



The Effect of Human Capital Inequality on Income Inequality: Evidence from Indonesia

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Abstract. Education inequality in Indonesia tends to experience a downward trend which indicates that the education distribution is more equally distributed from year to year. This phenomenon should lead to a reduction in income inequality. However, income inequality in Indonesia has increased compared to 9 years ago. This study intends to look at the human capital inequality condition in provinces in Indonesia and analyze the effect of human capital inequality on income inequality. The Gini coefficient concept is used to measure human capital inequality and income inequality. The annual panel data covered 34 provinces in Indonesia from 2015 – 2019. The analytical methods used dynamic panel data regression using the Generalized Method of Moment (GMM) Arellano-Bond approach. The results indicate income inequality with a lag of 1 year, literacy rate, and trade openness have a negative and significant effect on income inequality. Furthermore, the human capital inequality and the average years of schooling have a positive and significant effect on income inequality. So, to reduce income inequality, policymakers are advised to minimize human capital inequality, especially in the education sector by paying attention to conditions in priority provinces.

1. Introduction

Two major problems are generally faced by developing countries, namely inequality in income distribution between high-income groups and low-income groups and the level of poverty [1]. The existence of high-income inequality will affect sustainable economic growth and then will result in economic and financial instability which will hinder investment [2]. The effects of income inequality are far more dangerous in developing countries. With low income, a high level of income disparity will result in poverty, low education, malnutrition, and market inefficiency [3].

World Bank proves the role of human capital through the average length of education is one of the most important variables to reduce income inequality, especially in the 21st century [4]. However, a country's economic performance should not depend on the average level of human capital alone because human capital assets are not freely traded in the market. The equitable distribution of human capital in the country is also important in analyzing the country's economic performance and reducing income inequality. The indicator to measure the distribution of education that reflects the equitable distribution of human capital in an area is the education Gini index [4].

Indonesia ranks sixth as the country with the worst income inequality in the world [5]. Based on BPS data, income inequality in Indonesia shows a relatively increasing number from 2010 of 0.378 to 0.38 in 2019. In the last ten years, Indonesia's Gini coefficient has reached more than 0.36. The Gini coefficient of countries experiencing moderate inequality is between 0.36 – 0.49 [6]. This indicates



that in the last ten years there has been a fairly high inequality between the population so that appropriate handling is needed to overcome it.

In Indonesia, increasing human capital is based on development efforts in education. The scope of compulsory education was expanded at the beginning of Repelita VI to 9 years of compulsory education. With this program, it is hoped that within 10 years almost all residents aged around 7-15 years will follow the basic education level. Meanwhile, in 2019 the government compiled the 2020-2024 RPJMN where one of the policy directions is to increase the distribution of quality education services. By implementing this policy, it is hoped that in the future it can reduce the level of education inequality in Indonesia.

According to the United Nations Development Program [7], Indonesia is one of the countries with the third-highest educational inequality in Southeast Asia, after Laos and Cambodia. Nevertheless, education inequality in Indonesia tends to experience a downward trend. This illustrates that in the last 10 years the distribution of human capital in Indonesia has improved. This reduction in human capital inequality should lead to a reduction in income inequality in Indonesia. However, the fact is that income inequality in Indonesia has increased compared to 10 years ago. Therefore, the decrease in human capital inequality has not been able to reduce income inequality in Indonesia.

Theoretically, human capital inequality and income inequality have a positive relationship [8, 9]. The more unequal human capital is, the higher the level of income inequality will be. However, from the results of previous studies, it is proven that there are different results regarding the effect of human capital inequality on income inequality where previous researchers used different measurements to measure indicators of human capital inequality. In addition, empirically, many studies have examined the effect of human capital inequality on income inequality with mixed results using various measurements such as the standard deviation of the average years of education, the Gini coefficient, and Theil's Index in measuring human capital inequality.

Mahmood et al and Lee et al [10, 24] prove that the inequality of human capital has a positive and significant effect on income inequality where the Gini coefficient of education is used to measure the inequality of human capital. In another study, Pose and Tselios [11] have conducted a study on the relationship between education inequality and income inequality. The Theil index was used in the study to measure income inequality and education inequality and examine the relationship between the two in the European Union. The results show that higher inequality in human capital will lead to greater inequality in income.

