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Spatial Panel Regression Modelling of Middle-Income Trap in Indonesia

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Article Info	**ABSTRACT**
Keywords: *Spatial Panel Data Regression, Middle-Income Trap, GRDP per Capita, Inverse Distance Matrix*	*A phenomenon conceptualized as the "middle-income trap" manifests when a nation's per capita income remains persistently stagnant at the middle-income level for an extended period, inhibiting progression toward high-income status despite initial economic development. After decades of economic expansion, Indonesia is among the emerging nations stuck in this situation. This study examines the spatial relationships between provinces and the effects of gross fixed capital creation, life expectancy, foreign direct investment, and average years of education on Indonesia's gross national product per capita. The study used the spatial panel data regression method with inverse distance matrix approach using panel data from 34 provinces between 2015 and 2020. The model with the lowest AIC score is chosen for the spatial error (SEM). This research demonstrates the existence of statistically significant spatial interdependencies in Gross Regional Domestic Product per capita among Indonesian provinces experiencing the middle-income trap phenomenon. Empirical evidence from regression analyses indicates that mean educational attainment and gross fixed capital formation exert positive and statistically significant influences on per capita GRDP, whereas life expectancy indicators and foreign direct investment inflows do not yield statistically meaningful effects within this economic context. The investigation provides valuable insights into the spatial economic dynamics associated with middle-income trap conditions in Indonesia and offers potential strategic frameworks for addressing these developmental challenges.*

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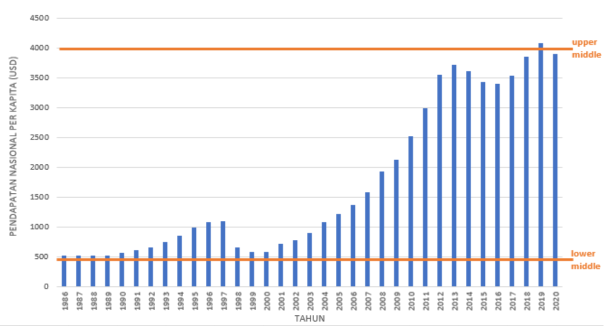
INTRODUCTION

One of the main goals of economic development is the raising of the population's per capita income. The increase in per capita income reflects an improvement in the overall welfare level of society (Sarlia & Hanum, 2019). Per capita income, calculated through the Atlas methodology, serves as the foundation for the World Bank's international categorization of countries into distinct economic classifications based on income levels. This method has the primary advantage of reducing the impact of exchange rate fluctuations on per capita income calculations, thus producing more stable and accurate estimates to represent a country's income level (Zhou & Hu, 2021). The country income level classification is updated by the World Bank annually on July 1. As of July 1, 2020, within the global economic taxonomy, nations are stratified into a quaternary classification system predicated on per capita income thresholds: economically disadvantaged economies (below USD 1,036), lower-intermediate economies (USD 1,036–4,045), upper-intermediate economies (USD 4,046–12,535), and advanced economies (exceeding USD 12,535)

In its 2007 report, the World Bank first introduced the term "middle-income trap" to describe the phenomenon of stagnation in economic growth in middle-income countries. However, this issue received deeper attention as economic growth in the People's Republic of China slowed following the global economic crisis in the same year (Akbas & Sancar, 2021). The middle-income trap refers to a condition where a country successfully achieves a middle-income level, yet fails to continue sustainable economic development to reach high-income status. This phenomenon is often associated with limitations in a country's capacity to create innovation, adopt cutting-edge technology, and significantly increase productivity. Additionally, this condition can be exacerbated by high levels of social and economic inequality that impede inclusive growth (Todaro & Smith, 2012).

After several decades of economic growth and development progress, Indonesia is categorized as one of the developing countries experiencing the middle-income trap phenomenon (Lindiawatie & Nurmalasari, 2019). According to the Asian Development Bank report, Indonesia and Pakistan are categorized as countries trapped in the middle-income trap phenomenon. This assessment is based on the criterion that a country is considered to be experiencing a middle-income trap if its income level remains stagnant for 28 years or more. In 2014, Indonesia, comprising 34 provinces, was recorded as maintaining its status as a lower-middle income country for more than 28 years, reflecting significant challenges in transitioning to a higher income category (Felipe, 2012).

