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ECONOMIC GROWTH AND ITS DETERMINANTS IN LESS-DEVELOPED REGIONS: A PANEL QUANTILE APPROACH

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ABSTRACT

Economic growth is an important phenomenon because it is closely related to the ultimate goal of development, namely community welfare. However, not all regions in Indonesia have experienced an increase in economic growth. Less-developed regions are among those with low economic growth. This study aims to analyze the determinant of economic growth in 40 less-developed regions of Indonesia during 2015-2022 using a quantile panel regression analysis tool. The results show that the fixed capital formation, population, and human development have a significant positive effect on economic growth at low, medium, and high levels of economic growth. The internet usage variable has a significant positive effect on low and medium economic growth levels but has no effect on high economic growth levels. The access to clean water variable has a significant positive effect on low economic growth levels but has a significant negative effect on medium economic growth levels. Meanwhile, at high economic growth levels, access to clean water has no effect. The government is more committed to accelerating development and the community must actively cooperate in regional development to increase regional economic growth.

Keywords: *Economic Growth, Panel Quantile Approach*

JEL: O1; O11; O12; O15; O18

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Introduction

Economic growth is a critical indicator of a country's prosperity, reflecting the increase in the production of goods and services within an economy. According to Todaro & Smith (2011), economic growth occurs when there is a sustained rise in the output of goods and services, which in turn enhances the overall well-being of society. Economic growth has become an important phenomenon for many countries over the past two centuries (Sukirno, 2011). Over time, countries where the majority of the population relied on agriculture have transitioned toward industrialization, driven by advancements in technology (Fajariah & Suryo, 2020). This shift has significantly boosted the production of goods and services, contributing to the overall economic prosperity of these countries.

Wau et al. (2022) argue that the phenomenon of economic growth is not universally applicable, as not all countries experience increases in the production of goods and services, resulting in uneven prosperity. United Nations (2023) highlights this disparity, emphasizing that economic growth remains a central focus of the global development agenda, specifically as the eighth Sustainable Development Goal: Decent Work and Economic Growth. This emphasis stems from the close relationship between economic growth and the overarching objective of sustainable development, which is the well-being of communities.

Indonesia has experienced consistent economic growth in recent years (Coordinating Ministry for Economic Affairs of the Republic of Indonesia, 2022). Despite being classified as a developing country, the Ministry of Finance of the Republic of Indonesia (2021) noted that the Indonesian economy demonstrated resilience during the Covid-19 pandemic, continuing to function amid global disruptions. According to The World Bank (2024), while Indonesia did experience a decline in economic growth during the pandemic, the contraction was relatively modest at -2.1%, especially when compared to other countries such as the United States (-2.8%), the United Kingdom (-10.4%), and Singapore (-3.9%). This resilience highlights the strength of the Indonesian economy in sustaining the needs of its population.

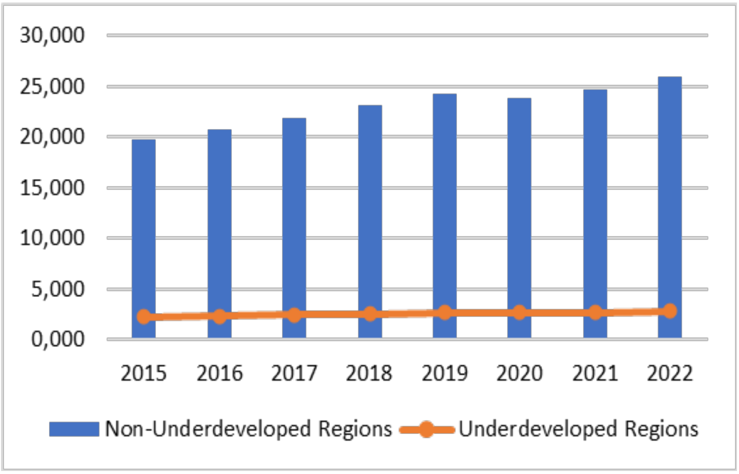

Figure 1: Comparison of Average Gross Regional Domestic Product Values between Developed Regions with Less-Developed Regions 2015-2022

However, despite Indonesia's overall positive economic growth, this progress has not been uniformly experienced across all regions. The Bandung City Government (2016) highlighted that many regions in Indonesia still suffer from low economic growth, commonly referred to as less-developed regions. According to Presidential Regulation No. 63 of 2020, these less-developed regions are characterized by lagging economic development, limited human resources, inadequate infrastructure, financial constraints, poor accessibility, and distinct regional characteristics. Ministry of National Development Planning/ National Development Planning Agency (2023) emphasizes that economic growth in these areas is typically measured by the gross regional domestic product (GRDP). As shown in Figure 1, while both less-developed and developed regions in Indonesia exhibited upward trends in GRDP from 2015 to 2022, there remains a significant disparity. The average GRDP in developed regions was 22.996 trillion rupiah, compared to just 2.526 trillion rupiah in less-developed regions. This stark difference underscores that the benefits of national economic growth have not been evenly distributed, with less-developed regions still struggling to keep pace.

Figure 1 highlights a significant discrepancy between the trends in GRDP value and GRDP growth rate in less-developed regions from 2015 to 2022. Specifically, while the GRDP value in these regions shows a fluctuating but generally upward trend, the GRDP growth rate exhibits a consistent decline. This indicates that economic output in less-developed areas is increasing over time, albeit unevenly. However, the rate of growth is slowing down, suggesting that, despite some progress, the pace at which economic activities are expanding is insufficient. To capitalize on their development potential, these regions require targeted support and initiatives to stimulate more strapping economic growth.

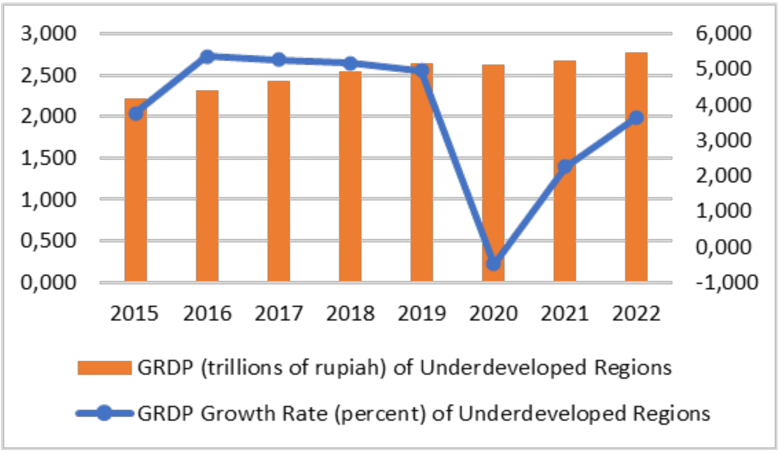

Figure 2: Product Value Comparison Gross Regional Domestic Product (GRDP) with the GRDP Growth Rate of Less-developed Regions 2015-2022

Economic growth plays a key role in the development of a region or country, as illustrated in Figure 1 and Figure 2. Manurung et al. (2022) emphasize the significance of economic growth as a key indicator for assessing the economic performance of a nation's development process. This importance is further supported by Guo & Zhang (2023) who note that many countries utilize economic growth to measure the potential and competitiveness of their economic development. This, in turn, impacts the formulation of economic policies and the regulation of social resource allocation.