Ram and Digdowiseiso found that human capital inequality had no significant effect on income inequality where they used the standard deviation to measure human capital inequality [12,13,14]. Ram uses the standard deviation of schools to measure educational inequality. Chani, et al [15] used the Gini coefficient of education to measure inequality in human capital and found that inequality in human capital had no significant effect on income inequality. Chiswick conducted a study on Earnings Inequality and Economic Development where the results of his research found that there was a positive correlation between education inequality and income inequality [18]. Gregorio and Lee's [19] research on Education and Income Inequality: New Evidence from Cross-Country Data where their findings show that education factors (higher education levels and more equitable distribution of education) play an important role in making income distribution more equitable. Both Chiswick and Gregorio and Lee use the standard deviation of the mean years of education to measure educational inequality.

Park conducted a study on Educational Expansion and Educational Inequality on Income Distribution where the results showed that the education inequality variable not only did not significantly affect income inequality but the coefficient of educational inequality also showed the opposite direction to conventional human capital theory [20]. Park uses the standard deviation of schools to measure educational inequality.

In Indonesia, studies on the effect of human capital inequality on income inequality have been carried out by Whardana et al and Lutfiani et al. Wardhana use income inequality, education inequality, economic growth per capita, level of urbanization, government spending on education, lag -1 income inequality, and lag -1 education inequality by using the 2SLS (two-stage least square) method with fixed effects. In addition, Luthfiani uses income inequality variables, GRDP-ADHK, the



total realization of APBD expenditures, and education inequality by using the FGLS-SUR estimation method analysis method with a fixed-effect model [35, 36]. Meanwhile, in this study, the variable used is income inequality, human capital inequality, income inequality with a lag of 1 year, GRDP per capita, literacy rate, and trade openness analyzed by the Generalized Method of Moment (GMM) Arellano-Bond approach.

Based on this, it is necessary to further investigate how the actual influence of human capital inequality on income inequality. The purpose of this study is to describe human capital inequality in all provinces in Indonesia and to analyze the effect of human capital inequality on income inequality in Indonesia. To measure the inequality of human capital and income inequality, the Gini coefficient concept is used as a consistent measurement in this study. To describe the distribution of education, the Gini of human capital is a good, consistent, and appropriate measure compared to other measures [16, 17].

2. Methodology

2.1. Income Inequality

Income inequality is the existence of differences in income received or generated by the community, resulting in an uneven distribution of national income among the community [22]. While income inequality according to Baldwin is the difference in prosperity in the economy between the rich and the poor [23]. To assess the severity of the inequality of income distribution can be measured through several benchmarks. Two of the most common and commonly used in measuring the problem of inequality in income distribution are Lorenz Curve and Gini Coefficient [24].

2.1.1. Lorenz Curve

The Lorenz curve illustrates the relationship between population and income distribution. The horizontal axis depicts the population, which is represented not in numbers but terms of a cumulative percentage. The vertical axis shows the total income received by each percentage of the population, which is explained not only in numbers but also cumulative form up to 100 percent. There is a diagonal line drawn through the origin to the upper right corner of the square. Each point on the diagonal line shows the percentage of income received. The diagonal line is commonly referred to as a perfect equalization line because it shows the distribution of income in a state of perfect equality. If the diagonal lines in the Lorenz Curve are further apart, the higher the level of inequality or inequality.

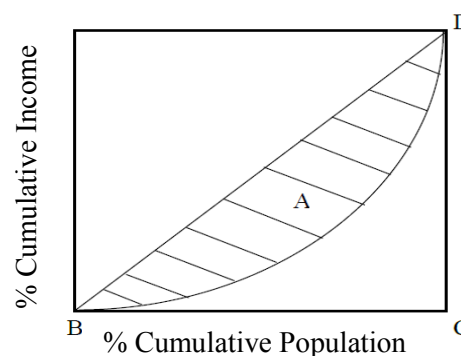


Figure 1. Lorenz Curve.

2.1.2. Gini coefficient

To analyze the inequality of income distribution, it can be measured using the Gini coefficient, where the number ranges from 0-1 which is used as a measure of the aggregate inequality of a region. The Gini coefficient is the result quantification of the Lorenz Curve Concept [22]. From Figure 1 it can be



seen that the Gini coefficient is the ratio between the area of the shaded A field and the area of the triangle BCD. From this description, it can be said that if income is perfectly evenly distributed, then all points will lie on a diagonal line. That is, the shaded area will be zero because the area is the same as the diagonal line. Thus, the coefficient number is equal to zero. On the other hand, if only one party receives all of the income, then the area of the shaded area will be equal to the area of the triangle, so the Gini coefficient is one. Therefore, it can be concluded that income distribution is said to be more even if the Gini coefficient value is close to zero, while the more uneven an income distribution is, the Gini coefficient value is getting closer to one.