Figure 1. Indonesia's Gross Domestic Product Per Capita for the Years 1986–2020



Source: World Bank (2021)

Indonesia faces significant challenges in its efforts to develop into an advanced country, one of which is the risk of being ensnared in the middle-income trap phenomenon. This risk is caused by stagnation or slowdown in economic growth that potentially strengthens the likelihood of such a condition occurring. Furthermore, the middle-income trap not only impacts economic aspects but can also indirectly trigger social instability. In facing this challenge, Indonesia needs to compete not only with other developing countries but also with developed countries that have already established their positions at the global economic level (Lumbangaol & Pasaribu, 2019).

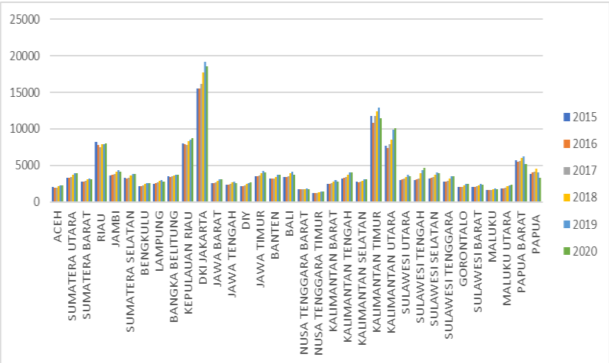
According to a study conducted by Ratnasari et al., (2023) efforts to release Indonesia from the middle-income trap require an increase in GDP per capita through optimization of several key variables. These variables include life expectancy, gross enrollment rate, and gross fixed capital formation, which have been proven to have a significant influence on increasing GDP per capita. By focusing on these variables, it is expected that Indonesia can accelerate its transition toward the high-income country category in a sustainable manner.

Zahira Virtyani et al., (2021) assert that to avoid entrapment in the middle-income country category, Indonesia requires the support of strategic elements capable of enhancing national productivity. One such key element is foreign direct investment, which plays a significant role in driving economic growth. Foreign direct investment contributes not only through technology transfer but also through the creation of employment opportunities that support sustainable productivity improvement. A study conducted by Dewi et al., (2021) further strengthens the argument that foreign direct investment has a significant positive impact on Gross Domestic Product. This is due to the contribution of foreign direct investment in facilitating the transfer of knowledge, technology, and capital flows into a country, which collectively promote economic growth and national productivity.

Based on Figure 2, the Gross Regional Domestic Product per capita of Indonesian provinces shows a consistent increasing trend annually during the 2015-2020 period. DKI Jakarta Province is recorded as having the highest average GRDP per capita at 17,112.30 USD, reflecting a dominant economic position compared to other provinces. Conversely, the average GRDP per capita of East Nusa Tenggara Province occupies the lowest position nationally, with a value of 1,287.87 USD, indicating significant economic disparities among Indonesian provinces.

Figure 2. GRDP by Province in Indonesia for the Years 2015–2020

Source: BPS processed (2020)



According to (Laut, Putri, & Septiani, 2020) the high Gross Regional Domestic Product (GRDP) per capita in a region may be attributed to the presence of individuals with extremely high incomes, who significantly influence the average income of that region. Additionally, income disparities between certain economic sectors contribute to differences in GRDP per capita levels between regions.

One of the primary factors influencing disparities in Gross Regional Domestic Product achievement is the development of human resource quality. Human capital, encompassing aspects of "human resources" and "health," constitutes a fundamental component in the economic development of a region. The effectiveness level of education in an area can serve as an indicator of success in human resource development. In this context, the mean years of schooling functions as a parameter reflecting the level of education completed or currently being pursued by residents in that region (Alexander, Nuryadin, & Suharsih, 2022). Study by Rianto, (2014) in his study, posits that mean years of schooling has a significant influence on Gross Regional Domestic Product per capita. This finding indicates that an increase in mean years of schooling, which reflects the educational level of the population, can contribute to enhancing productivity and economic competitiveness of a region, thereby positively impacting GRDP per capita.

Beyond education, health status also represents an important aspect in human resource development. Chairunnisa & Qintharah, (2022) in their study, state that life expectancy is an indicator that can reflect the quality of public health. Furthermore, life expectancy has a significant relationship with the increase in Gross Regional Domestic Product per capita, demonstrating that good health contributes to community productivity and overall regional economic growth.