Various factors contribute to the fluctuations in economic growth. Studies by Thaddeus et al. (2021), Manurung et al. (2022) and Zarkovic et al. (2022) suggest that significant capital inflows can attract investment, thereby enhancing economic growth. Additionally, Hadush et al. (2023) highlight that the number of workers influences productivity and the benefits derived from economies of scale.

Moreover, the quality of human resources, as measured by the Human Development Index, is crucial for economic productivity. Research by Hossain & Mitra (2013), Hutajulu et al. (2020), and Tampubolon et al. (2022) underscores the role of human development in driving economic outcomes. Similarly, Fridyansyah et al. (2023) demonstrate the impact of health on economic productivity. Furthermore, the adoption of technology, particularly the use of the internet, is identified as another critical factor influencing economic growth, as noted by

Putri & Idris (2022) and Purnamasari & Amaliah (2023). In summary, the interaction between capital investment, labor force dynamics, human resource quality, health, and technological advancements collectively shapes the trajectory of economic growth.

Despite the extensive body of research on economic growth, previous studies have yielded mixed results, particularly in the context of less-developed regions. Notably, there is a significant gap in the literature, as existing research has largely overlooked the economic growth potential of these regions, which are often included in the National Priority Areas (DPN). Given the substantial development potential in less-developed regions, it is crucial to explore the specific factors that drive their economic growth. This study aims to fill this gap by examining the determinants of economic growth in less-developed regions, with a particular focus on Indonesia. By employing a panel quantile regression approach, this research seeks to provide a more nuanced and accurate analysis of the factors influencing economic growth. The study will specifically investigate the roles of human development, internet usage, and access to clean water in shaping economic outcomes in these regions. Through this approach, the research addresses the critical need for tailored economic policies that can effectively leverage the unique characteristics and potential of less-developed regions. By identifying the key drivers of growth in these areas, the study aims to contribute to more equitable and sustainable economic development strategies.

Literature Review

The Solow growth theory model first developed by Robert M. Solow in 1970 describes how economic growth in developing countries assumes that economic growth is influenced by capital accumulation (savings and investment) labour (population growth), and technological progress (Nurwanda & Rifai, 2018). According to Munguía et al. (2019), technological progress is defined as a residual factor to explain long-term economic growth as an exogenous variable that describes the efficiency of capital and labor. In capital efficiency, the technology in question can be in the form of sophisticated machines or equipment used in the production process., while in labor efficiency, technology can be interpreted as public knowledge regarding the methods used during production activities. Varszegi (2018) added, these methods are referred to as the level of education, health, or skills of the community in production. Dietz & Rosa (1997) further stated that economic growth can be influenced by capital, labor, and technological progress. The technology is not only sophisticated machine tools but also socioeconomic factors that underlie it.

This study uses the Solow-Harrod neutral growth model which is one of the growth models that corresponds to the economy in a steady state condition so that the equation is written as,

$$Y = F(K,AL) \tag{1}$$

Time is assumed to exist but not written. is labor efficiency. If using the assumption of constant return to scale, the following equation is written,

$$\lambda Y = F(\lambda K, \lambda AL) \tag{2}$$

Then both sides are divided by AL so the incentive production function becomes,

$$\tfrac{Y}{AL} = F(\tfrac{K}{AL}, 1) \tag{3}$$

$$\widehat{y} = f(\widehat{k}) \tag{4}$$

The Solow-Harrod neutral model of technological progress fits into the Cobb-Douglass function.

$$F(K,AL) = K^{\alpha}(AL)^{1-\alpha} \tag{5}$$

Based on equation 4, Jones (2002) explains Y is the combined output of physical capital and human capital at constant returns to scale2. In Romer (1986) and Hall & Jones (1998) the equation becomes,

$$Y(t) = K(t)^{\alpha}[A(t)H(t)]^{1-\alpha} \tag{6}$$

is labor-augmenting technology whose growth is exogenous at level.

The Solow growth model, as referenced in equation 5, posits that technological progress is an exogenous factor, specifically a labor-augmenting technology that grows at a constant rate. This contrasts with the model proposed by Mankiw et al. (1992), which suggests that at any given level of consumption, the addition of both physical and human capital is critical, akin to Lucas's (1988) assumption that the time invested in skill acquisition is comparable to students attending school (Hall & Jones, 1998; Romer, 2012). Capital, in particular, plays a crucial role in driving economic growth as it underpins production activities. Gross fixed capital formation (GFCF), a key form of capital investment, encompasses expenditures on long-term capital goods such as buildings, machinery, and infrastructure. As noted by Ugochukwu & Chinyere (2013) and the Pemerintah Daerah Istimewa Yogyakarta (2018), GFCF is vital for fostering an investment climate conducive to economic growth, particularly in the form of social and economic infrastructure. Moreover, Zasriati (2022) emphasized that capital formation can be instrumental in addressing less-developed regions, highlighting its importance in economic policy.

The role of the population in economic growth is similarly significant, particularly through the lens of population density, which influences economies of scale (Bere et al., 2014; Darma, 2021; Zhang & Cheng, 2023). Adam Smith, as referenced by Deliarnov (2015), considered population growth a factor that can enhance productivity by increasing the labor force. This expansion in labor can lead to higher productivity levels, thereby contributing to economic growth. However, the relationship between population growth and economic outcomes is not unidirectional. Robert Malthus, in contrast to Smith, argued that excessive population growth could lead to high unemployment rates, ultimately dampening economic growth (Guo & Zhang, 2023; Mustika, 2011). This underscores the necessity of effective population control measures to ensure that economic growth is sustained (Harjanto, 2021). These varying perspectives highlight the complexity of the population-growth relationship and suggest that nuanced policy interventions are required.

Technological progress is universally recognized as a critical driver of economic growth, primarily through innovations that increase production efficiency while reducing labour and capital costs (Coordinating Ministry for Economic Affairs of the Republic of Indonesia, 2021). However, technology encompasses more than just physical tools or equipment; it also includes socioeconomic factors such as the Human Development Index (HDI), internet usage, and access to clean water. These factors are particularly relevant in less-developed regions, as they reflect the socioeconomic conditions that can either hinder or promote growth. A high HDI, for example, indicates a well-developed human resource base, which can enhance labor productivity, drive innovation, and ultimately increase per capita income, leading to economic growth (Mustain et al. 2023; Rahmawati, 2019). Similarly, the internet transforms business operations by expanding market reach and reducing promotional costs, thereby maximizing profits and stimulating economic activity (Lela et al., 2023; Liu & Feng, 2022). Access to clean water, as emphasized by Tropp (2005) and the World Bank (2024b), is another critical factor that supports productivity across all sectors and contributes to long-term economic and environmental sustainability.

