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**Education and Economic Growth in Indonesia:
A General Nesting Spatial Model**

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Abstract: Education is often associated with the main key driver of a country's economic growth. However, disparities in access of education between regions remain an obstacle to economic growth in Indonesia. This study examines the relationship between education and economic growth by incorporating spatial interdependencies across 34 provinces from 2013 to 2023. Using the General Nesting Spatial (GNS) model, the research analyzes the effects of capital, labor, and average years of schooling as key production factors. The findings reveal that while the average years of education have a negative direct impact on provincial economic growth, however exert a positive indirect (spillover) effect through neighboring regions. These results indicate that education quantity alone is insufficient to drive productivity without complementary improvements in quality and regional coordination. The study highlights the importance of regionally integrated and evidence-based education policies to enhance human capital formation and promote balanced, sustainable growth across Indonesia.

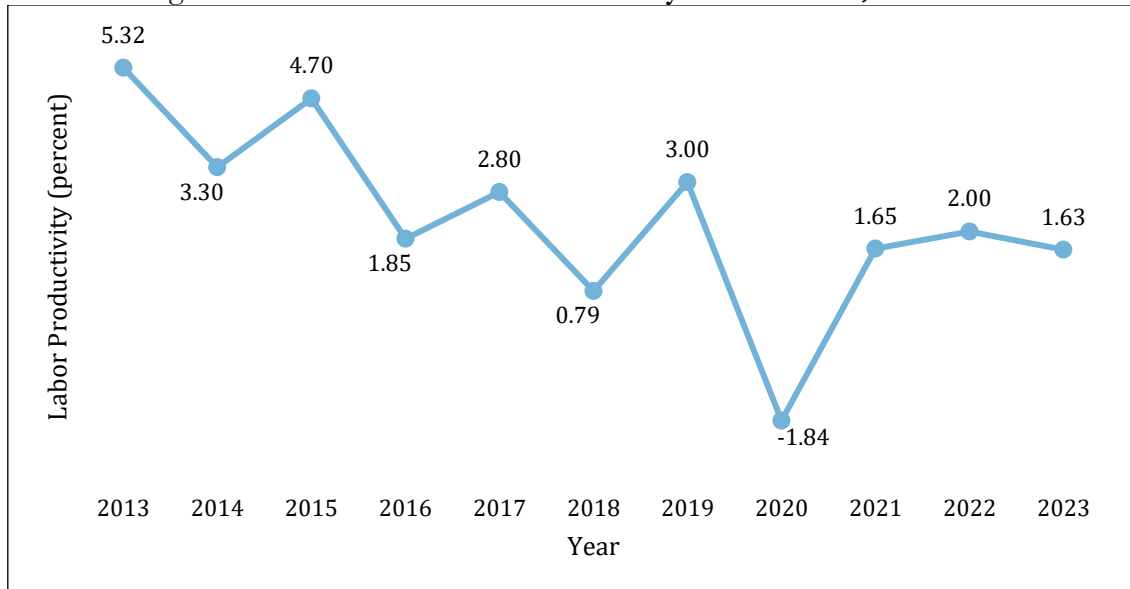
Keywords: Education, Economic Growth, General Nesting Spatial Model

Introduction

Economic growth can be defined as a process of increasing the amount of production of goods and services over a long period of time continuously. Economic growth is usually measured through an increase in Gross Domestic Product (GDP), which is known as the aggregate market value of goods and services produced (Bunyamin & Meyliana, 2021). An increase in Gross Regional Domestic Product at constant prices reflects an increase in the production of goods and services in a region from year to year (Hoeriyah et al., 2019). In addition, economic growth can also be seen from labor productivity, an increase in labor productivity can encourage economic growth (Merkulova, 2019). Figure 1 shows the growth rate of Indonesia's labor productivity over the past 11 years, which has fluctuated and tended

to decline. At the beginning of the period, especially in 2013, the growth rate of labor productivity reached its peak at 5.32 percent. Furthermore, there was a fairly consistent downward trend until 2019, with some small fluctuations. The sharpest decline occurred in 2020, where the growth rate of labor productivity became negative. This is most likely due to the COVID-19 pandemic. Many companies were forced to close or reduce their operating hours which had a direct impact on the decline in labor productivity, which in turn would reduce the economic output produced. After the COVID-19 pandemic, Indonesia is faced with a major challenge in restoring its economy to a more stable state.

Figure 1. Indonesia's Labor Productivity Growth Rate, 2013-2023



Source: Indonesian Central Statistics Agency (Processed)

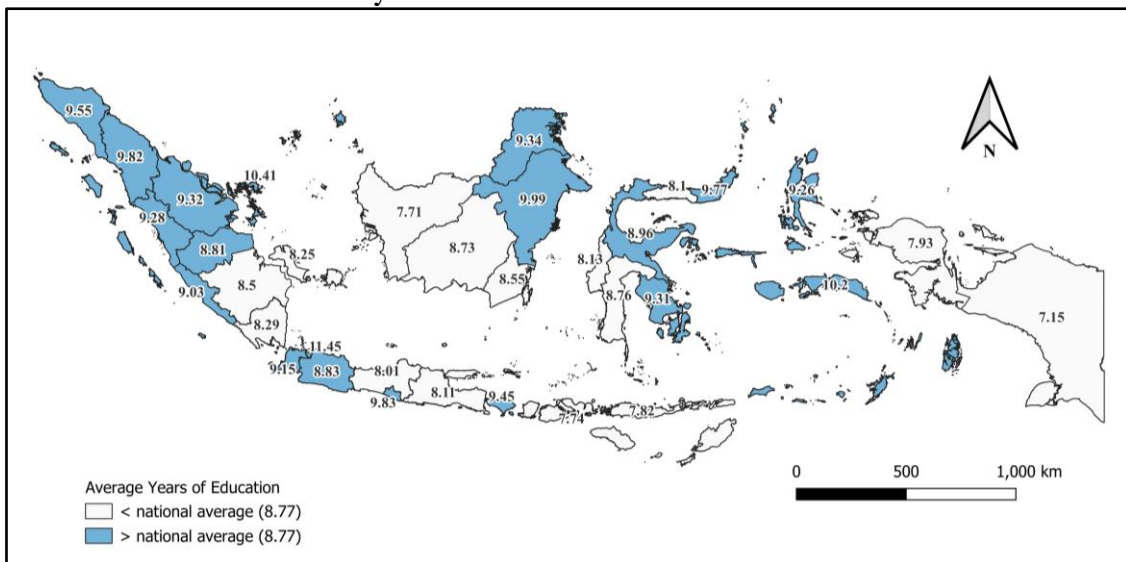
A country's economic recovery can depend on its human resources. Besides factors of production, financial capital and labor, technology and human capital are two important components that drive the economy. Human capital is a collection of traits, including knowledge, habits, social, and personality, which are manifested in the ability to do work to produce economic value (Valeriani et al., 2022). One form of human capital is knowledge gained through education. So in this case, education has a crucial role in the economic growth of a country. In general, the economic progress of a country will be in line with the level of education of its population (Riadyńska, 2022). Better education can have a positive impact on the quality of human resources, which in turn can improve one's quality of life (Arman et al., 2020). Improving the quality of human resources is considered capable of providing a multiplier effect on the economy of a region (Sari, 2023).