Kusuma Nigrum, (2023) explains that an increase in life expectancy correlates with the extended average lifespan of a population. With a longer lifespan, individuals have more time to participate in various productive economic activities. This creates greater opportunities for communities to increase individual income, which ultimately contributes to the rise in Gross Domestic Product (GDP) per capita. This GDP increase subsequently becomes an indicator of broader economic expansion.

The contribution of capital formation has a significant correlation with Indonesia's economic growth. Capital formation reflects an increase in the accumulation of capital goods, which function as the primary driver in supporting various economic activities. With increased capital accumulation, the capacity to enhance production activities is greater, which in turn can accelerate the overall rate of economic growth (Zahira Virtyani et al., 2021).

Investment represents one of the key factors driving a country's economic growth. Taufik, (2014) explains that a significant increase in investment can stimulate productivity enhancement, which forms the basis for sustainable economic growth. Herman, (2024), in his research, suggests that foreign capital investment has a positive influence on Gross Regional Domestic Product, demonstrating the strategic contribution of foreign investment in driving economic output. Additionally, Tajudin (2023)), in his research, suggests that foreign capital investment has a positive influence on Gross Regional Domestic Product, demonstrating the strategic contribution of foreign investment in driving economic output.

The middle-income trap issue in Indonesia, characterized by income stagnation and failure to transition to a high-income economy, has a close relationship with economic dynamics at the provincial level (Ratnasari et al., 2023). Based on principles in geographical law, everything is interconnected, with greater influence occurring among entities that are geographically proximate than those that are distant (Putu et al., 2018). A study conducted by (Yunitasari & Firdaus, 2022) reveals that similarities in GRDP values among provinces or geographically adjacent regions directly demonstrate the influence of spatial dependency. This research aims to analyze the impact of various determinants of GRDP per capita on the middle-income trap phenomenon by considering spatial effects at the provincial level through a spatial panel data regression approach.

METHODOLOGY

This study adopts a quantitative approach based on descriptive methodology, implemented through the calculation of numerical data, data collection, interpretation, and presentation of findings to address the research questions. The data utilized in this study is sourced from the Central Bureau of Statistics (Badan Pusat Statistik) and encompasses all 34 provinces in Indonesia. The calculation of Gross Regional Domestic Product (GRDP) per capita in this study employs the World Bank's Atlas method to illustrate the middle-income trap phenomenon in Indonesia.

Data analysis is conducted using spatial panel regression, with Pesaran's CD test employed to identify spatial dependency, and data processing facilitated by Stata 17 software. Spatial panels are defined as datasets that include time-series observations across specific spatial units, such as postal codes, districts, regions, or countries. To analyze spatial effects, the location data within the spatial dataset must be quantified appropriately.

This research examines the dependent variable of GRDP per capita, calculated using the Atlas method for 34 provinces in Indonesia during the period 2015–2020. Meanwhile, the independent variables analyzed include the average years of schooling, life expectancy, foreign direct investment, and gross fixed capital formation for each province over the same time period.

Spatial Panel Data Analysis

The integration of time-series data and individual subjects while accounting for location-based influences is referred to as spatial panel data analysis. Data containing time-series observations across various spatial units (such as postal codes, districts, regions, or countries) is categorized as spatial panel data. To identify spatial effects, the position of spatial data must be quantified. According to Kosfeld (2006), there are two primary sources for determining locational information:

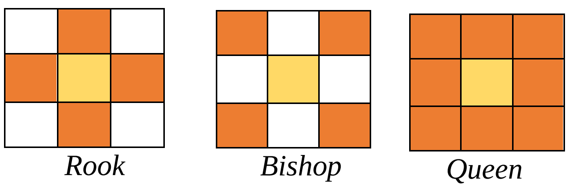
1. Neighborhood

The relative position of several spatial units or locations within a given space is reflected in neighborhood connections. These relationships are typically determined using map-based data. Compared to spatial units that are geographically distant, neighboring spatial units are expected to exhibit a higher degree of spatial dependency.