Empirical evidence supports the positive impact of these factors on economic growth. For instance, studies by Manurung et al. (2022) and Zarkovic et al. (2022) found that GFCF positively influences economic growth through panel regression analysis, while Thaddeus et al. (2021) confirmed similar results using the ARDL method. Furthermore, Hadush et al. (2023) demonstrated that population growth positively affects economic outcomes using dynamic panel methods, with corroborating findings by Hasegawa & Hamori (2016) through BMA analysis. The positive relationship between HDI and economic growth is also well-documented, as shown in studies by Hutajulu et al. (2020) and Tampubolon et al. (2022) who used LSDV methods and panel regression , respectively. Additionally, Purnamasari & Amaliah (2023) identified a positive impact of internet usage on economic growth through OLS regression, while Fridyansyah et al. (2023) demonstrated that access to clean water is similarly influential, using panel regression tools.

In light of these findings, it is evident that a multifaceted approach is necessary to drive economic growth in less-developed regions. Capital formation, population management, technological progress, and socioeconomic infrastructure, such as HDI, internet access, and clean water, are all critical components. Future research and policy should focus on integrating these elements to create a holistic strategy for sustainable development.

Data and Research Methods

This study uses a descriptive method with a quantitative approach that aims to analysis and test the effect of gross fixed capital formation (GFCF), population, Human Development Index (HDI), internet usage, and access to clean water on economic growth in less-developed regions in Indonesia in 2015-2022. The study utilizes secondary data sourced from BPS-Statistics Indonesia, and the data analysis is performed using quantile panel regression.

The selection of research areas for this study is motivated by the observed disparity in economic growth between less-developed regions and the national average in Indonesia. While national economic growth has shown a consistent upward trend, the economic performance in less-developed regions remains relatively low. This discrepancy presents an intriguing area for further investigation, with the goal of achieving equitable welfare for all Indonesian citizens. The study focuses on the period from 2015 to 2022, chosen based on the Presidential Regulations of the Republic of Indonesia Number 131 of 2015, which designates less-developed regions for the 2015-2019 period, and Number 63 of 2020, which extends this designation for the 2020-2024 period. As of 2022, there are 62 districts and cities in Indonesia classified as less-developed regions. From these 62 less-developed regions, a sample of 40 regions was selected for this study. The sampling was conducted using a systematic sampling technique, where the sample was determined based on the completeness of available data. Only 40 of the 62 regions met the criteria for data completeness, making them suitable for inclusion in the research.

Quantile panel regression, introduced by Koenker & Bassett (1978) in their work "Econometrica" and further developed by Koenker (2004) in "Quantile Regression for Longitudinal Data," is employed as the primary data analysis technique. This method models the relationship between dependent and independent variables by dividing the data into specific quantiles, which are hypothesized to yield different estimates, thereby producing more precise results (Li & Li, 2020). Unlike OLS regression, which provides a single estimate, quantile panel regression offers multiple estimates based on the selected quantile levels (Flores et al., 2014). This approach also has the advantage of not requiring classical assumptions, as it can control for individual heterogeneity (Buhai, 2004). In this study, the estimation was conducted multiple times to determine the appropriate number of quantiles, with the selected quantile levels being 0.25, 0.50, and 0.75.

The study also incorporates three approaches to diagnose cross-sectional dependency in the panel data, including the Pesaran test (2004), Friedman test (1937), and Frees test (1995, 2004). Cross-sectional dependency occurs when observations in panel data are interrelated, leading to a situation where observations in one sector or unit are not entirely independent of those in other sectors or units (Tugcu, 2018). Hoyos & Sarafidis (2006) noted that panel data models often exhibit significant cross-sectional dependencies, which can result from factors such as high correlations between cross-sections or the presence of unobserved components. These dependencies can lead to inaccurate standard error calculations and biased or inconsistent estimates. Baltagi (2005) emphasized the importance of testing for cross-sectional dependency to ensure the accuracy of panel data model analyses. In this study, the Pesaran test (2004) is employed to test the null hypothesis of no cross-sectional dependency, following the framework provided by Damrah et al. (2022). The formula is written as follows:

$$CD = \left(\frac{TN(N-1)^{\frac{1}{2}-P}}{2} \right) \tag{7}$$

where $P = \left(\frac{2}{N(N-1)} \right) \sum_{i=1}^{N-1} \sum_{j=i+1 \rho ij, \rho ij}^{N}$ is the correlation coefficient.

The Friedman test, introduced by Friedman (1937), is a non-parametric method used to detect differences across multiple groups by analyzing the average Spearman correlation. In panel data analysis, this test helps identify cross-sectional dependency, which occurs when observations in different units are not independent, often due to shared factors. In this study, the Friedman test is applied to ensure that the panel data model accurately accounts for any dependency among observations. By identifying such dependencies, the analysis becomes more reliable, providing stronger evidence on the factors influencing economic growth in less-developed regions. The formula is written as follows:

$$R_{ave} = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \widehat{r_{ij}} \tag{8}$$

where $\widehat{r_{ij}}$ is the rank correlation coefficient.

Moreover, the Frees test proposed by Frees (1995, 2004) is based on coefficients correlation ranking square with draft following.

$$R_{ave}^{2} = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \widehat{r_{ij}^{2}} \tag{9}$$

Another potential issue in regression analysis is heteroscedasticity, which refers to the non-uniformity of residual variance in the model. When heteroscedasticity is present, the variance of the residuals is inconsistent or changes with variations in the independent variables. This inconsistency leads to biased and inaccurate estimation results (Panjawa & Sugiharti, 2021; Widarjono, 2018). The second step, to detect heteroscedasticity in this study is the Breusch-Pagan test, which is a widely used method to identify whether the assumption of constant variance holds true.

Additionally, when working with time series data, it is crucial to examine for unit root problems. A unit root indicates a stochastic trend or a random walk in the time series, where deviations persist over time. If a time series contains a unit root, the model becomes unpredictable and unreliable (Burdisso & Sangi´acomo, 2016). Identifying unit roots is essential to distinguish variables that exhibit unstable long-term trends or stochastic behavior, which could compromise the validity of the analysis (Shariff & Hamzah, 2015). The third step, In this study, the CIPS (cross-sectionally augmented Im-Pesaran-Shin) unit root test, is applied to test for stationarity. Proposed by Pesaran (2007), the CIPS test builds on the augmented Dickey-Fuller model, with the null hypothesis assuming that the model is non-stationary. The formula is written as follows:

$$CIPS = N^{-1}\sum_{i=1}^{n} CADF \tag{10}$$

where is a cross-sectional augmented Dickey-Fuller regression that can be written through equality as following.