2.2. Human Capital Inequality

The concept of human capital according to the modern view was pioneered by Schultz and Becker. In its development, the concept of human capital can be explained as the ability or capacity either from birth or descent or collection formed during productive working-age followed by other forms of capital or inputs aimed at achieving economic stability [27]. Fuede and Ciccone in the Dae-Bong mention that another definition (about Human Capital) emphasizes knowledge and skills through education, especially formal education (including vocational education) [37]. Human capital is generally defined as the accumulation of education, including knowledge and skills accumulated through formal education, training, courses, and experience.

The basic assumption of the human capital theory is that a person can increase his income through increased education [25]. Each additional year of schooling means, on the one hand, increasing one's employability and income level, but on the other hand, delaying the receipt of income for one year in attending the school. Castelló and Doménec calculate the inequality of human capital using the Gini coefficient [17]. The Gini coefficient was chosen because the Gini coefficient is a measure that is often used to compare international income distributions. The formula for the Gini coefficient of human capital is as follows [16]:

$$G^h = \frac{1}{\mu} \sum_{i=2}^n \sum_{j=1}^{i-1} p_i |y_i - y_j| p_j \quad (1)$$

where:

- G^h : Gini coefficient of human capital (Education Gini)
- μ : average schooling of the population concerned
- p_i and p_j : The proportion of the population with a definite level of school achievement
- y_i and y_j : years of schooling at different levels of educational attainment
- n : number of school achievement categories in the data

Equation (1) above can be expanded to:

$$G^h = \frac{1}{\mu} [p_2(y_2 - y_1)p_1 + p_3(y_3 - y_1)p_1 + p_3(y_3 - y_2)p_2 + \dots + p_6(y_6 - y_1)p_1 + p_6(y_6 - y_2)p_2 + p_6(y_6 - y_3)p_3 + p_6(y_6 - y_4)p_4 + p_6(y_6 - y_5)p_5] \quad (2)$$

where:

- p_1 : proportion of the population not in school
- p_2 : proportion of the population who did not finish elementary school (SD)
- p_3 : proportion of population graduated from elementary school (SD)
- p_4 : proportion of population graduated from junior high school (SMP)
- p_5 : proportion of population graduated from Senior high school (SMA)
- p_6 : proportion of population graduated from university



While the formula for calculating years of schooling at the 6 levels of education is:

| | |
|-----------------------------------|--|
| Illiteracy | : $y_1 = 0$ years |
| Did not finish elementary school | : $y_2 = y_1 + 0,5SD = 3$ years |
| Graduated from elementary school | : $y_3 = y_1 + SD = 6$ years |
| Graduated from Junior High school | : $y_4 = y_3 + SMP = 9$ years |
| Graduated from Senior High school | : $y_5 = y_4 + SMA = 12$ years |
| Graduated from university | : $y_6 = y_5 + \text{university} = 15$ years |

where:

| | |
|---|-----------|
| SD: years of elementary school education (SD) | = 6 years |
| SMP: years of junior high school education | = 3 years |
| SMA: years of senior high school education | = 3 years |
| University: years of university education | = 3 years |

To calculate the year of school education at the university is done in 3 ways, the average measure, the average squared, and the average harmonic. All three give almost the same results around 3.01 to 3.2 so that they are rounded up to 3 years [26]. Meanwhile, the formula for the Average Year of Schooling is:

$$\mu = \sum_{i=1}^n p_i y_i \quad (3)$$

2.3. Human Capital Inequality and Income Inequality

Theoretically, some literature explained how the path of the effect of human capital inequality on income inequality. The first path is through the rate of return on human capital investment based on capabilities and income distribution theory. According to Becker [27], the distribution of income must be equal to the distribution of abilities if everyone invests the same amount of human capital. If abilities are distributed evenly, income will be the same. However, because there are people who have skills who will tend to invest more human capital than other people, income tends to be uneven. Another pathway is based on a study by Shultz where changes in investment in human capital are a basic factor in reducing inequality in the distribution of personal income. A faster increase in human capital compared to a conventional relative increase (physical) will cause income to be distributed more unequally. In addition, Fields (1980) implies a partial positive relationship between the average school level and income inequality, so it can be said that human capital inequality and income inequality have a positive relationship.