2. Distance

Locational information can also derive from places situated within an area defined by specific latitude and longitude coordinates. The distance between two points in space is calculated using these coordinates, with the expectation that spatial dependency diminishes as the distance increases. Establishing a spatial weighting matrix and testing for spatial effects are prerequisites for conducting spatial regression modeling. In geographical analysis, the existence of spatial weights—commonly referred to as the spatial weighting matrix—is essential. Based on the neighborhood relationships among locations, this matrix is utilized to compute the weight relationships between observed locations.

$$W = \begin{pmatrix} w_{11} & \cdots & w_n \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{pmatrix}$$



According to Lesage (1999), there are three types of spatial weight matrices classified based on the type of neighborhood relationships:

1. Rook Contiguity

This type of contiguity represents the relationship between the edges of one region and the edges of neighboring regions within a specific spatial framework.

2. Bishop Contiguity

This refers to the alignment or connection formed between the corners of one region and the corners of adjacent regions.

3. Queen Contiguity

This relationship is established when two regions share common boundaries or edges, including both their sides and corners.

In addition, the elements of spatial weight matrices can also be represented as a function of distance. The theoretical distance between two regions determines the weight assigned to the relationship between a location and its neighboring locations. One of the commonly used approaches is the inverse distance method, where the weights increase as the distance between locations decreases (Hikmah, 2017).

After defining the appropriate spatial weight matrix, normalization is typically applied. A common method of normalization involves row normalization, which transforms the matrix such that the sum of weights in each row equals one (Dubin, 2009). For this study, the inverse distance spatial weight matrix is utilized to support the spatial panel data modeling.

Spatial Effect Testing Using Pesaran's CD Test

To determine whether spatial effects are present in the data, a spatial effect test should be conducted. Pesaran's CD Test is utilized to examine whether variables exhibit spatial dependence. The null hypothesis (H0), which asserts the absence of dependence among individuals, is evaluated for cross-sectional dependence using this test (De Hoyos, 2006). The hypotheses for Pesaran's CD Test are as follows:

H_0 : no correlation exists

H_a : correlation exists

The criteria for evaluating Pesaran's CD Test are as follows:

a. H_0 is rejected, and H_a is accepted if the probability value is less than the significance level α (0.05). This result indicates the presence of cross-sectional dependence or correlation among residuals.
b. H_a is rejected, and H_0 is accepted if the probability value exceeds α (0.05), indicating the absence of cross-sectional dependence or residual correlation

Spatial lag factors within the response variable, commonly referred to as the Spatial Autoregressive Model (SAR), or spatial error processes within the residuals, known as the Spatial Error Model (SEM), are key features of linear regression models that incorporate spatial interactions across geographical units (Elhorst, 2010).

Model Selection

Following the testing of panel data and spatial analyses, several models were derived, including CEM, FEM, REM, SAR, and SEM. The subsequent step involves selecting the most appropriate model to determine which element best supports the research. The Akaike's Information Criterion (AIC) is employed as the selection criterion. Comparing models based on the smallest AIC value ensures optimal model selection; the smaller the AIC value, the better the model's performance (Nidyashofa & Darsyah, 2020).

RESULTS AND DISCUSSION

Selection of Panel Data Regression Model

Based on the specification test conducted, the best model selected is the Random Effect Model (REM). The estimation results of the panel data regression model are as follows:

Table 1. Random Effect Model

VARIABLES	REM
AYS	0.211***
	(0.000)
LE	0.00332
	(0.677)
LN_FDI	0.00627
	(0.318)
LN_GFCF	0.141***
	(0.001)
Constant	4.928***
	(0.000)
Observations	204
Number of ID	34

Legend:* p<0,05; ** p<0,01; ***p<0.001

Source: Stata 17, 2024 (processed)

In this study, in addition to using panel data regression, the researcher also employed spatial panel data regression. The primary objective of this approach is to examine the spatial interconnection between regions, specifically to determine whether the GRDP per capita of one region influences the GRDP per capita of other regions. This model is utilized to compare which approach is most effective in analyzing the GRDP per capita of provinces in Indonesia during the 2015–2020 period, particularly in the context of the middle-income trap threat.

Spatial Weight Matrix

The inverse distance matrix is utilized as the spatial weight matrix in this study. Once the spatial weight matrix is determined, the next step involves normalizing the matrix. The commonly applied normalization method is row normalization, which transforms the matrix so that the sum of each row equals one (Dubin, 2009).