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \delta_{0i}\Delta\overline{y}_t + \delta_{1i}\Delta\overline{y}_{t-1} + \varepsilon_{it} \tag{11}$$

The fourth step in the diagnostic testing process involves examining cointegration, which refers to a long-term relationship between variables that may exhibit stationary behavior (Anisa, 2010). Cointegration testing is crucial for understanding the enduring connections between economic variables, as it provides more stable and consistent estimates (Hjalmarsson & Österholm, 2007). In this study, the Westerlund test (2005) is employed to assess cointegration, with the null hypothesis suggesting the absence of cointegration. The Westerlund test is advantageous because it typically produces normally distributed results and accounts for short-term dynamic individual effects, individual trends, slope parameters, and cross-sectional dependencies. Additionally, the Pedroni test (1999, 2004) is utilized, which is based on a residual approach. This test calculates residuals from the cointegration regression and applies distribution restrictions to the model, thereby enhancing its robustness.

Following the cointegration analysis, the next step is to estimate the panel model to determine the most appropriate model to use. The Hausman test is conducted to decide between a fixed effect model and a random effect model, with the null hypothesis favoring the random effect model. Identifying the best panel regression model is essential for obtaining accurate estimation results. Once the optimal panel model is selected, the study proceeds with quantile panel regression, where different quantile levels are used to capture variations in the data. The selected quantile levels in this study include 0.25, 0.50, and 0.75. According to Koenker (2004), quantile panel regression is an extension of quantile regression, which assumes that all quantiles (Y_q) of the conditional distribution $(y \mid x)$ are linear function of (x). The quantile regression model is thus specified as follows. These steps ensure that the analysis is both thorough and methodologically sound, allowing for a deeper understanding of the relationships between variables and producing more reliable results. By carefully selecting and applying the appropriate tests and models, the study enhances the robustness of its findings and contributes to a more nuanced interpretation of economic dynamics.

$$Y_q(X_i) = X'_i\beta_q + u_i \text{ (i =1,2,...,n)} \tag{12}$$

where 0 < q < 1 is the quantile, β_q indicating the q-th quantile regression coefficient and its estimator can be obtained from the equation below.

$$\widehat{\beta_q} = \arg_{\beta_q}\min\left(\sum_i q \mid y_i - X'_i\beta_q \mid + \sum_i (1-q) \mid y_i - X'_i\beta_q \mid\right) \tag{13}$$

The application of quantile regression to panel data results in the development of a quantile panel regression model. This advanced modelling approach allows for the estimation of relationships between variables at different points in the conditional distribution of the dependent variable, rather than focusing solely on the mean. By incorporating the panel data structure, quantile panel regression offers a more nuanced analysis, capturing the heterogeneity across different quantiles while accounting for the unobserved individual effects that may influence the outcomes.

The quantile panel regression model is particularly useful in scenarios where the impact of independent variables varies across the distribution of the dependent variable. This method provides a comprehensive understanding of the data by revealing how these effects differ at various quantiles, offering insights that traditional mean-based regression models might overlook. As such, quantile panel regression is a powerful tool for exploring complex economic relationships, making it highly relevant for studies aiming to uncover differential impacts across various segments of the population or different levels of economic performance.

The integration of quantile regression within the panel data framework thus enhances the robustness and flexibility of the analysis, allowing researchers to derive more detailed and accurate conclusions from their data. This approach is especially valuable in economic studies where distributional effects are critical to understanding the full range of influences on key outcomes, such as growth. The following is a general quantile panel model:

$$Y_q(X_{it}) = \alpha_i + X'_i\beta_q + u_{it} \text{ (i=1,2,...,n;t=1,2,...,T)} \tag{14}$$

where α_i indicates individual heterogeneity that does not change over time and u_{it} exhibits a random error term. Based on equation 8, estimate the parameters of the quantile panel regression model can stated as follows:

$$\widehat{\alpha_q}, \widehat{\beta_q} = \underset{\widehat{\alpha_q}\widehat{\beta_q}}{\text{argmin}} \left\{\sum_i \sum_t \rho_q(y_{it} - \alpha_{i(q)} - X'_{it}\beta_q) + \lambda \sum_i \mid \alpha_{i(q)} \mid\right\} \tag{15}$$

where $\widehat{\alpha_q}, \widehat{\beta_q}$ is the final quantile regression estimator when $\lambda > 0$ and $\widehat{\alpha_q}, \widehat{\beta_q}$ is the fixed effects quantile estimator when $\lambda = 0$.

Empirical Model

This study employs Solow's labor-augmenting production theory, which incorporates technology (A) as an exogenous factor (Jones & Vollrath, 2013). The production function is expressed as follows:

$$Y = F(K, AL) \tag{16}$$

$$Y = K^\alpha (AL)^{1-\alpha} \tag{17}$$

Building on the work of Hall & Jones (1998) , which assumes constant returns to scale at time t, the production function is:

$$Y(t) = K(t)^{\alpha}[A(t)H(t)]^{1-\alpha} \tag{18}$$

where K represents capital, A denotes technology that enhances labour efficiency, H s the aggregate labor productivity across various skill levels, and ttt signifies continuous time. To linearize this function, we take the natural logarithm:

$$\ln Y_t = \alpha \ln K_t + (1-\alpha)\ln H_t + (1-\alpha)\ln A_t \tag{19}$$

In this model, Y is proxied by gross regional domestic product (GRDP). According to Hall & Jones (1998) and incorporating related studies, the proxies used include gross fixed capital formation (GFCF) for capita (K) (Zarkovic et al., 2022). Total population (Hadush et al., 2023); Human Development Index (HDI) (Tampubolon et al., 2022); internet usage (Purnamasari & Amaliah, 2023); and access to clean drinking water (Fridyansyah et al., 2023) for human capital (H). Thus, human capital is decomposed as follows:

$$H = f(population, HDI, \text{int}ernet\ usage, access\ to\ clean\ water) \tag{20}$$

$$H = \gamma_1 population + \gamma_2 HDI + \gamma_3 \text{int}ernet\ usage + \gamma_4 access\ to\ clean\ water \tag{21}$$

Based on the Solow residual concept, technology (A) is estimated as the residual in the equation. Consequently, the final form of the model is:

$$\begin{aligned} \ln GRDP = \alpha \ln GFCF + (1-\alpha)(\gamma_1 \ln Population + (1-\alpha)\gamma_2 \ln HDI + \\ (1-\alpha)\gamma_3 \ln \text{int}ernet\ usage + \gamma_4 \ln Access\ to\ clean\ water) \end{aligned} \tag{22}$$

