests for heteroscedasticity, show significance, reinforcing the adequacy of the fixed and random effects models. The Hausman test, which compares fixed and random effects, suggests a preference for the fixed effects model.

These results emphasize the importance of careful consideration when choosing the appropriate statistical model for economic analysis, highlighting the crucial role of education and access to basic services as drivers of economic growth.

Table 3 presents an analysis of three different models for economic data—pooled data models, fixed effects models, and random effects models—providing insights into the impact of variables such as education, energy consumption, and internet access on GDP. This table is comparable to Tables 1 and 2, but introduces a distinct variable, internet access, offering a different perspective on the elements that influence GDP.

In contrast to Table 1, which analyzed only two variables—average education and energy consumption—and Table 2, which added access to school, Table 3 swaps access to school for access to the internet. This makes it possible to assess the effects of these various variables related to knowledge and infrastructure on GDP.

Table 4: Panel estimation results (between *lnpib* and *lnmedio*, *lnk*, *lninternet*).

	Pooled data	Fixed effects	Random effects
lnmedium	-0,6004615	0,207534	-0,2792322
	(0,1743256)***	(0,0856915)**	(0,1556136)*
lnk	0,5157743	0,1810235	0,5106306
	(0,0705475)***	(0,0563295)***	(0,0975823)***
lninternet	0,8242747	0,0438659	0,2518173
	(0,0151021)***	(0,0164314)***	(0,027235)**
Constant	9,117609	24,08159	18,31321
	(0,5166423)***	(0,4805169)***	(0,7890738)***
Coefficient of determination (R^2)	0,9435	0,7140	0,9008
Chow test (F)			220,27***
Breusch-Pagan Lagrange multiplier test			157,52***
Hausman test			175,43***

Source: Authors' elaboration.
Note: *** 1% significance level;
** 5% significance level;
* 10% significance level.

The results in this table highlight the importance of the variables considered in the panel data model, covering three approaches: *pooled data*, fixed effects and random effects, to examine how specific variables - average level of education (*lnmédio*), energy consumption (*lnk*) and internet access (*lninternet*) - impact the GDP.

In the *pooled data* model, the variable representing the average level of education shows a negative impact on GDP, which may indicate that just increasing the level of average education without considering other quality and infrastructure factors may not be enough to boost economic growth. Energy consumption and internet access, on the other hand, show a significant positive effect, suggesting that these are important factors for economic development.

The fixed effects models adjust the variables for unobserved heterogeneities between the units, revealing that the average level of education has a smaller but still significant positive impact on GDP, while energy consumption and internet access continue to show strong positive effects. This model suggests that when controlling for unobserved effects, the level of education is still beneficial for economic growth.

The random effects, which consider variations between units as random components, show results consistent with the fixed effects model, but with slightly higher coefficients. Internet access stands out in this model, suggesting that improvements in internet infrastructure can have a significantly positive impact on economic growth.

The coefficients of determination in the three models vary, showing that the random effects model captures a slightly larger portion of the variability in GDP compared to the other models. The statistical tests, including the Chow Test and the Hausman Test, confirm the adequacy of the fixed and random effects models over the pooled data model, reinforcing the importance of considering individual and temporal effects in economic analysis.

These insights are crucial for formulating economic policies that promote the efficient use of educational resources and infrastructures to boost sustainable economic growth.

The results in Table 4 illustrate the estimation of different panel models, examining the relationships between GDP and variables such as the proportion of people with secondary education, energy consumption, schooling and internet access. In the grouped data, the proportion of people with secondary education and internet access shows a positive association with GDP, while the coefficients for schooling show a negative sign, suggesting that an increase in the variables may have a different impact on GDP.

Table 5: Panel estimation results (between *lnpib* and *lnmedio*, *lnk*, *lnescola* and *lninternet*).