In Indonesia, the role of education in driving economic growth is becoming increasingly relevant in line with the vision of *Indonesia Emas 2045* to make Indonesia a developed country with an inclusive and sustainable economy. One of the main pillars in this vision is to create a young generation that is competent and ready to compete in the global stage. However, the OECD's Program for International Student Assessment (PISA) assessed the average learning performance of 15-year-old students in Indonesia at 382, which is still very low compared to the average PISA score of students from other OECD countries, which is 488.33 (OECD, 2024). The still low quality of education is caused, among other things, by inadequate educational facilities and learning infrastructure, a limited number of highly competent

professional teachers, and their uneven distribution across all regions and educational units (Indonesia, 2024). This condition presents a significant challenge for Indonesia in achieving the vision of *Indonesia Emas 2045*, as low-quality education has the potential to hinder increased productivity and economic growth.

Despite the various policies that have been implemented to improve the education sector in Indonesia, the challenges faced by Indonesia to achieve the *Indonesia Emas 2045* are still considerable. There is a significant disparity in educational attainment between urban and rural areas and between provinces. Figure 2 shows the distribution of average years of education in each province compared to the national. Quantitatively, the population composition aged 15 and over has an average year of education of 8.77 years, which is equivalent to graduates of junior high school or lower. Although basic education is almost universal in Indonesia, there are still some provinces, especially in eastern Indonesia, that tend to have lower average years of education than the national average. Meanwhile, in western Indonesia, the majority of provinces have a higher average number of years of education than the national average. This illustrates that the inequality of education remains significant across regions.

Figure 2. Map of Distribution of Average Years of Education by Indonesian Provinces in 2023



Source: Indonesian Central Statistics Agency (Processed)

Previous research has shown that education has a positive and significant impact on economic growth (Affandi et al., 2019; Bah, 2023; Khan et al., 2023). For instance, Khan et al. (2023), by using the time series regression analysis between 1980 and 2013 in Pakistan, proved the existence of a positive significant correlation between education and economic growth, so the discussion emphasized the need for increased investment in education to promote economic development. Then, Bah (2023), by using the Generalized Method of Moments estimation technique, found that education has a significant and positive effect on economic growth across countries. However, other research indicates a negative relationship between education and labor force participation, suggesting that higher education does not always lead to higher economic growth (Fikri & Mohamed, 2024). This can happen especially in regions with unequal access to education and facilities that can result in income inequality, which in turn will hamper economic growth in the area (Muda et al., 2019).

In the Indonesian context, empirical studies related to education and economic growth is still lacking. Previous study has shown that the positive influence of human resources on economic output varies substantially across regions in Indonesia (Affandi et al., 2019). Other research also shows that knowledge and innovation spillovers can occur through educational investments in neighboring regions (Zhao & van Dijk, 2020). Although spatial interdependence between regions is probable, there have not been many studies that capture spatial effects in regression modeling. To address this gap, this study applies the General Nesting Spatial (GNS) model to analyze the effect of education on economic growth across 34 provinces in Indonesia, considering spatial factors. By capturing regional spillover effects, this research is expected to contribute to a better understanding of regional economic dynamics and offers policy insights to promote more sustainable economic growth in Indonesia.

Literature Review

Education and Economic Growth

One of the main drivers of economic growth is education. Human capital theory, first proposed by Schultz (1961) and further developed by Becker (1964), posits that education enhances an individual's productivity, which directly translates into economic growth through increased output and earnings. In the endogenous growth framework, education fosters not only skill development but also innovation and technological adoption key mechanisms emphasized by Lucas (1988) and Romer (1990) in explaining long run economic progress. Education is thus a mechanism for accumulating and disseminating knowledge that drives productivity. Valero (2021) underscores that a higher level of education leads to increased innovation capacity and knowledge spillovers, ultimately reinforcing long-term economic development.

Empirical evidence in the Indonesian context further supports this view. Hidayah & Hariyani (2024) show that government spending on education significantly boosts economic growth, with improvements in labor quality and infrastructure contributing positively, although the latter is not statistically significant. Then, education contributes to broader socioeconomic outcomes. Karaman Aksentijević & Ježić (2019) found that higher levels of education are associated with reduced income inequality in transitional economies, while Ifa & Firdaus (2023) confirmed its role in poverty alleviation in Indonesia. In line with this, Zhao & van Dijk (2020) demonstrate that investment in education within one province can generate positive externalities in neighboring regions through knowledge and innovation spillovers. This spatial diffusion of human capital highlights the broader regional benefits of education beyond localized impacts.