Figure 3. Invers Distance Matrix

Summary of spatial-weighting object **W_invn**

Matrix	Description
Dimensions	**34 x 34**
Stored as	**34 x 34**
Values	
min	**0**
min>0	**.0048079**
mean	**.0294118**
max	**.2650321**

Source: Stata 17, 2024 (processed)

Figure 3 presents the results of the spatial weight matrix constructed using the inverse distance method. Indonesia consists of 34 provinces, resulting in a spatial weight matrix of size 34 x 34. The largest spatial weight value is 0.2650321, while the smallest spatial weight value is 0.0048079.

Spatial Effect Test

Spatial effect testing is conducted to examine the presence of spatial effects in the data. Pesaran's CD Test is applied to determine whether there is dependence among individuals, with the null hypothesis stating that no dependence exists among them (Hoyos & Sarafidis, 2006). The hypotheses for Pesaran's CD Test are as follows:

H_0 : no correlation exists
H_a : correlation exists

The criteria for evaluating Pesaran's CD Test are as follows:

a. If the probability value is less than 0.05, H_0 is rejected, and H_a is accepted, indicating the presence of cross-sectional dependence or correlation among residuals
b. If the probability value is greater than 0.05, H_a is rejected, and H_0 is accepted, indicating the absence of cross-sectional dependence or correlation among residuals.

Table 2. Pesaran'S CD Test

Effect Test	Statistic	Probabilit
Pesaran's Test	23,775	0,0000

Based on Table 2 above, the probability value for Pesaran's CD Test is 0.0000, which is less than the threshold of 0.05. Consequently, H0 is rejected, and Ha is accepted, indicating the presence of cross-sectional dependence or spatial dependency in the GRDP per capita among provinces in Indonesia under the conditions of the middle-income trap.

Results of the Spatial Autoregressive Model (SAR) Estimation

The response variable in the spatial lag model depends on the observations of neighboring units' responses (Elhorst, 2014). The results of the Spatial Autoregressive Model (SAR) estimation reveal that at a significance level of α = 0.05, the significant variables influencing the outcome are AYS (average years of schooling) and LNGFCF (gross fixed capital formation). The spatial lag indicates a probability value of 0.0000, which is less than 0.05, confirming the presence of spatial effects on GRDP per capita. The coefficient of determination (R^2) for the SAR model is 0.6169 or 61.69%, which signifies that the variation in the independent variables included in the model explains 61.69% of the variation in GRDP per capita. Meanwhile, the remaining 38.31% is accounted for by other variables outside the scope of this study. The spatial lag model is expressed as follows:

Table 3. Spatial Autoregressive (SAR) Model Estimation Results

Variable	SARpnel
Main	
AYS	0.0706512*
	(0.027)
LE	0.0067331
	(0.350)
LN_FDI	0.0101944
	(0.068)
LN_GFCF	0.0981923*
	(0.014)
_cons	1.4296666
	(0.076)
Spatial	
rho	0.5848299***
	(0.000)
Variance	
lgt_theta	-3.1739861***
	(0.000)
sigma2_e	0.00221983***
	(0.000)
Statistics	
n	
r2	0.6169
r2_a	

Legend:* p<0,05; ** p<0,01; ***p<0.001

Source: Stata 17, 2024 (processed)

Spatial Error Model (SEM) Estimation Results

The SEM model focuses on the residual structure (Elhorst, 2014). Based on the SEM estimation results, the variables found to significantly influence the model at a significance level of α = 0.001 are AYS (Average Years of Schooling) and LNGFCF (Gross Fixed Capital Formation). Additionally, the spatial error term (*spatial lambda*) shows a probability value of 0.0000, which is less than 0.05. This indicates the presence of spatial effects on GRDP per capita**.**

The coefficient of determination (R^2) for the SEM model is 0.6178 or 61.78%, meaning that the variation in the independent variables included in the model explains 61.78% of the variation in GRDP per capita. The remaining 38.22% is attributed to other variables outside the scope of this study.