	Pooled data	Fixed effects	Random effects
lnmedium	-0,431408	0,2441248	0,2356506
	(0,1512936)	(0,0929375)***	(0,1294596)*
lnk	0,7262869	0,1874334	0,5158453
	(0,064962)***	(0,0566769)***	(0,0761879)***
lnescola	0,234588	0,1085934	0,693752
	(0,0255821)***	(0,1068192)	(0,0524301)***
lninternet	0,6786133	0,0479981	0,1829586
	(0,0205318)***	(0,0169254)***	(0,0222268)**
Constant	8,258595	23,0861	13,97068
	(0,454794)***	(1,090753)***	(0,6745326)***
Coefficient of determination (R^2)	0,9582	0,8793	0,8190
Chow test (F)			160,69***
Breusch-Pagan Lagrange multiplier test			230,31***
Hausman test			137,31***

Source: Authors' elaboration.

Note: *** 1% significance level;
** 5% significance level;
* 10% significance level.

In the fixed and random effects models, the variables maintain consistency in the signs of their coefficients, with the majority showing statistical significance. Notably, the constant in the fixed effects is significantly negative, indicating possible adjustments or differences not observed in the analysis that may influence the GDP result when controlled for fixed effects.

The coefficient of determination (R^2) statistic reveals that random effects models have a slightly better ability to explain the variation in GDP compared to fixed effects models, suggesting that the consideration of random effects may be more suitable for capturing unobserved variations in the data. Additionally, the Chow, Breusch-Pagan and Hausman tests provide substantial evidence to support the choice of the fixed effects model as the most appropriate for this analysis, indicating the importance of controlling for unobserved individual effects that are constant over time but vary between units.

These analyses are crucial to understanding how social and economic variables interact and influence economic growth, providing valuable insights for public policies and economic development strategies.

5. CONCLUSION

This article sought to investigate the nature of human capital as a fundamental precursor to economic growth. The neoclassical perspective, emphasized by theorists such as Barrow, Mincer, Schulz and Becker, stresses education as an important investment that increases worker productivity and leads to significant economic development. This analysis highlighted the delicate balance workers face when deciding how to allocate their time and resources between education and current income, highlighting the inherent trade-offs.

Human capital theory emphasizes not only immediate improvements in the workforce but also the positive effects that span generations, reinforcing the need for continued investment in education and training. This article has emphasized the positive externalities of human capital on knowledge accumulation, considering endogenous growth models proposed by theorists such as Romer and Lucas Jr.

Analyses of various academic articles on the relationship between human capital and economic growth, including the incorporation of the Human Development Index, have provided an understanding that human capital is not just a factor of production, but an essential driver of technological progress, innovation and, therefore, sustainable economic growth. The recognition that the quality of education is a fundamental part of this equation reinforces the continued need for policies to invest in and develop human capital.

In short, the analysis of the different models presented in the tables offers valuable *insights into* the impact of key variables on GDP. The models examined various factors, such as education, energy consumption, access to school and internet access, providing a detailed understanding of their respective influences on economic growth.

The comparison between the models highlights the importance of selecting an appropriate statistical approach when analyzing economic data, since the results can vary significantly depending on the model used. The use of both fixed and random effects models proves crucial when considering heterogeneities between individuals and over time, resulting in more robust and reliable conclusions.

Overall, the results emphasize the crucial role of knowledge-related variables, such as education and access to information, as well as infrastructural factors, such as energy consumption, in promoting economic development. These insights are in line with established theories in economics, reinforcing the importance of these factors in fostering economic growth and innovation.

AUTHOR CONTRIBUTIONS

All authors contributed equally to this study.

CONFLICT OF INTEREST

None.