This study uses the model from Mahmood and Noor [28] with some modifications to estimate the effect of human capital inequality on income inequality. Where in this study did not include the initial income Gini variable and the globalization index. However, the literacy rate variable was added. The specifications of the empirical model are as follows:

$$\ln GINI_{j,t} = \beta_1 \ln GINI_{j,t-1} + \beta_2 \ln G^h_{j,t} + \beta_3 \ln AYS_{j,t} + \beta_4 \ln LR_{j,t} + \beta_5 \ln GRDP_{j,t} + \beta_6 \ln GRDP^2_{j,t} + \beta_7 \ln TO_{j,t} + \varepsilon_{j,t} \quad (4)$$

where:

| | |
|----------|--|
| GINI | : Gini coefficient for income inequality |
| G^h | : Inequality of human capital |
| AYS | : Average Year of Schooling |
| LR | : Literacy rate |
| GRDP | : Gross Regional Domestic Product per capita |
| $GRDP^2$ | : Gross Regional Domestic Product per capita squared |
| TO | : Trade openness |



2.4. Data and Method Estimation

This study uses annual panel data covering 34 provinces in Indonesia years 2015 – 2019. This study uses secondary data obtained from the Central Statistics Agency of the Republic of Indonesia (BPS). This study uses several main variables and control variables as controls for omitted variables. The dependent variable in this study is income inequality which is represented by the Gini coefficient value. The independent variable is the human capital inequality which is calculated based on the Gini coefficient formula of human capital. Then the second independent variable that describes the condition of education is the average years of schooling. For the control variable used, the first is the literacy rate where there are empirical studies that prove that the literacy rate has a negative and significant effect on income inequality [29]. The next control variable is GRDP per capita and GRDP per capita squared. Previous research has shown that income per capita has a positive and significant effect on income inequality [11, 19, 30]. The last control variable is trade openness which is the ratio of exports and imports to GDP. Trade openness also has a positive and significant effect on income inequality [21, 28].

The analytical method used is descriptive analysis and also inferential analysis. Descriptive analysis was carried out using maps to describe human capital inequality in all provinces in Indonesia. Meanwhile, the inferential analysis used to estimate the effect of human capital inequality on income inequality in Indonesia is dynamic panel data regression using the Generalized Method of Moment (GMM) Arellano-Bond approach.

GMM is a general estimation method (generalization) to overcome the shortcomings of other estimation methods. GMM only requires a few assumptions about the so-called moment conditions so that GMM is much more flexible than other estimation methods. Moment condition is a statement that involves data and parameters. This study uses the GMM method because GMM allows controlling for effects that are not observed by the first difference data and control for the potential endogeneity of all explanatory and control variables for the simultaneity bias caused by the possibility that some explanatory variables may be endogenous. This is because several authors have found that inequalities in human capital, average years of schooling, and trade openness are assumed to be endogenous. To overcome the possible simultaneous bias of the explanatory variables and the correlation between $(\ln GINI_{j,t-1} - \ln GINI_{j,t-2})$ and $(\varepsilon_{j,t} + \varepsilon_{j,t-1})$, Arellano and Bond proposed the lagged level of regressors be used as an instrument [31]. This becomes valid with the assumption that the error term is not serially correlated and the lag of the explanatory variable is weakly exogenous. The stages for analysis using the GMM method are as follows:

2.4.1. Parameter Significance Test

Parameter significance testing is used to determine whether there is a relationship in the model. Wald's test is used as a test of the significance of the model simultaneously (simultaneously) in the equation. Hypotheses and Wald test statistics on the equation [31]:

$H_0: \beta_1 = \beta_2 = \dots = \beta_p = 0$ (There is no significant coefficient on the model)

$H_1: \text{There is at least one } \beta_j \neq 0, j=1, 2, \dots, p$ (There is at least one significant coefficient on the model).

$$w = \hat{\beta} \tilde{V}^{-1} \hat{\beta} \sim \chi^2(K) \quad (5)$$

Where:

K: number of independent variables

The decision is that H_0 is rejected if the value of the w test statistic is greater than the Chi-square table (χ^2) or p-value $< \alpha$.