This approach provides a detailed analysis of economic growth by integrating various proxies and capturing the effects of technological and human capital on output. Furthermore, parameterization is carried out as follows: $\beta_1 = \alpha$; $\beta_2 = (1-\alpha)\gamma_1$; $\beta_3 = (1-\alpha)\gamma_2$; $\beta_4 = (1-\alpha)\gamma_3$; $\beta_5 = (1-\alpha)\gamma_4$

The following are the parameterization results of equation 22.

$$\begin{aligned} \ln GRDP_{it} = \beta_1 \ln GFCF + \beta_2 \ln Population_{it} + \beta_3(q)\ln HDI + \\ \beta_4 \ln Internet\ usage + \beta_5 \ln Access\ to\ clean\ water \end{aligned} \tag{23}$$

Equation 23 is transformed into a quantile panel econometric model into,

$$\begin{aligned} \ln GRDP_{it}(q) = \beta_1(q)\ln GFCF_{it} + \beta_2(q)\ln Population_{it} + \beta_3(q)\ln HDI_{it} + \\ \beta_4(q)\ln Internet_{it} + \beta_5(q)\ln Akses\ air\ \min um\ bersih_{it} + \varepsilon_{it} \end{aligned} \tag{24}$$

The natural logarithm (ln) transformation of the Log-Log model is performed because the Solow growth model is a derivative of the Cobb-Douglas production function and to avoid equation errors in interpreting the intercept coefficient. Another reason is to reduce excessive data fluctuations, avoid heteroscedasticity, determine the coefficient that shows elasticity, and bring the scale of the data closer (Kwakwa, 2023). Referring to research conducted by Kwakwa (2023), Zahiripour (2023), Ali et al. (2024) and Taussig (2024), there is a need for data transformation into the form of natural logarithms to produce more efficient and accurate estimates. According to Nachrowi & Usman (2006), there are three types of natural logarithm transformation models, as follows.

1. Log-Log model, the dependent variable and the independent variable are transformed into natural logarithms.

2. Log-Lin model, the dependent variable is transformed into the natural logarithm form while the independent variable remains.
3. Lin-Log model, the independent variable is transformed into a natural logarithm while the dependent variable is fixed.

The transformation into the natural logarithm form in equation 24 can also be written as,

$$\ln g\, rdp_{it}(q) = \alpha_i(q) + \beta_1(q)\ln g\, fcf_{it} + \beta_2(q)\ln pop_{it} + \beta_3(q)\ln hdi_{it} + \beta_4(q)\ln net_{it} + \beta_5(q)\ln cwa_{it} + \varepsilon_{it} \quad (25)$$

Where:

$\ln g\, rdp$: Gross Regional Domestic Product (logarithm natural).

$\ln g\, fcf$: Gross Fixed Capital Formation (logarithm natural).

$\ln pop$: population (logarithm natural).

$\ln hdi$: Human Development Index (logarithm natural).

$\ln net$: internet or internet usage (logarithm natural).

$\ln cwa$: clean water or access to clean water (logarithm natural).

ε : error term.

it : panel data (for cross-sections and for time series).

q : quantile.

Finding and Discussion

Diagnostic Test

Testing dependency cross sectoral through the Pesaran test approach (2004), Friedman test (1937), and Frees test (1995, 2004) produces output as following. The null hypothesis formulation is that there is no cross-sectoral dependence with the selected significance level of α = 0.05. The test criteria state that H_0 is rejected if the probability value is < α. Based on Table 4.2, in the Pesaran test, the probability value shows the number 0.000 < α 0.05. The decision to reject H_0 means that the model has a dependence on cross-sectoral or cross-section. While in the Friedman test the probability value shows the number 0.2731 > α 0.05. Moreover, with the Frees test the statistical value is more than the critical value, which is 7.115 > 0.4325 (α 0.05). The decision to fail to reject H_0 means that the model does not have a dependence on cross-sectoral or cross-sectional.

Table 1: Cross-sectional Dependence Test

Pesaran's test = 9.804	0.0000
Friedman's test = 43.858	0.2731*
Frees' test = 7.115	alpha = 0.10 : 0.3169*
	alpha = 0.05 : 0.4325*
	alpha = 0.01 : 0.6605*

Note: *significant α = 0.05

Cross-section dependence testing in the Friedman test and the Frees test shows that there is no cross-sectoral dependence. However, the Pesaran test shows cross-sectoral dependence or cross-sectional dependence. If ignored, it will reduce the efficiency of panel data. This can be caused by several reasons, such as the presence of unobserved common factors, spatial correlation, or economic distance. Ignoring cross-sectional dependence in panel data can interfere with the precise parametric value of the estimate. In this regard, unit root testing is needed to produce efficient and accurate estimates (Damrah et al., 2022).

Second, the Breusch-Pagan/Cook-Weisberg test is employed for detecting heteroscedasticity. This testing determines whether the variance of residuals is constant across different levels of the independent variables. The null hypothesis is there is no heteroscedasticity problem with a significance level of α = 0.05. The test criteria state that is rejected if the probability value is > α. In Table 2, the results of the heteroscedasticity test show that the chi square probability value is > α 0.05, which is 0.5373. The decision fails to reject , which means that there is no heteroscedasticity problem and the model is homoscedastic. This shows that the residual variance in the model is constant so that it can estimate the estimation results accurately and without bias.

Table 2: Heteroscedasticity Test

Breusch-Pagan/Cook-Weisberg Test for Heteroscedasticity	
chi2(1) = 0.38	Prob > chi2 = 0.5373*

Note: *significant α = 0.05

The third step is unit root test. Based on the results of the Pesaran test which showed cross-sectoral dependency, a unit root test was conducted to identify whether the model was stationary or not. This means that the variables have an unstable trend and behave stochastically or run at a constant level. The null hypothesis of the model is not stationary with a significance level of α = 0.01; 0.05; and 0.10. The test criteria state that is rejected if the CIPS value < critical value. The requirement for a stationary model or one that does not contain a unit root is that in testing the unit root of each variable, all variables must be stationary at the same level.

Table 3: Unit Root Test

Variable	Intercept		Intercept with Trend	
	Levels	1 stDiff	Levels	1 stDiff
lngrdp	-2.251***	-2.508*** +	-2.403	-2.552
lngfcf	-2.018*	-2.566*** +	-2.697*	-2.109
lnpop	-3.178***	-5.611***	-5.714***	-5.969*** +
lnhdi	-1.948	-3.344***	-3.145***	-4.045*** +
lnnet	-2.059*	-3.297***	-2.966***	-3.553*** +
lncwa	-2.264***	-3.688***	-3.147***	-4.371*** +

Note: ***CIPS < 0.01 (critical value -2.36); **CIPS < 0.05 (critical value -2.16); *CIPS < 0.10 (critical value -2.05) on intercept; ***CIPS < 0.01 (critical value -3.00); **CIPS < 0.05 (critical value -2.75); *CIPS < 0.10 (critical value -2.63) on intercept with trend; + selected first difference model.