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REFERENCES

1. Levy F, Murnane RJ, 2018. The new division of labor: How computers are creating the next job market (2nd edn). São Paulo, Brazil: WMF Martins Fontes.
2. Power C, 2015. The power of education: Education for all, development, globalization and UNESCO. Singapore, London: Springer. ISBN: 978-981-2877-221-0
3. Heckman J, et al., 1999. The economics and econometrics of active labor market programs. Chapter 31 in *Handbook of Labor Economics*, Vol. 3, Part A, pp 1865-2097. https://econpapers.repec.org/bookchap/eeelabchp/3-31.htm
4. Cascio WF, 2014. Investing in people: The financial impact of human resources initiatives. İstanbul, Turkey: Atlas Publishing.
5. Mincer J, 1958. Investment in human capital and personal income distribution. Journal of Political Economy; 66(4), 281–302. https://doi.org/10.1086/258055
6. Schultz TW, 1961. Investment in human capital. American Economic Review; 51(1), 1–17. https://www.jstor.org/stable/1818907
7. Becker GS, 1964. Human capital: A theoretical and empirical analysis, with special reference to education. Chicago, IL: University of Chicago Press.
8. Becker GS, 1962. Investment in human capital: A theoretical analysis. Journal of Political Economy; 70(5), 9–49. https://www.jstor.org/stable/1829103
9. Becker GS, *et al.*, 1990. Human capital, fertility, and economic growth. Journal of Political Economy; 98(5), S12–S37.
10. Nakabashi L, Figueiredo L, 2005. Human capital: A new proxy to include qualitative aspects. Belo Horizonte, Brazil: UFMG.
11. Romer PM, 1986. Increasing returns and long-run growth. Journal of Political Economy; 94(5), 1002–1037.
12. Lucas RE Jr, 1988. On the mechanics of economic development. Journal of Monetary Economics; 22, 3–42.
13. Solow RM, 1956. A contribution to the theory of economic growth. Quarterly Journal of Economics; 70(1), 65–94.
14. Barro RJ, Lee JW, 2013. A new data set of educational attainment in the world, 1950-2010. Journal of Development Economics; 104(C), 184-198.
15. Barro JR, 2001. Human capital and growth. American Economic Review; 91, 12–17.
16. Cravo TA, Soukiazis E, 2009. Human capital and growth: The case of the Brazilian states (Working Paper, No. 17). Coimbra, Portugal: University of Coimbra, Faculty of Economics.
17. Pelinescu E, *et al.*, 2019. Human capital, innovation and economic growth in the EU countries. Romanian Journal of Economic Forecasting; 22(4), 160–173.
18. Prasetyo PE, 2020. Human capital as the main determinant of regional economic growth. International Journal of Advanced Science and Technology; 29(3), 6261–6267.
19. Barro JR, 1991. Economic growth in a cross section of countries. Quarterly Journal of Economics; 106, 407–443.
20. Harvard Business School, 2021. 4 Types of Data Analytics to Improve Decision-Making.
21. Baltagi BH, 2021. Econometric analysis of panel data. 6th edn., NJ: Springer. ISBN: 978-3-030-53953-5
22. Monteiro SMS, Silva ST, 2020. Human capital and economic growth in Brazil: A panel data approach. Revista Brasileira de Economia; 74(1), 5–28.