A critical dimension of education's impact lies in measuring not only access but also inequality, for which average years of education is a widely accepted proxy. The average years of education reflects cumulative educational attainment across regions and helps capture long term disparities in human capital development. As argued by Barro & Lee (2013), average years of education provides a more stable indicator of educational investment outcomes than short-term metrics like enrollment rates. Regional disparities in average years of education signify unequal access to educational opportunities, which can suppress the overall growth potential and widen interregional economic gaps. This is especially relevant in decentralized

economies like Indonesia, where uneven development and education spending across provinces persist (Hanushek & Woessmann, 2021). Moreover, Castelló & Doménech (2002) emphasized that educational inequality, measured by average years of education dispersion, negatively affects economic performance by limiting upward mobility and weakening aggregate productivity.

The use of average years of education in this study thus aligns with both theory and empirical literature. It not only serves as a proxy for educational attainment but also highlights structural inequalities in human capital distribution that may influence regional economic divergence. As Donou-Adonsou et al. (2016) observed in Sub-Saharan Africa, better access to education leads to higher economic returns, but unequal distribution limits national growth potential. In support, Mifrahi & Rahmat (2023) researched the effect of human capital on economic growth in Indonesia using the Autoregressive Distributed Lag (ARDL) model, which states that there is a long-term relationship between per capita economic growth and the education budget, average years of education, primary school enrollment, and investment levels in Indonesia. Using average years of education provides a nuanced measure to understand how disparities in education contribute to regional differences in economic performance.

Adjusted Production Function

The standard neoclassical growth model assumes output as a direct function of capital, labor, and technical progress (Solow in Antenucci et al., 2020). Sugiyanti et al. (2020) modified this basic production function by incorporating the stock of human capital into labor, emphasizing its role as a factor of production. This links output in the form of GRDP (Y) with physical capital (K), labor (L), and A indicates the level of technology available. The Cobb-Douglas production function can be formulated as follows (Sato in Smirnov & Wang, 2019):

$$Y = F(K, L) = AK^{\alpha}L^{\beta}$$

The measure of human capital used in country-level research is most often the average years of education. This implicitly assumes that an additional year will result in the same increase in knowledge and skills, regardless of the stage of education and the type of education provided. On the years of education perspective, Krueger & Lindahl in Marquez-Ramos & Mourelle (2018) use average years of education as a measure of human capital, but depart from the implicit assumption that its relationship with economic growth is linear. They found evidence of nonlinearity with an inverted U-shaped relationship between average years of education and economic growth. Turning to the education quality perspective, Hanushek & Woessmann (2021) successfully prove the positive impact of education quality on growth. They argue that measurement issues in the previous literature using measures of human capital quantity such as average years of education, or even different levels of educational attainment, have obscured the fundamental relationship between education and economic growth. In addition, this study will use average years of education as human capital and consider the spatial conditions, so the Cobb-Douglas production function above will be modified as follows:

$$Y = AK^{\alpha}L^{\beta}H^{\gamma}$$

where H is human capital or can be expressed as $H = EL$ where E is the average years of education per worker and L is the number of workers. Solow in Sheng et al. (2024) states that the Solow growth model assumes that the production function is Constant Return to Scale (CRS), so the following formula can be written:

$$zY = F(zK, zL, zH)$$

for any positive number z , which means that if capital, labor, and human capital are multiplied by z , then total output is also multiplied by z . All quantities in the economy relative to the amount of labor may be analyzed in a production function with constant returns to scale. To prove this, set $z = 1/L$ in the previous equation to obtain.

$$\begin{aligned} \frac{Y}{L} &= F\left(\frac{K}{L}, 1, \frac{H}{L}\right) \\ y &= f(k, 1, E) \\ y &= f(k, E) \end{aligned}$$

This equation shows that output per worker (y) is a function of the amount of capital per worker (k) and the length of education per worker ($H/L = EL/L = E$). Hence, the aggregate production function is as follows:

$$y = Ak^\alpha E^\gamma$$

Theoretically, there is a positive correlation between output per labor and increases in capital per labor and average years of education. Since the purpose of this study is to investigate the impact of education on economic growth, the econometric model obtained using logarithmic transformation is as follows:

$$\log y = \log A + \alpha \log k + \gamma \log E + \varepsilon$$

In the given context, the variables are defined as follows: $\log y$ denotes the logarithm of output (Gross Regional Domestic Product or GRDP) per labor (L), while $\log k$ represents the logarithm of capital (Gross Fixed Capital Formation or GFCF) per labor (L). The term $\log E$ corresponds to the logarithm of average years of education (E), and $\log A$ signifies the logarithm of the technology level. Additionally, α indicates the share of income attributed to capital per worker, γ represents the share of income associated with average years of education per worker, and ε denotes the error term in the model.

Methods

This research uses secondary data from two sources. There is one response variable as an indicator of economic growth, namely Gross Regional Domestic Product (GRDP) at constant prices and the three predictor variables, namely Gross Fixed Capital Formation (GFCF) as a proxy for capital (K), Employed Population Aged 15 Years and Over as a proxy for the number of workers (L), and Average Years of Education as a proxy for the years of education indicator (E). All data used were transformed using natural logarithm to ensure that the data were normally distributed (Benoit in Men et al., 2018) and strengthen the linearity relationship and maintain the stability of the results (Curran-Everett, 2018). All data

is taken for each province in Indonesia for the period 2013 to 2023 and comes from Central Bureau of Statistics Indonesia. In addition, the are geographical data such as geographical coordinates of each province and maps of administrative areas at the provincial level obtained from Geospatial Information Agency.

The descriptive analysis in this study employed boxplot visualization and bivariate mapping to compare the distribution and spatial relationship of each variable across regencies from 2013 to 2023, and their average, to observe any differences. Boxplots were used to illustrate the spread, central tendency, and potential outliers in the data, providing a clear representation of variability within each region (Kebonye et al., 2023). Meanwhile, the bivariate map enabled the visualization of the spatial correlation between two variables, allowing for the detection of patterns and regional clusters (Gao et al., 2020). This dual approach helped highlight variations and similarities, ensuring a more comprehensive understanding of the data distribution across Indonesia.

This research also used a quantitative study with a spatial econometric approach that aims to analyze the production factors of labor, capital, and education on economic growth in Indonesia. This research tries to use the production function method approach that has been adjusted to the spatial method. The following is an explanation of the methods used.