Furthermore, the Z test was used as a partial model significance test because of the large number of observations. Hypothesis and Z test statistics:

$H_0: \beta_j = 0$



$H_1: \beta_j \neq 0, j = 1, 2, \dots, p$

$$Z_{value} = \frac{\hat{\beta}_j}{se(\hat{\beta}_j)} \tag{6}$$

The decision is that H_0 is rejected if the Z value is greater than the Z table or the p-value $< \alpha$.

2.4.2. Model Specification Test

The model specification test used is the Arellano-Bond test (consistency test) and the Sargan test (instrument validity test) as follows [31]:

Arellano-Bond test

The Arellano-Bond test is used to test the consistency of the estimates obtained from the GMM process. Arellano and Bond's test hypotheses are as follows:

$$m(2) = \frac{\Delta \hat{v}'_{i,t-2} \Delta \hat{v}_*}{(\Delta \hat{v})^{0.5}} \tag{7}$$

Where:

$\Delta \hat{v}'_{i,t-2}$: Error vector on the second lag with orde $q = \sum_{i=1}^N T_i - 4$

$\Delta \hat{v}_*$: Error vector cropped to fit $\Delta \hat{v}'_{i,t-2}$ which is $q \times 1$

The decision is that H_0 is rejected if Z value $> Z$ table. This means that the consistency of GMM is indicated by a statistically insignificant value (failed to reject H_0) [2]. This shows there is autocorrelation in the first difference residual i^{th} orde and vice versa.

Sargan Test

To find out the results of the validity of the use of instrument variables whose number exceeds the number of estimated parameters (overidentifying restriction conditions), this study uses the Sargan Test. Sargan test hypothesis and test statistics:

$$S = \hat{v}' Z \left(\sum_{i=1}^N Z_i' \hat{v}_i \hat{v}_i' Z_i \right)^{-1} Z' \hat{v} \sim \chi^2_{L-(k+1)}(K) \tag{8}$$

Where:

\hat{v} : Error from model estimation

The decision is that H_0 is rejected if the value of the S test statistic is greater than the chi-square table (χ^2) or the p-value $< \alpha$. This shows the condition of overidentifying restriction in the estimation model is invalid and vice versa.

2.4.3. Classic assumption test

In the dynamic panel data model of the Arellano Bond estimation of GMM, the assumptions that must be met are that the residuals must be non-autocorrelation (independent), heteroscedasticity (identical), and normally distributed. Identical criteria were tested with the Arellano Bond test such as equation (7), where the results of the first-order 2nd difference should not have autocorrelation problems. This is explained by the acceptance condition of H_0 (no autocorrelation occurs in the residuals) or p-value > 0.05 . Residual criteria are heteroscedastic tested by Sargan test with equation (8). Residual is heteroscedastic when p-value > 0.05 . For the normality test, this study used the Shapiro-Wilk test (see appendix D).



3. Results and Discussion

3.1. Human Capital Inequality in Indonesia

The main focus of the current Government of Indonesia's Nawa Cita is to improve the quality of human capital. Many programs have been launched which aim to improve the education and welfare of the Indonesian people. For more than a decade, Indonesia has been trying to improve its education system by allocating 20% of the state budget to education. In 2019 the Indonesian government allocated a budget of 492.5 trillion rupiahs for the education sector. However, the large amount of funds disbursed for the education sector does not guarantee even distribution and quality of human capital in Indonesia. This can be seen from the picture below where there is still quite large inequality in several provinces in Indonesia.

Oshima [32] divides the level of inequality into three criteria, namely low inequality if the Gini index is less than 0.3; moderate inequality if the Gini index is between 0.3 to 0.4, and high inequality if the Gini index is more than 0.4. Based on this, in this study, the provinces in Indonesia are divided into three categories, namely provinces with low human capital inequality, provinces with moderate human capital inequality, and provinces with high human capital inequality. From **Figure 2**, it can be seen that the position of inequality in human capital in each province in Indonesia can be seen. Papua is included in the category of provinces with high human capital inequality. This indicates that although the development and expansion of education participation to increase human capital in Papua continues to be carried out, it has not been able to show significant results inequitable distribution of human capital. This is supported by the fact that the average years of schooling in Papua is the lowest in Indonesia. In addition, the percentage of the illiterate population in Papua reaches 22 percent. This figure is very far when compared to the achievements of other provinces where the average percentage of the illiterate population in provinces other than Papua is only 3.13 percent. Economic conditions, culture, and geographical accessibility are limitations for many children in Papua to even get a basic education. Therefore, providing comprehensive access and equitable distribution of education in Papua is a major challenge for the government. So, the government should make extra efforts to create policy programs that can effectively reduce the inequality of human capital by taking into account conditions in Papua that may hinder the achievement of the objectives of the program.