APPENDIX

```
. reg lnpib lnmedio lnk

          Source | SS df MS Number of obs = 243
------------------ ----+-----------------------------------------     F(2, 240) = 37.69
           Model | 86.221515 2 43.1107575 Prob > F = 0.0000
        Residual | 274.537485 240 1.14390619 R-squared = 0.2390
------------------ ----+-----------------------------------------     Adj R-squared = 0.2327
           Total | 360.759 242 1.49073967 Root MSE = 1.0695

------------------------------------------------------------------------------------------------------
         lnpib | Coef.   Std. Err. t P>|t| [95% Conf. Interval]
------------------------- -+----------------------------------------------------------------------------
      lnmedio | 1.033556 .6288515 1.64 0.102 -.2052167 2.27233
          lnk | 1.854576 .2422091 7.66 0.000 1.377449 2.331703
        _cons | 15.65351 1.840292 8.51 0.000 12.02832 19.2787
------------------------------------------------------------------------------------------------------

. xtset uf year
       panel variable: uf (strongly balanced) time
        variable: year, 2012 to 2020
                delta: 1 unit

. xtreg lnpib lnmedio lnk, fe
```

```
 Fixed-effects (within) regression Number of obs = 243
 Group variable: uf Number of groups = 27

 R-sq: Obs per group:
      within = 0.1072 min = 9
      between = 0.2198 avg = 9.0
      overall = 0.2065 max = 9

                                                F(2,214) = 12.84
 corr(u_i, Xb) = 0.4075 Prob > F = 0.0000

------------------------------------------------------------------------------
        lnpib | Coef.   Std. Err. t P>|t| [95% Conf. Interval]
-------------+----------------------------------------------------------------
     lnmedio | .3449524 .0694823 4.96 0.000 .207995 .4819098
         lnk | .1594452 .056539 2.82 0.005 .0480006 .2708898
       _cons | 25.05109 .3191358 78.50 0.000 24.42204 25.68015
-------------+----------------------------------------------------------------
     sigma_u | 1.2096033
     sigma_e | .05942096
         rho | .99759261 (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0: F(26, 214) = 2982.30 Prob > F = 0.0000

 . estimates store fixed

 . xtreg lnpib lnmedio lnk, re

 Random-effects GLS regression Number of obs = 243 Group
 variable: uf Number of groups = 27

 R-sq: Obs per group:
      within = 0.1071 min = 9
      between = 0.2221 avg = 9.0
      overall = 0.2093 max = 9

                                                Wald chi2(2) = 26.80
 corr(u_i, X) = 0 (assumed) Prob > chi2 = 0.0000

------------------------------------------------------------------------------
        lnpib | Coef.   Std. Err. z P>|z| [95% Conf. Interval]
-------------+----------------------------------------------------------------
     lnmedio | .3526036 .0700201 5.04  0.000 .2153666 .4898405
         lnk | .1709551 .0568622 3.01  0.003 .0595073 .2824029
       _cons | 24.9909 .3876786 64.46  0.000 24.23106 25.75073
-------------+----------------------------------------------------------------
     sigma_u | 1.1185869
     sigma_e | .05942096
         rho | .99718605 (fraction of variance due to u_i)
------------------------------------------------------------------------------

 . xttest0

 Breusch and Pagan Lagrangian multiplier test for random effects lnpib[uf,t] =

        Xb + u[uf] + e[uf,t]

        Estimated results:
                         | Var sd = sqrt(Var)
               ------------ -+-------------------------
                    lnpib | 1.49074 1.220959
                        e | .0035309 .059421
                    u | 1.251237 1.118587

        Test: Var(u) = 0
                            chibar2(01) = 940.88 Prob >
                         chibar2 = 0.0000
```

```
. hausman fixed ., sigmamore

                  ---- Coefficients ----
              | (b)  (B)  (b-B) sqrt(diag(V_b-V_B))
              | fixed .          Difference S.E.
------------------ -+------------------------------------------------------------------------------
          lnmedio | .3449524 .3526036 -.0076512 .0035343
              lnk | .1594452 .1709551 -.0115098 .0046147
---------------------------------------------------------------------------------------------------
                            b = consistent under Ho and Ha; obtained from xtreg B =
             inconsistent under Ha, efficient under Ho; obtained from xtreg

     Test: Ho: difference in coefficients not systematic chi2(2)

                   = (b-B)'[(V_b-V_B)^(-1)](b-B)
                           = 6.24
                 Prob>chi2 = 0.0442

.



. reg lnpib lnmedio lnk lnescola

        Source | SS df MS Number of obs = 243
------------------ ----+------------------------------------------     F(3, 239) = 261.58