Spatial Weight Matrix

A matrix that quantifies spatial interactions in the form of weights is called a spatial weight matrix. The following is the arrangement of spatial weight matrix elements (W) (Suryowati et al., 2023):

$$W_{ij} = \begin{pmatrix} W_{11} & W_{12} & \cdots & W_{1n} \\ W_{21} & W_{22} & \cdots & W_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ W_{n1} & W_{n2} & \cdots & W_{nn} \end{pmatrix}$$

The rows and columns of the spatial weight matrix represent the regions that are the units of analysis. W_{ij} is the linkage weight of the i-th and j-th regions, where W_{ij} greater than or equal to 0 and W_{ii} equal to 0 for i equal to $1, 2, 3, \dots, N$.

The method works by minimizing the deviation function between the expected value and the sample value (Cardone & Di Martino, 2025). The IDW formula used is as follows:

$$W_{ij} = d_{ij}^{-1}$$

d_{ij} distance is measured from the midpoint (center) between regions using latitude and longitude coordinates.

Random Effect Test and Spatial Autocorrelation Test

The random region effect test in spatial panel data regression is used to check whether the variation in panel data is better explained by random region effect or fixed region effect. To test this, researchers used the Baltagi, Song, and Koh LM1 marginal test, where the null hypothesis is that there is no random region effect ($H_0: \sigma^2$ equal to 0) and ignores series

correlation or spatial error (*assumption is that ρ and λ are equal to 0*). While the spatial autocorrelation test in panel data spatial regression is used to measure the dependency or correlation between observation units that are influenced by their geographic location. To test this, we used the Baltagi, Song, and Koh LM2 marginal test, where the null hypothesis is that there is no series correlation ($H_0: \rho$ equal to 0) and ignores the random region effect or spatial error correlation (assumption is that σ_μ^2 and λ are equal to 0). Besides, we also tested random region effect and spatial autocorrelation simultaneously with Baltagi, Song, and Koh LMH marginal test, where the null hypothesis is that there is no random region effect and no series correlation (H_0 : is that σ^2 and ρ are equal to 0) thus ignoring spatial error correlation (assumption λ equal to 0) (Baltagi in Bera et al., 2018).

Lagrange Multiplier Test and Robust Multiplier Test

Testing for spatial lag dependence in spatial regression models uses the Lagrange Multiplier Lag Test. Where the null hypothesis is that there is no spatial lag dependence (ρ equal to 0). While testing the existence of spatial error dependencies using the Lagrange Multiplier Error test. Where the null hypothesis is that there is no spatial dependence of error (λ equal to 0). If the LMlag and LMerror tests fail to reject H_0 , then the model used is Ordinary Least Squares (OLS) (Anselin in Bera et al., 2018).

Panel Data Regression

Panel data regression is used for data collected at a specific point in time across different observations (Madany et al., 2022). The typical format of panel data regression is as follows:

$$Y_{it} = \beta_0 + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \varepsilon_{it}$$

In this format, Y_{it} represents the value of the dependent variable for the $i - th$ observation at time t ; (i equal to $1, 2, 3, \dots, N$); (t equal to $1, 2, 3, \dots, T$); $X_{k,it}$ indicates the value of the $k - th$ independent variable for the $i - th$ observation at time t ; β denotes the estimated parameters; and $\varepsilon_{it} = \alpha_{it} + u_{it}$ encapsulates the error term for the $i - th$ observation at time t .

The three primary modeling approaches that can be employed in panel data regression are the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM). The CEM assumes that both the intercept and slope values for each variable are consistent across all cross-sectional units and time periods, implying that the behavior of the data remains constant across different intervals. The equation for this model is given by $Y_{it} = \beta_0 + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \beta_3 X_{3,it} + e_{it}$. On the other hand, the FEM proposes that the intercept values differ for each cross-sectional unit, though the slopes remain the same across the variables. This model allows for the inclusion of dummy variables to account for these varying intercepts, and it is also known as the Least Square Dummy Variable (LSDV) model. The equation for the FEM is $Y_{it} = (\beta_0 + \alpha_i) + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \beta_3 X_{3,it} + e_{it}$. Finally, the REM assumes that each observation has its own unique intercept value, which is treated as a random or stochastic variable. The equation for this model is $Y_{it} = \beta_0 + \beta_1 X_{1,it} + \beta_2 X_{2,it} + \beta_3 X_{3,it} + (\alpha_{it} + e_{it})$.

Panel Data Regression Selection Test

To find the most appropriate model, three tests can be conducted: the Chow test, the Hausman test, and the Breusch-Pagan test. Chow test assists in determining the best model between the Fixed Effect Model (FEM) and the Common Effect Model (CEM). Hausman test evaluates which model is preferable between the Random Effect Model (REM) and the Fixed Effect Model (FEM). Breusch-Pagan test helps in deciding the most suitable model between the Random Effect Model (REM) and the Common Effect Model (CEM) (Baltagi in Indrasetianingsih & Wasik, 2020). If the resulting p-value is lower than the significance level (α), we will reject the null hypothesis (H_0). Below are descriptions of these tests:

Table 1. Panel Data Regression Selection Test

Testing	Hypothesis	Test Statistics
Chow Test	$H_0 : \alpha_1 = \alpha_2 = \dots = \alpha_i = 0$ $H_1 : a_i \text{ least 1 value of } \alpha_i \neq \alpha_j$ for $i \neq j$	$F_{hitung} = \frac{(RSS_1 - RSS_2) / (N-1)}{RSS_2 / (NT - N - K)}$
Hausman Test	$H_0 : E(u_i X_{it}) = 0$ $H_1 : E(u_i X_{it}) \neq 0$	$W = (\hat{\beta}_{MET} - \hat{\beta}_{MEA})' [\text{var}(\hat{\beta}_{MET} - \hat{\beta}_{MEA})]^{-1} (\hat{\beta}_{MET} - \hat{\beta}_{MEA})$
Breusch-Pagan Test	$H_0 : \sigma_{ui}^2 = 0$ $H_1 : \sigma_{ui}^2 \neq 0$	$LM = \frac{NT}{2(T-1)} \left[\frac{\sum_{i=1}^N [\text{Te}]^2}{\sum_{i=1}^N \sum_{t=1}^T e_{it}^2} - 1 \right]$