Based on the results of the Pesaran test which showed cross-sectoral dependency, a unit root test was conducted to identify whether the model was stationary or not. This means that the variables have an unstable trend and behave stochastically or run at a constant level. The null hypothesis of the model is not stationary with a significance level of α = 0.01, 0.05, and 0.10. The test criteria state that H_0 is rejected if the CIPS value <critical value. The requirement for a stationary model or one that does not contain a unit root is that in testing the unit root of each variable, all variables must be stationary at the same level.

The last diagnostic test**,** cointegration testing is employed to explore the long-term relationships between variables, even when these variables exhibit short-term fluctuations that are independent of each other. This approach is crucial for producing more stable and consistent estimates by identifying whether variables move together over the long term despite their short-term volatility (Hjalmarsson & Österholm, 2007). The null hypothesis for cointegration testing posits that no cointegration exists among the variables, with a significance level set at α = 0.05. According to the test criteria, the null hypothesis is rejected if the p-value is less than α. As demonstrated in Table 4, the results from the Westerlund and Pedroni cointegration tests yield p-values of 0.004 and 0.000, respectively, both of which are below the significance level of 0.05. This indicates strong evidence against the null hypothesis, leading to its rejection. Consequently, the results suggest the presence of cointegration, affirming a significant long-term relationship between the variables under study.

Table 4: Cointegration Test

Testing	Model	Statistics	Prob.
Westerlund		3.3368	0.0004*
Pedroni	Modified Phillips–Perron	10.1474	0.0000*
	Phillips–Perron	-12.3560	0.0000*
	Augmented Dickey–Fuller	-9.3868	0.0000*

Note: *significant α = 0.05

Result

Hausman test

Hausman test is utilized to determine the most suitable model for estimating panel data, specifically whether the fixed effect or random effect model should be applied. The null hypothesis of the Hausman test posits that the random effect model is appropriate, while the alternative hypothesis suggests that the fixed effect model is more suitable. This hypothesis is tested at a significance level of α = 0.05, with the criterion for rejecting the null hypothesis being a p-value less than α. As presented in Table 5, the Hausman test results in a p-value of 0.000, which is below the 0.05 threshold. This p-value leads to the rejection of the null hypothesis, indicating that the fixed effect model is more appropriate for this analysis than the random effect model. Consequently, the fixed effect model is selected as the most suitable approach for panel data estimation. Given that the random effect model and common effect model are deemed inappropriate, the Lagrange Multiplier test for model selection is not necessary.

Table 5: Hausman test

chi2(5) = 71.90	Prob > chi2 = 0.0000*

Note: *significant α = 0.05

Quantile Panel Regression

Quantile panel regression is employed to examine the impact of independent variables across different quantiles, providing a more nuanced and accurate understanding of these effects. Unlike ordinary least squares (OLS) regression, which estimates a single average effect, quantile panel regression evaluates the relationship between variables at multiple quantile levels. This approach allows for the analysis of how variables influence different points of the conditional distribution, thereby capturing a broader range of potential outcomes.

In this study, quantile panel regression is conducted at three quantile levels: 0.25, 0.50, and 0.75. This methodology provides insights into the effects of the independent variables—specifically, lngfcf, lnpop. lnhdi, lnnet, and lncwa across these quantile levels. Table 6 presents the results of this quantile panel regression analysis, highlighting how the relationships between the variables vary at each quantile level. This detailed examination facilitates a deeper understanding of the variable effects and improves the precision of the output

Table 6: Quantile Panel Regression

	0.25		**0.50**		**0.75**	
Variables	**Coef.**	**Prob.**	**Coef.**	**Prob.**	**Coef.**	**Prob.**
lngfcf	0.6940	0.000***	0.6676	0.000***	0.7635	0.000***
lnpop	0.1717	0.000***	0.1626	0.000***	0.0676	0.021**
lnhdi	1.1719	0.000***	0.5869	0.000***	1.4184	0.000***
lnnet	0.0053	0.014**	0.0386	0.000***	-0.0140	0.718
lncwa	0.0219	0.000***	-0.0313	0.005*	0.0323	0.372

Note: ***significant α = 0.01; **significant α = 0.05; *significant α = 0.10.

The estimation results presented in Table 6 reveal that the variable for gross fixed capital formation (GFCF) denoted as lngfcf has a positive and statistically significant impact on economic growth in less-developed regions. The probability value of the z-statistic is less than 0.05 (0.000) across all quantile levels—0.25, 0.50, and 0.75. Additionally, the positive coefficient values for these quantiles are 0.6940, 0.6676, and 0.7635, respectively. These results indicate that increases in GFCF are associated with enhanced economic growth at low, medium, and high levels of economic growth in less-developed regions.

Similarly, the variable for population lnpop also demonstrates a positive and significant effect on economic growth. The z-statistic probability values are 0.000 at the 0.25 and 0.50 quantile levels, and 0.021 at the 0.75 quantile level, all of which are below the significance threshold of 0.05. The coefficient values for population are 0.1717, 0.1626, and 0.0676 at the 0.25, 0.50, and 0.75 quantiles, respectively. This suggests that an increase in population contributes positively to economic growth across various levels of economic activity in less-developed regions.

The Human Development Index (HDI), represented by lnhdi, also has a notable and significant positive effect on economic growth. The z-statistic probability values are 0.000 at all three quantile levels (0.25, 0.50, and 0.75), with positive coefficient values of 1.1719, 0.5869, and 1.4184, respectively. This indicates that higher HDI values are associated with increased economic growth at all quantile levels in less-developed regions.

Internet usage (lnnet) shows a positive and significant influence on economic growth at the 0.25 and 0.50 quantile levels, with z-statistic probability values of 0.014 and 0.000, respectively, and coefficient values of 0.0053 and 0.0386. This suggests that increases in internet usage positively affect economic growth at low and medium levels. However, at the 0.75 quantile level, the z-statistic probability value is 0.718, indicating that internet usage does not significantly impact economic growth at high levels.

Finally, access to clean water (lncwa) presents mixed results. At the 0.25 quantile level, it has a significant positive effect on economic growth, with a z-statistic probability value of 0.000 and a coefficient of 0.0219. Conversely, at the 0.50 quantile level, the effect is negative, with a probability value of 0.005 and a coefficient of -0.0313, suggesting that increased access to clean water may actually reduce economic growth at moderate levels. At the 0.75 quantile level, the effect is not significant, as indicated by a z-statistic probability value of 0.372.

The diagnostic tests conducted in this study, including heteroscedasticity testing, cointegration analysis, cross-sectional dependency tests, and unit root tests, collectively affirm the robustness and reliability of the econometric models used. The Hausman test provided additional validation by confirming the suitability of the fixed effect model over alternative specifications, with a probability value indicating a clear preference for this model. These rigorous diagnostic checks, including cross-sectional dependency and unit root tests, collectively enhance the credibility of the findings, ensuring that the estimated effects of gross fixed capital formation, population growth, Human Development Index, internet usage, and access to clean water on economic growth are both robust and reliable. This comprehensive approach supports the formulation of well-grounded policy recommendations based on robust empirical evidence.