         Model | 276.536922 3 92.1789739 Prob > F = 0.0000
      Residual | 84.2220784 239 .352393633 R-squared = 0.7665
------------------ ----+------------------------------------------     Adj R-squared = 0.7636
         Total | 360.759 242 1.49073967 Root MSE = .59363

---------------------------------------------------------------------------------------------------
        lnpib | Coef.   Std. Err. t P>|t| [95% Conf. Interval]
------------------ -+------------------------------------------------------------------------------
     lnmedio | .5800665 .3495784 1.66 0.098 -.1085819 1.268715
         lnk | 1.755797 .1345012 13.05 0.000 1.490838 2.020756
    lnescola | .8887397 .038243 23.24 0.000 .8134033 .964076
       _cons | 8.023432 1.072895 7.48 0.000 5.909894 10.13697
---------------------------------------------------------------------------------------------------

. xtset uf year
       panel variable: uf (strongly balanced) time
        variable: year, 2012 to 2020
                delta: 1 unit

. xtreg lnpib lnmedio lnk lnescola, fe

Fixed-effects (within) regression Number of obs = 243
Group variable: uf Number of groups = 27

R-sq: Obs per group:
     within = 0.1076 min = 9
     between = 0.5446 avg = 9.0
     overall = 0.5187 max = 9

                                                 F(3,213) = 8.56
corr(u_i, Xb) = 0.6860 Prob > F = 0.0000

---------------------------------------------------------------------------------------------------
        lnpib | Coef.   Std. Err. t P>|t| [95% Conf. Interval]
------------------ -+------------------------------------------------------------------------------
     lnmedio | .3613038 .0846115 4.27 0.000 .1945207 .528087
         lnk | .1608901 .0568152 2.83 0.005 .0488981 .2728822
    lnescola | .0358462 .1053934 0.34 0.734 -.1719014 .2435939
       _cons | 24.75263 .9339753 26.50 0.000 22.91162 26.59365
------------------+--------------------------------------------------------------------------------
     sigma_u | 1.1812081
     sigma_e | .05954412
```

```
          rho | .99746532 (fraction of variance due to u_i) F
------------------------------------------------------------------------------
 test that all u_i=0: F(26, 213) = 905.45 Prob > F = 0.0000

 . estimates store fixed

 . xtreg lnpib lnmedio lnk lnescola, re

 Random-effects GLS regression Number of obs = 243 Group
 variable: uf Number of groups = 27

 R-sq: Obs per group:
      within = 0.0759 min = 9
      between = 0.6775 avg = 9.0
      overall = 0.6749 max = 9

                                                 Wald chi2(3) = 51.18
 corr(u_i, X) = 0 (assumed) Prob > chi2 = 0.0000

------------------------------------------------------------------------------
        lnpib | Coef.   Std. Err. z P>|z| [95% Conf. Interval]
-------------+----------------------------------------------------------------
      lnmedio | .5615612 .0846726 6.63 0.000 .395606 .7275164
          lnk | .2111667 .0610451 3.46 0.001 .0915205 .3308128
     lnescola | .427246 .0856739 4.99 0.000 .2593282 .5951637
        _cons | 21.31188 .8003913 26.63 0.000 19.74314 22.88062
-------------+----------------------------------------------------------------
      sigma_u | .61766818
      sigma_e | .05954412
          rho | .99079233 (fraction of variance due to u_i)
------------------------------------------------------------------------------

 . xttest0

 Breusch and Pagan Lagrangian multiplier test for random effects lnpib[uf,t] =

         Xb + u[uf] + e[uf,t]

         Estimated results:
                          | Var sd = sqrt(Var)
               ------------ -+--------------------------------------
                    lnpib | 1.49074 1.220959
                        e | .0035455 .0595441
                        u | .381514 .6176682

         Test: Var(u) = 0
                             chibar2(01) = 862.02 Prob >
                          chibar2 = 0.0000

 . hausman fixed ., sigmamore

                  ---- Coefficients ----
              | (b) (B) (b-B) sqrt(diag(V_b-V_B))
              | fixed .          Difference S.E.
------------- -+----------------------------------------------------------------
      lnmedio | .3613038 .5615612 -.2002574 .0360943
          lnk | .1608901 .2111667 -.0502765 .0096717
     lnescola | .0358462 .427246 -.3913997 .0761916
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg B =
            inconsistent under Ha, efficient under Ho; obtained from xtreg

     Test: Ho: difference in coefficients not systematic chi2(3)

                   = (b-B)'[(V_b-V_B)^(-1)](b-B)
                           = 39.58
                 Prob>chi2 = 0.0000
```

```
.



. reg lnpib lnmedio lnk lninternet

         Source | SS df MS Number of obs = 243