Figure 2. Human Capital Inequality in Indonesia in 2019.

Furthermore, the provinces of East Java, West Kalimantan, South Sulawesi, West Sulawesi, West Nusa Tenggara, and East Nusa Tenggara are included in the category of provinces with moderate human capital inequality. This is supported by the fact that these provinces are the provinces with the highest percentage of illiteracy rates after Papua. The percentage of the illiterate population in West Nusa Tenggara Province is 12.41 percent, East Java is 7.68 percent, South Sulawesi is 7.55 percent,



West Kalimantan is 6.79 percent, East Nusa Tenggara is 6.76 percent, and Sulawesi is West by 6.41 percent. Therefore, the government needs to develop programs to increase equity in these provinces by taking into account the different conditions in each of these provinces, considering that some provinces are Eastern Indonesia Regions where the conditions are certainly not the same as provinces which are Western Indonesia Regions. So that in the future it is hoped that these provinces will be able to enter the category of provinces with low human capital inequality.

Meanwhile, in addition to the provinces mentioned above, these provinces are included in the category of provinces with low human capital inequality. This indicates that the programs implemented by the government so far have been quite effective in creating an equal distribution of human capital in these provinces. However, even so, the government must not be negligent and must continue to innovate new programs so that equity in these provinces is not only maintained but also improved.

3.2. Effect of Human Capital Inequality on Income Inequality

The estimation used in this study uses the GMM Arellano-Bond two-step estimator. Testing the significance of the parameters simultaneously using the Wald test results that the p-value is 0.000. So, the decision is to reject H_0 which indicates that there is at least one significant coefficient on the model. Next, do a partial parameter significance test where the results can be seen in Table 1.

Table 1. Parameter Significance Test Results.

| Variable | Coefficient | Z | P-Value |
|---------------------|-------------|-----------|---------|
| lnGINI(-1) | -0.577306 | -1.799073 | 0.0770 |
| lnG ^h | 1.153198 | 3.656649 | 0.0005 |
| lnAYS | 1.221721 | 2.806816 | 0.0067 |
| lnLR | -4.875950 | -2.717879 | 0.0085 |
| lnGRDP | -2.727806 | -0.961461 | 0.3401 |
| lnGRDP ² | 0.591164 | 0.838337 | 0.4051 |
| lnTO | -0.116271 | -2.056388 | 0.0440 |
| Wald test | | | 0.0000 |

Eviews 10.0 output

Based on Table 1, it can be seen that income inequality with a lag of 1 year has a p-value of 0.0770. This shows that income inequality with a lag of 1 year has a significant effect on the model of 10 percent. Furthermore, the p-value of human capital inequality is 0.0005, the average years of schooling is 0.0067, the literacy rate is 0.0085, and trade openness is 0.0440. This indicates that the variables of human capital inequality, the average years of schooling, literacy rate, and trade openness have a significant effect on the model with an of 5 percent. Meanwhile, GRDP per capita has a p-value of 0.3401, and GRDP per capita squared has a p-value of 0.4051 which indicates that the two variables have no significant effect on the model.

After testing the significance of the parameters, the next step is to measure the criteria for the best model. The dynamic panel method with the Arellano-Bond GMM approach can be said to be good if it meets the criteria for consistency and instrument validity. The results of testing the criteria for the best model can be seen in Table 2.

Table 2. Model Specification Test Results

| Arellano-Bond Test Statistical Values | P-Value |
|---------------------------------------|---------|
| -0.732658 | 0.4638 |
| Sargan Test Statistical Values | P-Value |
| 3.455672 | 0.8399 |

Eviews 10.0 output



Based on Table 2, it can be seen that the dynamic panel method with the Arellano-Bond GMM approach has met the criteria for the best statistical model, namely consistency and the instrument variables used are valid. The Arellano-Bond (AB) results show a p-value of 0.4638 using 5 percent, so the decision is failed to reject H_0 . Therefore, the estimate can be said to be consistent and there is no autocorrelation in the second-order first difference error. The test that is no less important is to see whether the dynamic panel model used is valid or not. Whether or not the dynamic panel model is valid can be seen from the probability of the Sargan test. Sargan's estimation results show a p-value of 0.8399 with an of 5 percent, so the decision is failed to reject H_0 . Therefore, there is no correlation between residuals and over-identifying restrictions or the instrument variables used are more than the number of predicted parameters. The conclusion is that the dynamic panel model used in this study is valid so that the dynamic panel model is appropriate to use.