Source: Baltagi in Indrasetianingsih & Wasik, 2020

In the given context, the variables are defined as follows: N represents the total number of individuals (or cross-sectional data), while T stands for the number of time periods. The term $RSS_1 = \sum e_i^2$ denotes the residual sum of squares from the Common Effect Model estimation, and $RSS_2 = \sum e_j^2$ indicates the residual sum of squares from the Fixed Effect Model estimation. The vector $\hat{\beta}_{MET}$ refers to the Fixed Effect Model's slope estimate vector, while $\hat{\beta}_{MEA}$ represents the Random Effect Model's slope estimate vector. Finally, e_{it} is the residual for the unit i and time interval t.

General Nesting Spatial Model

The General Nesting Spatial (GNS) model is one approach in spatial econometrics that combines several forms of spatial dependencies. Elhorst in Bera et al. (2018) explains that the GNS model integrates spatial lag effects (SLM), spatial error effects (SEM), and other mixed forms in one comprehensive framework. This allows for a more in-depth analysis of the spatial dynamics in panel data. According to Elhorst (2022), the general formula of the GNS model is as follows:

$$Y = \delta WY + X\beta + WX\theta + u + e$$

where $e = \lambda Wu + \varepsilon$

In this context, the variables are defined as follows: Y represents the dependent variable, and X is the independent variable. The matrix W is the spatial weight matrix, while δ is the spatial lag coefficient of the dependent variable. The coefficient of the independent variable is denoted by β and θ represents the spatial lag coefficient of the independent variable. Additionally, λ refers to the spatial autocorrelation coefficient of the error, u is the error spatial autocorrelation, and ε is the error term.

The use of the GNS model can not only explain the relationship between independent variables and dependent variables in a region, but can also explain the relationship between dependent variables and independent variables outside the region. Therefore, the use of this model must be based on several theories that support the relationship.

This study considers the spatial effects of the independent variable, the dependent variable, and the error. Therefore, the production function above will be adjusted as follows:

$$\log y_{it} = \log A + \delta \sum_{j=1, j \neq i}^N W_{ij} \log y_{jt} + \beta_1 \log k_{it} + \beta_2 \log E_{it} + \theta_1 \sum_{j=1, j \neq i}^N W_{ij} \log k_{jt} + \theta_2 \sum_{j=1, j \neq i}^N W_{ij} \log E_{jt} + u_i + e_{it}$$

where,

$$e_{it} = \lambda \sum_{j=1, j \neq i}^N W_{ij} u_{jt} + \varepsilon_{it}$$

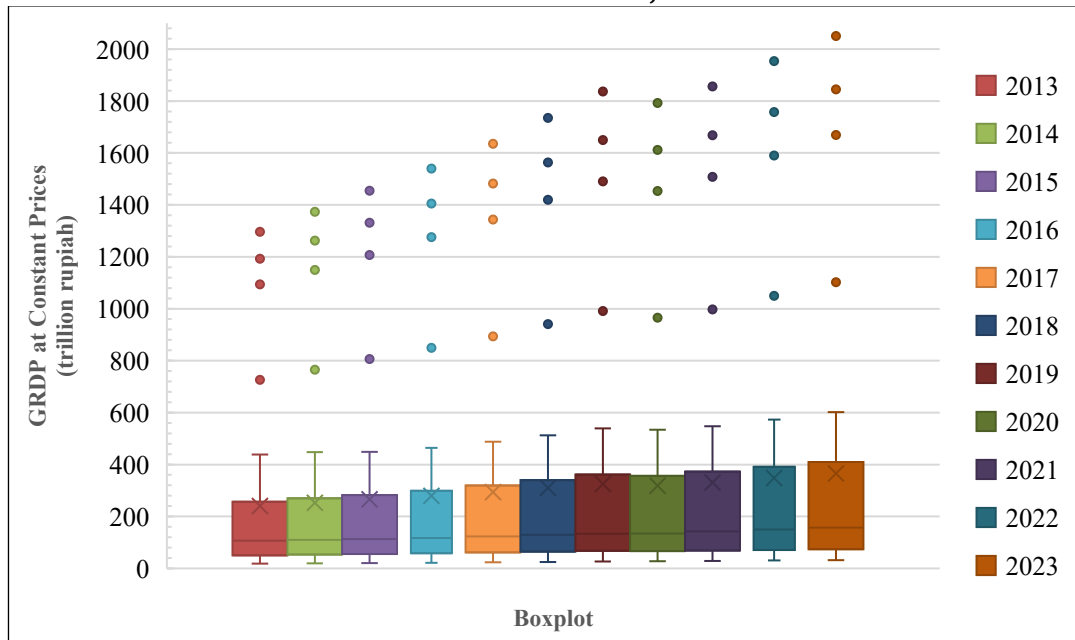
In the given context, the variables are defined as follows: $\log y_{it}$ represents the logarithm of output (Gross Regional Domestic Product or GRDP) per labor (L) for observation i at time t, while $\log y_{jt}$ also denotes the logarithm of output per labor for observation j at time t. $\log k_{it}$ refers to the logarithm of capital (Gross Fixed Capital Formation or GFCF) per labor (L) for observation i at time t. $\log E_{it}$ signifies the logarithm of average years of education (E) for observation i at time t, and $\log A$ represents the logarithm of the technology level. The term W_{ij} denotes the spatial weighting between the i-th and j-th observations. $\beta_{1,2}$ corresponds to the coefficient of an independent variable, δ represents the spatial lag coefficient of the dependent variable, $\theta_{1,2}$ indicates the spatial lag coefficient of the independent variable, λ signifies the spatial autocorrelation coefficient of the error term. Additionally, ε_{it} represents the spatial autocorrelation of the error for observation i at time t, while u_{jt} denotes the spatial autocorrelation of the error for observation j at time t. Finally, u_i is the error term for equation 1, and ε_{it} is the error term for equation 2.