Table 4. Spatial Error Model (SEM) Model Estimation Results

Variable	SEMpnel
Main	
AYS	0.1581319*** (0.000)
LE	0.0083860 (0.240)
LN_FDI	0.0080291 (0.139)
LN_GFCF	0.1383979*** (0.001)
_cons	5.0294002*** (0.000)
Spatial	
lambda	0.7055767*** (0.000)
Variance	
ln_phi	4.4816887*** (0.000)
sigma2_e	0.0021845*** (0.000)
Statistics	
n	
r2	0.6178
r2_a	

Legend:* p<0,05; ** p<0,01; ***p<0.001

Source: Stata 17, 2024 (processed)

Results of Spatial Panel Model Selection

In this study, the determination of the optimal model was conducted by comparing the lowest AIC (Akaike's Information Criterion) values among the tested models. The lower the AIC value achieved, the better the model's performance (Nidyashofa & Darsyah, 2020). Based on the comparison results, the most suitable model for identifying the factors influencing GRDP per capita under the middle-income trap conditions in Indonesia is the Spatial Error Model (SEM).

Table 5. Comparison of AIC for Model REM, SAR, dan SEM

Method	AIC
REM	-234,965
SAR	-427,593
SEM	-434,025

Source: Stata 17, 2024 (processed)

Based on the comparison of AIC values, the SEM model achieves the lowest AIC at -434.025, which indicates its superiority over the SAR and REM models, both of which have AIC values of -427.593. The selection of the SEM model is further supported by the spatial effect test, which reveals spatial dependency in GRDP per capita under middle-income trap conditions in Indonesia.

The results show that two variables significantly influence the model at a significance level of α = 0.001: AYS (Average Years of Schooling) and LNGFCF (Gross Fixed Capital Formation). The significant spatial lambda value, which is less than 0.05, confirms the presence of spatial interconnection in GRDP per capita among provinces. Moreover, the significance of other parameters suggests that the GRDP per capita in a given region is influenced by both the independent variables within that region and the spatial residuals from neighboring regions with similar characteristics.

Below is the equation for *Spatial Error Model* (SEM):

$$\hat{y}_{it} = 5{,}0294 + 0{,}1581\ AYS_{it} + 0{,}0083\ LE_{it} + 0{,}0080\ LNFDI_{it} + 0{,}1384\ LNGFCF_{it} + u_{it} \quad (1)$$

$$u_{it} = 0{,}70558 \quad \sum_{j=1, i\neq 1}^{N} w_{ij} + \varepsilon_{it}$$

with:

- $\hat{y}_{it}$: GRDP per capita calculated using the Atlas method for province *i* in period *t*.
- AYS_{it} : Average years of schooling in province *i* during period *t*.
- LE_{it} : Life expectancy in province *i* during period *t*.
- $LNFDI_{it}$: Foreign direct investment in province *i* during period *t*.
- $LNGFCF_{it}$: Gross fixed capital formation in province *i* during period *t*.
- w_{ij} : Element of the spatial weighting matrix for unit pair *i* and *j*.
- u_{it} : Spatial residual of province *i* during period *t*.
- ε_{it} : Residual of province *i* during period *t*.

The AIC value for the SEM model is the smallest at -434.025 compared to the REM and SAR models, both of which have higher AIC values. The smaller the AIC value, the better the model performance. Furthermore, the spatial dependency observed indicates that the SEM model is more suitable for analyzing GRDP per capita under middle-income trap conditions in Indonesia than the REM model.

DISCUSSION

Average Years of Schooling

Based on the regression results presented in Table 4, the probability value for AYS is 0.000, with a coefficient of 0.1581319. This indicates that the AYS variable has a positive and significant effect on GRDP per capita under middle-income trap conditions. The coefficient value of 0.1581319 implies that an increase of 1% in AYS would raise the GRDP per capita of a province in Indonesia by 0.1581319, *ceteris paribus*.

This finding aligns with the human capital theory proposed by Schultz (1961), which suggests that individuals with higher levels of education tend to earn higher wages and have better access to employment opportunities compared to those with lower education levels. If wages reflect productivity, then many people would pursue higher education to enhance their productivity. Consequently, this can contribute to improving national economic outcomes.