3.3. Discussion

Income inequality with a lag of 1 year has a negative and significant effect on income inequality. The coefficient value of income inequality with a lag of 1 year is -0.577306. This means that if there is an increase in income inequality in the previous year by 1 percent, the impact will reduce current income inequality by 0.577306 percent (*ceteris paribus*), and vice versa. The results of this study are in line with the results of research from Agussalim and Pohan [33] which states that income inequality in the first lag has a negative effect on income inequality.

Human capital inequality has a positive and significant effect on income inequality. The value of the coefficient of human capital inequality is 1.153198, meaning that if the inequality of human capital decreases by 1 percent, it will result in a decrease in income inequality by 1.153198 percent (*ceteris paribus*), and vice versa. This is in line with the results of research from Pose and Tselios; and Mahmood and Noor [11, 28]. Research results from Pose and Tselios show that there is a positive and strong relationship between human capital inequality and income inequality. Mahmood and Noor (2015) conclude that human capital inequality has a positive relationship to income inequality in the world and developing countries. Therefore, the government needs to pay attention to investment in human capital and the distribution of human capital because it has the potential to reduce income inequality.

Furthermore, income inequality is positively and significantly affected by the average years of schooling. The coefficient value of the average years of schooling is 1.221721. The coefficient value of the average years of schooling is 1.221721, which means that if there is a decrease in the average years of schooling by 1 percent, income inequality will decrease by 1.221721 percent (*ceteris paribus*), and vice versa. The literacy rate has a negative and significant effect on income inequality with a coefficient value of -4.875950. This means that if the literacy rate increases by 1 percent, income inequality will decrease by 4.875950 percent (*ceteris paribus*), and vice versa.

Then, trade openness has a negative and significant effect on income inequality. The value of the trade openness coefficient is -0.116271, which means that if trade openness increases by 1 percent, the impact will reduce income inequality by 0.116271 percent (*ceteris paribus*), and vice versa. The results of this study are in line with several previous studies. Empirical evidence from research conducted by Daumal shows that trade openness has a negative impact on inequality in Brazil [34].

Meanwhile, GRDP per capita and GRDP per capita squared have no significant effect on income inequality. This is in line with the results of research from Mahmood and Noor (2015). Research conducted by Mahmood and Noor has 3 scopes, namely the world, developed countries, and developing countries where the results show that GDP per capita and GDP squared do not significantly affect income inequality in developed and developing countries [28].

4. Conclusion

Several conclusions can be drawn from the findings of this study. First, the province with a high level of human capital inequality is Papua. Meanwhile, the provinces of East Java, West Kalimantan, South Sulawesi, West Sulawesi, West Nusa Tenggara, and East Nusa Tenggara are included in the category of provinces with moderate human capital inequality. Furthermore, Provinces other than those mentioned above are included in the category of provinces with low human capital inequality. The



second conclusion, income inequality with a lag of 1 year, literacy rate, and trade openness have a negative and significant effect on income inequality. Furthermore, the inequality of human capital and the average years of schooling has a positive and significant effect on income inequality. Meanwhile, GRDP per capita and GRDP per capita squared have no significant effect on income inequality.

Based on the explanation that has been given, it can be concluded that human capital inequality is an indicator that should be taken into account to reduce income inequality in Indonesia. This is supported by the trend of decreasing inequality in human capital, which is represented by the number of educational inequality and the trend of increasing the average years of schooling of the population aged 15 years and over in the last 9 years. Therefore, it is hoped that with a sufficiently large allocation of funds from the APBN, the government can develop programs that can effectively support the increase in human capital, especially in provinces with high and moderate inequality while taking into account the different conditions in each province. Meanwhile, for provinces with low inequality, the government should make new program innovations so that equity in these provinces is not only maintained but also improved. In addition, at the time of implementation, these government programs must be monitored and evaluated so that the results can be as expected.