Discussion

The estimation results presented in Table 6 reveal a significant and positive impact of gross fixed capital formation (GFCF) on economic growth across less-developed regions. Specifically, increases in GFCF are associated with higher economic growth in regions with low, moderate, and high levels of economic activity. For example, areas such as Tambrauw Regency, Puncak Jaya, and South Sorong, which have low levels of economic growth with an average gross regional domestic product (GRDP) of approximately 827.26billion rupiah, benefit from increased GFCF. Similarly, regions with moderate economic growth, such as the Bintang Islands, Mappi, and East Seram, with GRDP ranging from 1,656.32 billion rupiah, and high-growth areas like the Aru Islands, Boven Digoel, East Sumba, and Bintuni Bay, boasting a GRDP of 4,927.05 billion rupiah, also experience positive effects from GFCF. These findings align with established hypotheses and theoretical expectations that capital investment drives economic growth. The results corroborate previous research by Thaddeus et al. (2021), Manurung et al. (2022), and Zarkovic et al. (2022) which demonstrated that increases in GFCF lead to economic growth in various contexts including Cameroon, the European Union, and Banten Province.

The positive impact of GFCF on economic growth is attributed to the inflow of additional capital, which enhances economic activity through infrastructure development such as roads and bridges. This investment not only improves accessibility but also encourages further investment by providing a more attractive environment for investors (Ugochukwu & Chinyere, 2013). In less-developed regions with initially low to moderate economic growth, such as Tambrauw Regency and the Bintang Islands, the effect of GFCF is particularly pronounced due to the high dependence on central government funding and limited local revenue. Increasing the GFCF budget in these areas could address infrastructure deficiencies and boost local economic activity (Directorate General of Financial Balance, 2017). In regions with high economic growth, such as the Aru Islands and East Sumba, enhanced GFCF continues to spur economic development. The active involvement of district governments in promoting regional potential and participating in innovation competitions has attracted more investment, thereby increasing GFCF and improving infrastructure. This, in turn, enhances productivity and economic growth (Saba, 2024).

The results presented in Table 6 underscore the significant positive relationship between population size and economic growth in less-developed regions. This effect is evident across various levels of economic activity. For instance, in areas with low economic growth, such as Tambrauw Regency, Puncak Jaya, and South Sorong—where Gross Regional Domestic Product (GRDP) averages around 827.26 billion rupiah—an increase in population correlates with enhanced economic performance. Similarly, regions experiencing moderate economic growth, including the Bintang Islands, Mappi, and East Seram, with GRDP ranging from 1,656.32 billion rupiah, also show positive growth effects from rising population numbers. High-growth areas like the Aru Islands, East Sumba, and Bintuni Bay, with GRDP averaging 4,927.05 billion rupiah, further illustrate this trend. These findings align with previous research by Hasegawa & Hamori (2016), Fridyansyah et al. (2023) and Hadush et al. (2023), which demonstrates the positive impact of population growth on economic development in Bali, East Africa, and East Asia, respectively. The results confirm the hypothesis that an increasing workforce contributes to economic growth, supporting the theory that a larger population enhances productivity and drives economic expansion.

Population growth serves as a proxy for workforce expansion, which directly influences economic output. A larger population not only boosts production capabilities but also expands market size, fostering higher consumer demand and stimulating economic activity (Darma, 2021). In less-developed areas with varying levels of economic growth, such as Tambrauw, Mappi, and Teluk Bintuni Regencies, increasing the population could significantly enhance economic prospects. Despite high birth rates, these regions often face challenges related to geographical and topographical constraints, which limit habitation and reduce the available labour force (Kusnandar, 2023). By boosting population numbers, these areas can better utilize their potential, accelerate economic activities, and promote growth (Romdiati et al., 2019).

The Human Development Index (HDI) has been proven to have a positive and significant effect on economic growth based on Table 6. Every increase in the HDI will increase economic growth both in less-developed areas with low economic growth levels with GRDP values ranging from 827.26 billion rupiah, including in Tambrauw Regency, Puncak Jaya, and South Sorong. The level of economic growth is moderate with a range of 1,656.32 billion rupiah, namely in the Bintang Islands, Mappi, and East Seram. As well as a high level of economic growth with a range of 4,927.05 billion rupiah such as the Aru Islands, East Sumba, and Bintuni Bay. This is in accordance with research conducted by Hasegawa & Hamori (2016) where the HDI positively influences economic growth in East Asia. Likewise with research conducted by Manurung et al. (2022) and Purnamasari & Amaliah (2023) which shows that a significant increase in the HDI can increase economic growth successively both in Banten Province and on a national scale, namely throughout Indonesia.

The reason why the increasing HDI can also increase economic growth in less-developed areas is because there is an increase in the quality of life, income, education, and health of the community as a benchmark for the HDI value. According to Tampubolon et al. (2022), increasing income indicates that the economy in the area is running well. High levels of education and health mean that accessibility and public awareness of the importance of education and health are also good, so it can be interpreted that the quality of human resources is high. Mustain et al. (2023) added that the high quality of human resources affects labor productivity through innovation and creativity by creating effective and efficient systems, techniques, and equipment in economic activities so that productivity increases and increases economic growth rates.

Tambrauw, Puncak Jaya, and South Sorong Regencies as less-developed areas with low levels of economic growth are directly proportional to the low HDI value. This is because the number of teachers in the area is very lacking so that teaching and learning activities do not run smoothly (Sucahyo, 2023). Meanwhile, in less-developed areas with moderate and high levels of economic growth such as the Bintang Islands Regency, East Seram, East Sumba, and Bintuni Bay, the increase in the HDI value is also directly proportional to the increase in economic growth. This is because the increase in school participation rates indicates that many residents have received education (Papua Provincial Government, 2017b).

The results presented in Table 6 highlight the positive and significant impact of internet usage on economic growth, particularly in less-developed regions. The influence of internet usage is notably significant in areas with low and moderate economic growth. For instance, in regions such as Tambrauw Regency, Puncak Jaya, and South Sorong, with GRDP values around 827.26 billion rupiah, as well as in the Bintang Islands, Mappi, and East Seram, where GRDP ranges from 1,656.32 billion rupiah, increased internet usage is associated with enhanced economic performance. These findings corroborate the theoretical expectation that internet usage positively affects economic growth. They also align with the research of Putri & Idris (2022) and Purnamasari & Amaliah (2023), which demonstrated that greater internet accessibility boosts economic development in Indonesia.