Findings

Overview of GRDP at Constant Prices and Factors of Production in Indonesia

Based on Figure 3, it shows that during the period of 2013 to 2023, in general, production output has increased in Indonesia. The increase can be seen in the box that is getting longer in the following year period, it can be interpreted that more and more outputs are clustered in a higher range of output values (GRDP). It should be noted that the center value line inside the box for the past 11 years shows a slow increase in output. Although in 2020 the output gain had experienced a slight decline, which is indicated by the shorter length of the box, after the recovery period of the COVID-19 pandemic, it shows an increasing trend in output until 2023.

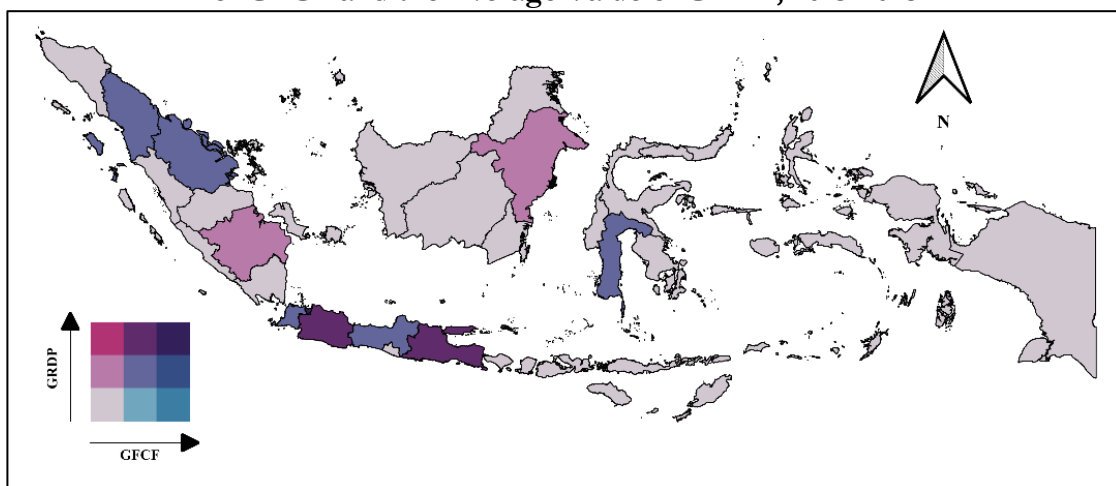
Figure 3. **Distribution of GRDP at Constant Prices (trillion rupiah) of Provinces in Indonesia, 2013-2023**



Source: Indonesian Central Statistics Agency (Processed)

In general, the distribution of provincial-level GRDP in Indonesia is skewed to the right, indicating that there are still many regions in Indonesia that have output values clustered in the lower range. Based on Figure 3, there are four points that are outside the whisker line, i.e. the output value is much larger than the other provinces in Indonesia. DKI Jakarta, West Java, East Java and Central Java are the four regions with the highest output values. These four provinces consistently show an increase in GRDP output from 2013 to 2023. The large contribution of these four provinces in the national GDP makes these provinces have a big role in overseeing the increase in economic growth in Indonesia. The acceleration of Indonesia's economic growth is needed in an effort to stabilize and realize Indonesia's economic targets in the future.

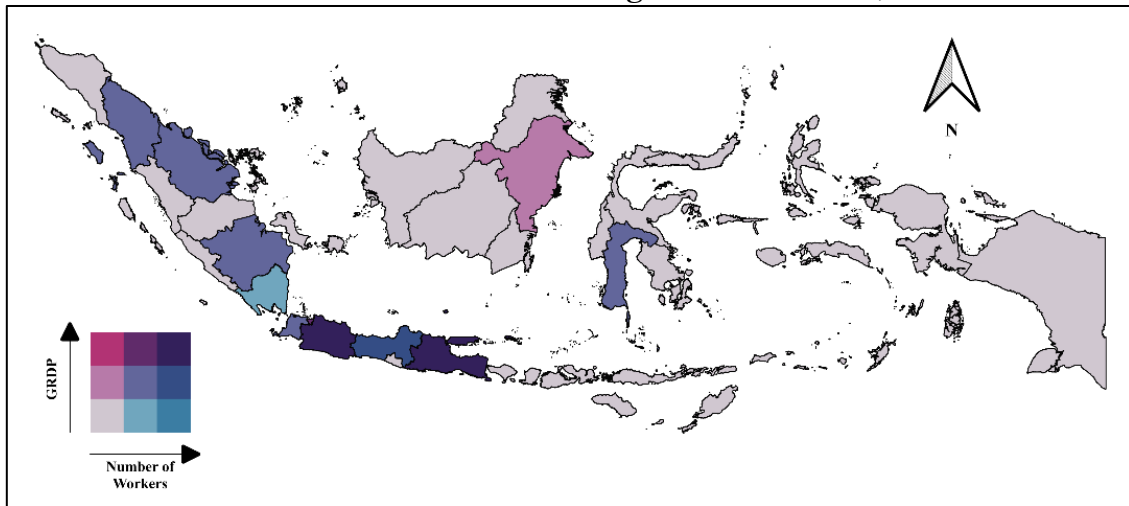
Figure 4. **Map of the Combination of the Distribution of the Average Value of GFCF and the Average Value of GRDP, 2013-2023**



Source: Indonesian Central Statistics Agency (Processed)

Figure 4 shows the combination of the distribution of the average value of GFCF and the average value of output (GRDP) from 2013 to 2023. It is known that several provinces in Java and Sumatera have high values of GFCF and output (GRDP). Meanwhile, the majority of provinces in eastern Indonesia have low values of GFCF and output (GRDP), reflecting disparities in investment and economic growth between regions. This pattern indicates that fixed capital investment plays a crucial role in driving regional economic growth, but there are inequalities that underscore the urgency of an equitable development strategy to accelerate growth in regions with low GFCF.