Efforts that can be made by policymakers are to equalize educational facilities and infrastructure, especially in Papua. In addition, the availability of teaching staff is also very important. Free school fees for all are indeed important, but no less important is the provision of free teaching and learning support tools, such as stationery, uniforms, and so on. Supervision of programs related to educational equality must also be carried out strictly, considering that the more difficult it is to access a monitoring area, the more difficult it will be.

The weakness of this research is that this research only looks at human capital from the education side. Meanwhile, other indicators can represent human capital, such as health. Therefore, for further research, other indicators that represent human capital, such as health, can be used so that later they can see the effect of inequality in human capital represented by health inequality on income inequality. It needs to be investigated again whether if using other indicators, the results will be the same as this study and other previous studies.

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6. Appendices

Appendix A. Model Estimation

Dependent Variable: LNGINI
 Method: Panel Generalized Method of Moments
 Transformation: First Differences
 Date: 08/22/21 Time: 17:03
 Sample (adjusted): 2018 2019
 Periods included: 2
 Cross-sections included: 34
 Total panel (balanced) observations: 68
 White period-instrument weighting matrix
 White period standard errors & covariance (no d.f. correction)
 Convergence achieved after 12 weight iterations
 Instrument specification: @DYN(LNGINI,-2) LNGRDP2(-1) LNTO(-1)
 LNGRDP(-1) LNGH(-1) LNGH(-2) LNGRDP2(-2) LNGRDP(-2) LNLN(-2) LNTO(-2)



Constant added to instrument list

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|------------|-------------|------------|-------------|--------|
| LNGINI(-1) | -0.577306 | 0.320891 | -1.799073 | 0.0770 |
| LNGH | 1.153198 | 0.315370 | 3.656649 | 0.0005 |
| LNAYS | 1.221721 | 0.435269 | 2.806816 | 0.0067 |
| LNLR | -4.875950 | 1.794028 | -2.717879 | 0.0085 |
| LNGRDP | -2.727806 | 2.837145 | -0.961461 | 0.3401 |
| LNGRDP2 | 0.591164 | 0.705163 | 0.838337 | 0.4051 |
| LNT0 | -0.116271 | 0.056542 | -2.056388 | 0.0440 |

Effects Specification

Cross-section fixed (first differences)

| | | | |
|--------------------|-----------|--------------------|----------|
| Mean dependent var | -0.012891 | S.D. dependent var | 0.030527 |
| S.E. of regression | 0.043842 | Sum squared resid | 0.117252 |
| J-statistic | 3.455672 | Instrument rank | 14 |
| Prob(J-statistic) | 0.839898 | | |

Appendix B. Sargan Test

Dependent Variable: LNGINI
 Method: Panel Generalized Method of Moments
 Transformation: First Differences
 Date: 08/22/21 Time: 17:03
 Sample (adjusted): 2018 2019
 Periods included: 2
 Cross-sections included: 34
 Total panel (balanced) observations: 68
 White period instrument weighting matrix
 White period standard errors & covariance (no d.f. correction)
 Convergence achieved after 12 weight iterations
 Instrument specification: @DYN(LNGINI,-2) LNGRDP2(-1) LNT0(-1)
 LNGRDP(-1) LNGH(-1) LNGH(-2) LNGRDP2(-2) LNGRDP(-2) LNLR(-2) LNT0(-2)

Effects Specification

Cross-section fixed (first differences)

| | | | |
|--------------------|-----------|--------------------|----------|
| Mean dependent var | -0.012891 | S.D. dependent var | 0.030527 |
| S.E. of regression | 0.043842 | Sum squared resid | 0.117252 |
| J-statistic | 3.455672 | Instrument rank | 14 |
| Prob(J-statistic) | 0.839898 | | |

Appendix C. Arellano-Bond Test

| Test order | m-Statistic | rho | SE(rho) | Prob. |
|------------|-------------|-----------|----------|--------|
| AR(2) | -0.732658 | -0.006428 | 0.008773 | 0.4638 |

*Standard errors could not be computed. Try different covariance matrix options



Appendix D. Classic assumptions testing

Normality Test

Normality Test
 Date: 10/06/21 Time: 13:10
 Sample: 2015 2019
 Included observations: 170

| Test | Statistic | Prob. |
|-----------------|-----------|----------|
| Shapiro-Wilk | 0.975409 | 0.197963 |
| Shapiro-Francia | 0.971167 | 0.104784 |

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