The internet, as a tool for rapid communication and information transfer, significantly transforms business operations. It enables manufacturers to source raw materials globally with ease and facilitates market expansion and reduced promotional costs, thereby optimizing profits (Purnamasari & Amaliah, 2023; Putri & Idris, 2022). Additionally, consumers benefit from improved access to goods and services, further accelerating economic activities and growth (Nasution & Rachmawati, 2020). In less-developed areas with low to moderate economic growth, such as Tambrauw Regency, Puncak Jaya, and Mappi, expanding internet access represents a substantial opportunity for economic enhancement. Addressing internet service gaps, or “blank spots,” can spur entrepreneurial activities and broaden market reach, ultimately fostering rapid economic development (Katingka, 2024; Nasution & Rachmawati, 2020).

Conversely, in regions experiencing high economic growth, such as the Aru Islands, Boven Digoel, East Sumba, and Bintuni Bay—where GRDP reaches approximately 4,927.05 billion rupiah—the impact of internet usage on economic growth is less pronounced. This finding is consistent with Abdillah (2023), which suggests that, despite the high economic output, the optimal utilization of internet resources remains limited. Residents in these areas primarily use the internet for communication rather than for business purposes, indicating that the full potential of internet-driven economic benefits is yet to be realized (Papua Provincial Government, 2017a). Thus, while internet access contributes to economic growth, its benefits are maximized when coupled with effective utilization for business and market expansion.

The quantile panel regression results presented in Table 6 reveal that access to clean water exerts a positive and significant influence on economic growth in less-developed regions with low economic growth levels. Specifically, in areas such as Tambrauw Regency, Puncak Jaya, and South Sorong, which have a GRDP of approximately 827.26 billion rupiah, increased access to clean water correlates with enhanced economic growth. This finding supports the established hypothesis that access to clean water impacts economic development. The results are consistent with prior studies by Fridyansyah et al. (2023) and Thalib et al. (2023), which indicate that improvements in access to clean water contribute to economic growth by elevating living standards and boosting productivity.

Clean water is a crucial natural resource that supports various economic activities, including industry, agriculture, fisheries, and tourism. Its availability directly affects public health and productivity, thereby influencing economic performance. In less-developed regions with low economic growth, enhanced access to clean water can lead to significant economic benefits. This improvement often reflects an increase in living standards, which contributes to overall economic growth. Given the challenging geographical conditions in these regions, expanding access to clean water can drive economic development from low to higher levels (Fridyansyah et al., 2023; Thalib et al., 2023).

Conversely, the impact of access to clean water on economic growth in regions with moderate economic growth levels—such as the Bintang Islands, Mappi, and East Seram, which have a GRDP of around 1,656.32 billion rupiah—is notably negative. In these areas, increased access to clean water can actually detract from economic growth. This adverse effect is attributed to the limited availability of water sources and the associated costs of procuring water, particularly during the dry season, which can range from IDR 480,000 to IDR 1,200,000 per month (Wahana Visi Indonesia, 2023). The high costs of water access can place a financial burden on households, potentially detracting from economic growth.

In regions with high economic growth, such as the Aru Islands, East Sumba, and Bintuni Bay—where the GRDP is approximately 4,927.05 billion rupiah—increased access to clean water does not significantly impact economic growth. This is because clean water in these areas is primarily used for basic household needs, such as bathing, cooking, and washing, rather than for agricultural activities. As these regions rely on river irrigation for agriculture, the demand for clean water for economic activities is relatively low, limiting its effect on economic growth.

Conclusion

The findings of this study highlight the significant effects of gross fixed capital formation (GFCF), population size, Human Development Index (HDI), internet usage, and access to clean water on economic growth in less-developed regions. Specifically, GFCF, population growth, and HDI consistently exhibit positive and significant impacts on economic growth across low, medium, and high levels of economic activity. Increases in these variables are associated with enhanced economic performance, supporting established economic theories and previous research.

Internet usage positively influences economic growth at low and moderate levels but shows no significant effect at high levels of economic growth. Conversely, access to clean water has a nuanced impact: it significantly boosts economic growth in regions with low economic activity but exhibits a negative effect in regions with moderate economic growth. In high-growth areas, access to clean water does not significantly affect economic performance.

The results underscore the need for targeted policy interventions to foster economic growth in less-developed regions. Governments should prioritize investments in GFCF, including infrastructure development such as roads, bridges, and internet connectivity. These investments are crucial for stimulating economic activity and attracting further investment. Moreover, enhancing population growth through education and healthcare improvements can drive economic expansion by increasing productivity and market demand.

For regions with low economic growth, improving access to clean water is vital as it contributes significantly to economic development. However, in areas with moderate economic growth, policymakers should address the high costs associated with water access to avoid potential negative economic impacts. In high-growth regions, focusing on optimizing the use of internet resources and exploring other areas of economic potential could yield better results.

This study is limited by the availability and scope of data, which restricts the ability to generalize findings beyond the sampled regions. The analysis is based on a subset of less-developed areas rather than the entire population, which may impact the comprehensiveness of the results. Additionally, the study does not account for potential variables such as tourism or alternative measures of population dynamics, which could influence economic growth.

Future research should consider expanding the dataset to include a broader range of less-developed regions to enhance the generalizability of the findings. Incorporating additional variables, such as tourism activity or employment metrics, could provide deeper insights into the factors influencing economic growth. Furthermore, exploring alternative research methodologies may refine the estimation results and yield more robust conclusions. Investigating the interplay between different variables and their cumulative effects on economic growth could also offer valuable perspectives for policy formulation and regional development strategies.

Originality

Research on the determinants of economic growth in less-developed regions remains scarce, typically focusing on individual regions or areas without providing a comprehensive analysis of multiple less-developed regions as a whole. Furthermore, there is a notable absence of studies employing the quantile panel regression method to explore these determinants. This method, which segments data into specific conditional quantiles, offers more accurate estimations and better reflects the actual conditions of the study areas.

This study addresses these gaps by utilizing the quantile panel regression approach, which is relatively novel in Indonesia. By applying this method, the research provides a more precise analysis of economic growth determinants across a broader range of less-developed regions. The selected variables are carefully chosen to represent the key issues faced by these regions. Consequently, the study's findings are expected to make a significant contribution to the formulation of government policies, offering insights that are both accurate and relevant to the specific challenges encountered by less-developed regions in Indonesia.

Declaration

In this section, we declare that this research: (1) No conflict of interest (2) Availability of data and material, (3) Authors' contributions, (4) Funding Source and (5) Acknowledgments

Conflict of Interest

We declare that there is no conflict of interest.

Availability of Data and Materials

All data used in this paper are publicly available (BPS-Statistics Indonesia).

Author's Contribution

Conceptualization, writing draft and writing-review by all authors; Data curation by First author; Supervision and Methodology by Second author; Visualization and Validation by

Third author; Format analysis and editing by Fourth author. All authors have read and agreed to the published version of the manuscript.

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