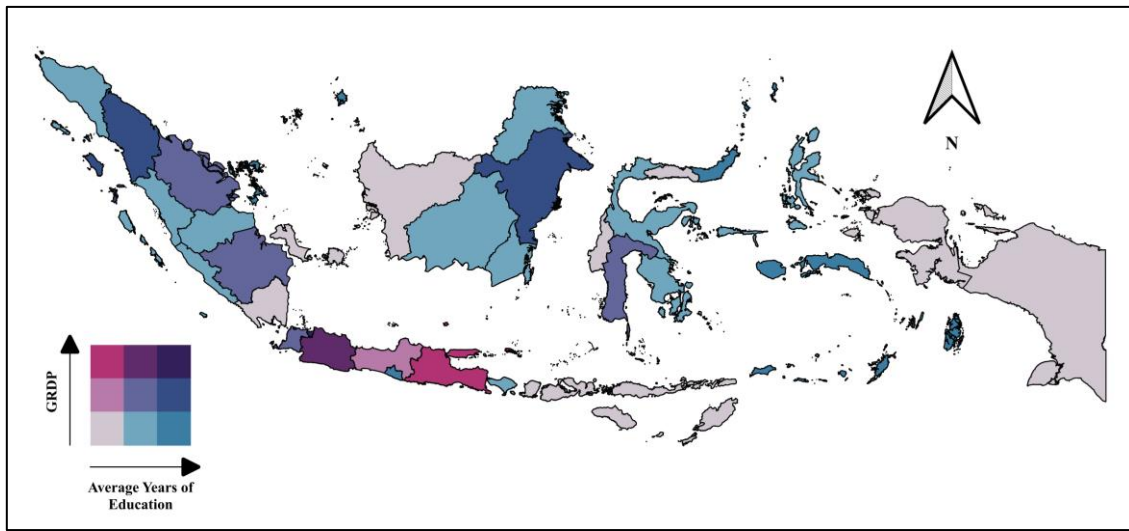
Figure 5. Map of the Combination of the Distribution of the Average Value of Number of Workers and the Average Value of GRDP, 2013-2023



Source: Indonesian Central Statistics Agency (Processed)

Figure 5 shows the combination of the distribution of the average value of Number of Workers and the average value of output (GRDP) from 2013 to 2023. It is known that several provinces in Java and Sumatera have high Number of Workers and output (GRDP) values. Meanwhile, the majority of provinces in eastern Indonesia have low Number of Workers and output (GRDP) values, reflecting limited employment opportunities that have the potential to slow regional economic growth. In addition, there are two provinces that attract attention, namely Lampung Province and East Kalimantan Province. Lampung Province has quite a lot of JOBS, but the output produced is low. On the other hand, East Kalimantan Province has few JOBS, but the output produced is quite a lot. This pattern confirms that a large accumulation of labor does not always guarantee a high value of output (GRDP) without being balanced by high productivity, quality, and efficiency of the workforce.

Figure 6. **Map of the Combination of the Distribution of the Average of Years of Education and the Average Value of GRDP, 2013-2023**



Source: Indonesian Central Statistics Agency (Processed)

Figure 6 shows the combination of the distribution of the average years of education and the average output (GRDP) from 2013 to 2023. It is known that the majority of provinces in the western and central parts of Indonesia have relatively high values of average years of education and output (GRDP) and tend to be evenly distributed. Meanwhile, the eastern part of Indonesia, especially Papua Island, has a low value of average years of education and output (GRDP), indicating challenges in access and quality of education that have an impact on labor productivity, which in turn reduces the output produced. This pattern indicates that increased investment in the education sector has the potential to be a major catalyst in driving more sustainable and equitable regional economic growth.

Spatial Modeling

In the initial stage, testing for individual effects and spatial autocorrelation is required to test for spatial linkages of economic growth per worker between regions. If the linkage is proven, then the analysis can be modeled spatially through the models that will be proposed. Lagrange Multiplier test is used to detect the presence of individual effects and spatial correlation of errors.

Table 2. **Test for Individual Effects and Spatial Autocorrelation**

Test	Statistic Value	p-value
LM ₁	41.972	0.000*
LM ₂	3.1487	0.002*
LM _H	1771.6	0.000*

note: *) significant at 10 percent significance level

Source: Data Processing Result

Based on Table 2, the Lagrange Multiplier test results LM₁, LM₂, LM_H are significant at 10 percent significance level, which indicates that the panel data used has random region effect and spatial autocorrelation both partially and simultaneously.

Table 3. **Spatial Dependence Test**

Test	Statistic Value	p-value
LM Spatial Lag	10.794	0.001*
LM Spatial Error	9.914	0.002*

note: *) significant at 10 percent significance level

Source: Data Processing Result

Based on Table 3, with a significance level of 10 percent, it shows that the LM test on spatial lags and spatial errors is significant to reject H_0 , which means that there is a spatial dependence on economic growth per labor in each province in Indonesia so that the spatial model to be proposed needs to consider the spatial lag effect and the spatial error effect. GNS modeling is formed by including both spatial effects and supplemented by the spatial lag effect of independent variables. In other words, the economic growth of a region is influenced by factors of production from its own and neighboring regions, the effect of spatial error, and economic growth achievements in surrounding regions.