These findings align with the study conducted by (Handayani, Bendesa, & Yuliarmi, 2016) , which states that average years of schooling have a positive and significant effect on GRDP per capita. The higher the average years of schooling in a region, the higher the GRDP per capita in that region. Similarly, research by (Islam, Ghani, Kusuma, & Theseira, 2016) as well as (Syamsuddin et al., 2021) jointly explains that average years of schooling positively and significantly affect economic growth. These studies highlight that higher education levels produce skilled workers, which subsequently enhance individual productivity. This, in turn, increases income both at the individual level and on a national scale.

Life Expectancy

Based on the regression results in Table 4, the probability value for LE is 0.240, with a coefficient of 0.008386. This indicates that the LE variable does not significantly influence GRDP per capita under middle-income trap conditions. These findings are consistent with the study by (Alexander et al., 2022) which suggests that life expectancy has a positive but insignificant effect on economic growth.

High life expectancy, if not accompanied by adequate skills, can become a burden for regional development. This issue is exacerbated by the lack of job opportunities for older but still productive individuals. The dependency ratio, reflecting the proportion of the population that is either too young or too old to be productive, places an increasing burden on the working-age population. A study by Hepi and Zakiah (2018) revealed that in 2019, the dependency ratio in Lampung Province was 49%, meaning that every 100 individuals in the productive age group supported 49 non-productive individuals. A high dependency ratio can hinder economic development and growth, as the income earned by the productive population must be divided to support those who are not yet or no longer productive.

Foreign Direct Investment

The results presented in Table 4 indicate that the probability value for LNFDI is 0.139, with a coefficient of 0.0080291. This suggests that the LNFDI variable does not significantly influence GRDP per capita under middle-income trap conditions. These findings align with the study by (Asiyan, 2020) which concluded that foreign direct investment does not significantly impact economic growth. One contributing factor is the fluctuating growth of foreign investment.

Challenges in obtaining permits and the lack of coordination among relevant departments continue to hinder the growth of foreign investment in Indonesia. Additionally, inadequate quality and efficiency of human resources imply that technology transfer plans have not been properly implemented. The competition among advanced and developing countries to attract foreign investment further complicates the situation. Limited domestic markets in Indonesia negatively impact capital returns, while a lack of necessary infrastructure—such as skilled labor, transportation, and technology—further constrains foreign investment growth.

Gross Fixed Capital Formation

The regression results in Table 4 indicate that the probability value for LNGFCF is 0.000, with a coefficient of 0.1383979. This suggests that the LNGFCF variable has a positive and significant effect on GRDP per capita under middle-income trap conditions. A coefficient of 0.1383979 implies that a 1% increase in LNGFCF would raise the GRDP per capita of provinces in Indonesia by 0.1383979, *ceteris paribus*.

Research conducted by (Peoha & Pambudyaningtyas, 2022) also confirms that gross fixed capital formation significantly influences economic growth. Therefore, an increase in gross fixed capital formation can be seen as a driver of economic growth. The Indonesian government should focus on increasing capital formation by allocating state budgets to finance the procurement of capital goods, such as physical infrastructure, which can strengthen the local economy and foster further capital formation efforts.

CONCLUSION

The regression estimation results identify the Spatial Error Model (SEM) as the best-performing model. This model demonstrates two variables that significantly influence GRDP per capita under the middle-income trap conditions in Indonesia, namely the average years of schooling and gross fixed capital formation.

The analysis for 2015–2020 reveals that average years of schooling and gross fixed capital formation positively and significantly affect GRDP per capita in Indonesia, where higher education levels and increased capital formation boost economic outcomes. Conversely, life expectancy and foreign direct investment show no significant impact, with factors like inadequate skills and fluctuating investment levels hindering their influence. Additionally, spatial interdependence exists among provinces, where the GRDP per capita in one region influences its neighboring regions, highlighting the interconnected nature of economic development across Indonesia.

Based on the findings of this research, several recommendations are proposed. The government is encouraged to enhance human resource quality through equitable and accessible education systems to foster human development, drive research and innovation, and establish a knowledge-based economy, enabling Indonesia to transition to a high-income economy and escape the middle-income trap. Additionally, efforts should be focused on increasing capital stock through public investments in infrastructure and facilities to boost production and support regional economic growth. For future researchers, it is recommended to apply Moran's Index for spatial dependency analysis and enhance spatial weight matrices using contiguity-based methods to achieve more accurate and comprehensive results.

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