------------------ ----+-----------------------------------------    F(3, 239) = 1329.88
          Model | 340.369204 3 113.456401 Prob > F = 0.0000
       Residual | 20.3897965 239 .085312956 R-squared = 0.9435
------------------ ----+-----------------------------------------    Adj R-squared = 0.9428
          Total | 360.759 242 1.49073967 Root MSE = .29208

------------------------------------------------------------------------------------------------------
        lnpib | Coef.   Std. Err. t P>|t| [95% Conf. Interval]
------------------------ -+----------------------------------------------------------------------------
     lnmedio | -.6004615 .1743256 -3.44 0.001 -.9438724 -.2570507
         lnk | .5157743 .0705475 7.31 0.000 .3768 .6547486
  lninternet | .8242747 .0151021 54.58 0.000 .7945246 .8540249
       _cons | 9.117609 .5166423 17.65 0.000 8.099855 10.13536
------------------------------------------------------------------------------------------------------

. xtset uf year
       panel variable: uf (strongly balanced) time
        variable: year, 2012 to 2020
                delta: 1 unit

. xtreg lnpib lnmedio lnk lninternet, fe

Fixed-effects (within) regression Number of obs = 243
Group variable: uf Number of groups = 27

R-sq: Obs per group:
     within = 0.1361 min = 9
     between = 0.7409 avg = 9.0
     overall = 0.7140 max = 9

                                                  F(3,213) = 11.18
corr(u_i, Xb) = 0.8182 Prob > F = 0.0000

------------------------------------------------------------------------------------------------------
        lnpib | Coef.   Std. Err. t P>|t| [95% Conf. Interval]
------------------ -+-----------------------------------------------------------------------------------
      lnmedio | .207534 .0856915 2.42 0.016 .038622 .3764461
          lnk | .1810235 .0563295 3.21 0.002 .0699889 .2920582
   lninternet | .0438659 .0164314 2.67 0.008 .0114769 .0762549
        _cons | 24.08159 .4805169 50.12 0.000 23.13442 25.02877
 -----------------+-------------------------------------------------------------------------------------
      sigma_u | 1.1506941
      sigma_e | .05858817
          rho | .99741431 (fraction of variance due to u_i)
 -------------------------------------------------------------------------------------------------------
F test that all u_i=0: F(26, 213) = 220.27 Prob > F = 0.0000

. estimates store fixed

. xtreg lnpib lnmedio lnk lninternet, re

Random-effects GLS regression Number of obs = 243 Group
variable: uf Number of groups = 27

R-sq: Obs per group:
     within = 0.0900 min = 9
     between = 0.9214 avg = 9.0
     overall = 0.9008 max = 9

                                                  Wald chi2(3) = 117.23
corr(u_i, X) = 0 (assumed) Prob > chi2 = 0.0000
```

```
------------------------------------------------------------------------------
       lnpib | Coef.   Std. Err. z P>|z| [95% Conf. Interval]
-------------+----------------------------------------------------------------
     lnmedio | -.2792322 .1556136 -1.79 0.073 -.5842292 .0257648
         lnk | .5106306 .0975823 5.23 0.000 .3193729 .7018884
  lninternet | .2518173 .027235 9.25 0.000 .1984376 .305197
       _cons | 18.31321 .7890738 23.21 0.000 16.76666 19.85977
-------------+----------------------------------------------------------------
     sigma_u | .1918045
     sigma_e | .05858817
         rho | .91465832 (fraction of variance due to u_i)
------------------------------------------------------------------------------

. xttest0

Breusch and Pagan Lagrangian multiplier test for random effects lnpib[uf,t] =

        Xb + u[uf] + e[uf,t]

        Estimated results:
                         | Var sd = sqrt(Var)
                ---------+-----------------------------
                   lnpib | 1.49074 1.220959
                       e | .0034326 .0585882
                       u | .036789 .1918045

        Test: Var(u) = 0
                             chibar2(01) = 157.52 Prob >
                          chibar2 = 0.0000

. hausman fixed ., sigmamore

                ---- Coefficients ----
             | (b) (B) (b-B) sqrt(diag(V_b-V_B))
             | fixed .          Difference S.E.
-------------+----------------------------------------------------------------
     lnmedio | .207534 -.2792322 .4867662 .055165
         lnk | .1810235 .5106306 -.3296071 .0475029
  lninternet | .0438659 .2518173 -.2079514 .0161403
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg B =
            inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test: Ho: difference in coefficients not systematic chi2(3)

                  = (b-B)'[(V_b-V_B)^(-1)](b-B)
                            = 175.43
                    Prob>chi2 = 0.0000

.


. reg lnpib lnmedio lnk lnescola lninternet Source |