Table 4. **Parameter Estimation of GNS Fixed Effect**

Test	Parameter	Coefficient	Standard Error	t-statistics	p-value
Intercept	log A	-0.085	0.242	-0.350	0.726
W x log (y)	δ	-0.951	0.391	-2.432	0.015*
log (k)	β_1	0.909	0.035	25.953	0.000*
log (E)	β_2	-0.614	0.280	-2.190	0.028*
W x log (k)	θ_1	1.004	0.413	2.429	0.015*
W x log (E)	θ_2	1.635	0.378	4.330	0.000*
W x u	λ	0.507	0.173	2.936	0.003*
R-Squared		0.9908	F-statistic		523.389
Adj. R-Squared		0.9907	Prob (F-statistics)		0.000*

note: *) significant at 10 percent significance level

Source: Data Processing Result

After the GNS model is formed, the next stage is testing the spatial panel data model with the Hausman test. The test results show a statistical value of 9.177 with a p-value of 0.057. Thus, with a significance level of 10 percent, it is evident that the fixed effect GNS model is better than the random effect GNS model. Table 4 shows the parameter estimation results of the GNS fixed effect model with the maximum likelihood estimation method. Based on Table 4, the average years of education and capital per worker variables significantly affect the level of economic growth per worker in Indonesia, both directly and indirectly. Adjusted R-Squared of 0.991, can be interpreted that the spatial model formed is able to explain 99.1 percent of the variation of economic growth per labor in each province in Indonesia. In table 4, the parameter estimation results of the GNS model are obtained as follows:

$$\widehat{\log y_{it}} = (-0.085 + \mu_i) - 0.951 \sum_{j=1, j \neq i}^{34} W_{ij} \log y_{jt}^* + 0.909 \log k_{it}^* - 0.614 \log E_{it}^* + 1.004 \sum_{j=1, j \neq i}^{34} W_{ij} \log k_{it}^* + 1.635 \sum_{j=1, j \neq i}^{34} W_{ij} \log E_{it}^* + u_i + 0.507 \sum_{j=1, j \neq i}^{34} W_{ij} u_{jt}^* \dots \dots \dots (16)$$

note: *) significant at 10 percent significance level

Based on the estimation conducted, researchers found that capital per labor has a significant influence on economic growth in Indonesia, both directly and indirectly. Assuming other variables remain constant, a 1 percent increase in capital per labor can increase economic

growth directly by 0.909 percent. In addition, indirectly, economic growth in a province will increase by 1.004 percent times the spatial weighting in each province when capital per labor in another province increases by 1 percent. Furthermore, the length of education variable also shows a significant effect on economic growth. Directly, an increase in average years of education by 1 percent can result in a decrease in economic growth by 0.614 percent. However, indirectly, economic growth in a province will increase by 1.635 percent times the spatial weighting in each province when the length of education in another province increases by 1 percent.

The model also shows that the spatial lag effect of the dependent variable is significant and negative, amounting to -0.951. This indicates that an increase in economic growth in a province can cause a slowdown in economic growth in other provinces. Meanwhile, the spatial effect of error (λ) has a value of 0.507 with a positive relationship direction, which means that the economic growth of a province can increase by 0.507 times its spatial weighting when the average error in other provinces increases by about 1 unit.

The results of this study are in line with several previous studies. The effect of capital on economic growth is supported by Battisti et al. (2018), which shows that capital accumulation contributes significantly to increasing labor productivity and economic growth. Bloom (2020) also found that demographic and capital changes in labor investment affect economic growth across regions.

The negative effect of average years of education on economic growth observed in this study may reflect the limited capacity of Indonesia's education system to translate educational attainment into productive human capital. While several studies have shown that an increase in the average years of schooling has a positive and significant impact on economic output (Amalia et al., 2023; Sari, 2023), other evidence suggests that this relationship weakens or even turns negative when education quality and regional disparities are not adequately addressed (Agusalim et al., 2022; Hutabarat & Dias Satria, 2020). This implies that merely increasing the quantity of education does not guarantee higher productivity or economic growth, particularly when learning outcomes and skill relevance remain low. Moreover, studies emphasize that education equality and access are more critical to sustaining long-term growth than average schooling years alone (Sabur et al., 2021). Indonesia still faces substantial regional disparities in education quality and infrastructure, which limit the diffusion of human capital benefits and may generate negative spatial spillovers (Simatupang et al., 2023). In line with broader international evidence, the positive effect of education on growth tends to emerge only after an economy crosses a certain development threshold, where the accumulated years of schooling are complemented by improvements in education quality and institutional capacity (Ahsan & Haque, 2017).

The negative impact of interprovincial economic growth linkages can be attributed to the findings of Marré (2020), which states that urban economic growth can cause economic decline in rural areas due to labor migration. Meanwhile, the effect of spatial errors on economic growth is reinforced by the research of Qasim Alabed et al. (2021) which shows that errors in estimation can have an impact on economic growth across regions. Astuti et al. (2023) also found that how economic dependencies between regions can lead to estimation errors affecting GDP and foreign direct investment spillovers.

Conclusion

This study provides evidence that Indonesia's economic growth is influenced not only by traditional production factors such as capital and education, but also by spatial interdependencies between provinces. The General Nesting Spatial (GNS) model confirms that the average years of education have a negative direct effect and a positive indirect (spillover) effect on economic growth. These findings suggest that while increased educational attainment within a province may not immediately accelerate local growth, improvements in neighboring provinces can generate positive regional spillovers through shared knowledge, labor mobility, and interregional linkages.

However, the inferences drawn from this study are subject to several limitations. First, the use of average years of schooling captures only the quantity of education, not its quality or relevance to labor market needs. Therefore, conclusions about education's role should be interpreted as reflecting educational attainment rather than skill or productivity outcomes. Second, the spatial relationships modeled are limited to provincial level data, which may obscure local heterogeneity. Finally, the model does not include other important determinants of growth such as technological innovation, institutional quality, or infrastructure which may interact with education in shaping economic outcomes.

Based on these findings, three specific policy implications can be drawn. First, enhance the quality and relevance of education, not just its duration. The government should prioritize policies that strengthen learning outcomes such as teacher training, curriculum modernization, and industry-linked vocational programs to ensure that schooling translates into productive skills. Second, promote spatially coordinated development policies. Central and local governments should jointly design education and investment programs that consider spatial spillovers for example, by developing regional innovation hubs and cross-provincial workforce development initiatives. Third, target lagging provinces through place-based education and capital investment programs. Equalizing access to education infrastructure and training facilities can help reduce interprovincial disparities and maximize the indirect (positive) effects observed in the spatial model.

To achieve sustainable and inclusive growth, Indonesia must move beyond aggregate education expansion toward regionally integrated, quality-focused, and evidence-based education policies. Strengthening intergovernmental coordination and data driven planning is crucial to ensure that every additional year of schooling contributes meaningfully to productivity and long-term prosperity across all provinces.

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