      SS df MS Number of obs = 243
-------------+------------------------------     F(4, 238) = 1365.19
       Model | 345.692445 4 86.4231112 Prob > F = 0.0000
    Residual | 15.0665551 238 .063304853 R-squared = 0.9582
-------------+------------------------------     Adj R-squared = 0.9575
       Total | 360.759 242 1.49073967 Root MSE = .2516

------------------------------------------------------------------------------
       lnpib | Coef.   Std. Err. t P>|t| [95% Conf. Interval]
-------------+----------------------------------------------------------------
     lnmedio | -.431408 .1512936 -2.85 0.005 -.7294536 -.1333624
```

```
         lnk | .7262869 .064962 11.18 0.000 .598313 .8542608
    lnescola | .234588 .0255821 9.17 0.000 .1841917 .2849842
  lninternet | .6786133 .0205318 33.05 0.000 .638166 .7190606
       _cons | 8.258595 .454794 18.16 0.000 7.362659 9.154531
------------------------------------------------------------------------------

. xtset uf year
       panel variable: uf (strongly balanced) time
        variable: year, 2012 to 2020
               delta: 1 unit

. xtreg lnpib lnmedio lnk lnescola lninternet, fe

Fixed-effects (within) regression Number of obs = 243
Group variable: uf Number of groups = 27

R-sq: Obs per group:
     within = 0.1402 min = 9
     between = 0.8894 avg = 9.0
     overall = 0.8793 max = 9

                                                F(4,212) = 8.65
corr(u_i, Xb) = 0.9150 Prob > F = 0.0000

------------------------------------------------------------------------------
       lnpib | Coef.   Std. Err. t P>|t| [95% Conf. Interval]
-------------+----------------------------------------------------------------
     lnmedio | .2441248 .0929375 2.63 0.009 .0609249 .4273248
         lnk | .1874334 .0566769 3.31 0.001 .075711 .2991558
    lnescola | .1085934 .1068192 1.02 0.310 -.1019704 .3191572
  lninternet | .0479981 .0169254 2.84 0.005 .0146344 .0813617
       _cons | 23.0861 1.090753 21.17 0.000 20.93599 25.23621
-------------+----------------------------------------------------------------
     sigma_u | 1.0605205
     sigma_e | .05858357
         rho | .99695778 (fraction of variance due to u_i) F
------------------------------------------------------------------------------
test that all u_i=0: F(26, 212) = 160.69 Prob > F = 0.0000

. estimates store fixed

. xtreg lnpib lnmedio lnk lnescola lninternet, re

Random-effects GLS regression Number of obs = 243 Group
variable: uf Number of groups = 27

R-sq: Obs per group:
     within = 0.1046 min = 9
     between = 0.8220 avg = 9.0
     overall = 0.8190 max = 9

                                                Wald chi2(4) = 401.43
corr(u_i, X) = 0 (assumed) Prob > chi2 = 0.0000

------------------------------------------------------------------------------
       lnpib | Coef.   Std. Err. z P>|z| [95% Conf. Interval]
-------------+----------------------------------------------------------------
     lnmedio | .2356506 .1294596 1.82 0.069 -.0180856 .4893868
         lnk | .5158453 .0761879 6.77 0.000 .3665197 .6651708
    lnescola | .693752 .0524301 13.23 0.000 .590991 .796513
  lninternet | .1829586 .0222268 8.23 0.000 .1393949 .2265223
       _cons | 13.97068 .6745326 20.71 0.000 12.64862 15.29274
-------------+----------------------------------------------------------------
     sigma_u | .17855924
     sigma_e | .05858357
         rho | .90281773 (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

```
. xttest0

Breusch and Pagan Lagrangian multiplier test for random effects lnpib[uf,t] =

        Xb + u[uf] + e[uf,t]

        Estimated results:
                        | Var sd = sqrt(Var)
              ------------ -+--------------------------------------
                      lnpib | 1.49074 1.220959
                          e | .003432 .0585836
                      u | .0318834 .1785592

        Test: Var(u) = 0
                            chibar2(01) = 230.31 Prob >
                         chibar2 = 0.0000

. hausman fixed ., sigmamore

                 ---- Coefficients ----
             | (b) (B) (b-B) sqrt(diag(V_b-V_B))
             | fixed .          Difference S.E.
-------------+-----------------------------------------------------------------
     lnmedio | .2441248 .2356506 .0084742 .0575612
         lnk | .1874334 .5158453 -.3284118 .040751
    lnescola | .1085934 .693752 -.5851586 .1541703
  lninternet | .0479981 .1829586 -.1349605 .0131042
-------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg B =
            inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test: Ho: difference in coefficients not systematic chi2(4)

                  = (b-B)'[(V_b-V_B)^(-1)](b-B)
                            = 137.31
                    Prob>chi2 = 0.0000
```