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Investigating the Income Inequality in Indonesia: An Application of Autoregressive Distributed Lag Approach

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Abstract

This study investigates the effect of economic growth, urban population, unemployment, and human capital on income inequality in Indonesia. Annual data collected from World Development Indicator (WDI) is used from 1984 to 2019. The analytical method of this research is Autoregressive distributed lag (ARDL) to examine the short and long-term relationships. The results show that economic growth positively and significantly affects income inequality in the short and long term. The urban population variable has a significant negative effect in the short term but not in the long term. The unemployment variable has a significant positive effect in the long run. Finally, human capital negatively affects the short term while not in the long term. Based on these findings, it is recommended that the government stabilize inequality by increasing progressive taxes, creating jobs, providing soft skills training beyond formal education, and socializing the concept of commuter work.

Keywords: Income Inequality, Economic Growth, Urban Population, Unemployment, Human Capital.

1. Introduction

The problem of income inequality is the main problem faced by every country besides the problem of poverty. However, generally, the problem of income inequality mostly happens in developing countries compared to developed countries (Lee and Lee, 2018). Some of developing countries are Indonesia (Suhendra et al., 2020), India (Sehrawat and Singh, 2019), Vietnam (Ha et al., 2019), Brazil (Vincens and Stafström, 2015), Iran (Shahpari and Davoudi, 2014), and Afrika Selatan (Tregenna, 2011). In comparison, the examples of developed countries are Europe, including Italy (Odoardi et al., 2020).

Currently, Indonesia is one of the developing countries with low-income status. In low-income developing countries, macroeconomic problems frequently arise, including income inequality that becomes sensitive. Based on World Development Indicator by World Bank (2021), in early 1984, it showed that the Gini ratio of Indonesia was 32.4. In the coming next year, it showed the decreasing trend in 1987 as much as 30.6. But then there was a significant increase in 1997 with the Gini ratio as much as 34.5. When the monetary crisis happened in Indonesia during 1997-1998, all of the economic sectors experienced a decreasing performance up to minus, and it happened high unemployment in Indonesia during that time. The effect was the decrease in income inequality up to 31.1 in 1999 and 28.6 in 2000. During the economic recovery in the 2000s, the real sector experienced the improvement that caused higher labor absorption. But the income inequality had continued to increase in 2019 with a value of 38.2. This value was not a good category based on the disparities category (Todaro and Smith, 2015).

There were a lot of factors that caused the increase or the decrease in income inequality. The previous studies proved that economic growth, urban population, unemployment, and human resources had been the factors that affect income inequality (Sunde, 2017; Fadliansah et al., 2021; Pusra et al., 2021; Wintara et al., 2021). Theoretically, economic growth implies a decrease in income inequality because the increase in economic growth has been a sign of higher aggregate demand. In the production function, the increasing components are capital and labor. At the same time, the urban population has become the second problem because urban and rural are different. The high job vacancy and employment cause the migration from rural to urban areas. Besides that, the better education quality in an urban area than in rural has caused migration (Rahajuni, et al. 2017; Turok and McGranahan, 2013).

The third factor affecting income inequality is unemployment, which explains job loss and reducing income. Besides that, unemployment arises because of the substitution between laborers intensive to capital intensive for efficiency. As a result, the job vacancy is filled by other labor, and there is a shift in labor use in the firm with the extra burden that causes income inequality.

Finally, the factor that affects income inequality is human resources that become an important issue in reducing income inequality, but at the same time, it can also increase income inequality. Furthermore, human resources have become an important thing in reducing income inequality and increasing income inequality. Human resource frequently is proxies by education. The skill significantly influences the availability of employment in one region, and if the job is suitable for education and skill, the income will be earned. But if no employment in the region is suitable for labor, migration will happen (Ehrenberg and Smith, 2012). The effect is the concentration of human resources in one region that causes the disparities (Bucevska, 2019).

This research is aimed to give several contributions. First, it is the additional literature for income inequality in Indonesia. Second, as long as the researcher observed the previous studies mostly used panel data because of the limitation of data and the research finding is static. At the same time, this research focuses on dynamic analysis. Dynamic analysis can give short-run and long-run conclusions such that the decision-making is accurate. The example is whether the increase in human resources occurs in the short run or long run? As we know, human resource development via education and training has the time to get the impact.

2. Literature Review

The study on income inequality has long been studied with many indicators and their impacts. However, the scope of previous research is limited to economic growth, urban population, and human resource. Below are the previous researches.

Cysne (2004) took the case of the interaction between unemployment and income inequality in UK. The research used Markov Technique. The result shows a positive correlation between unemployment and income inequality. If there is an increase in unemployment, then there is an increase in income inequality. Furthermore, Ogus Binatli (2012) research used as many as 151 countries' samples from 1958 to 1999 with the observation were 2185. The estimation was undertaken using panel regression estimation. The results show that economic growth has a positive but not significant effect on income inequality. Whereas elementary school education level and high school education level positively affect income inequality, while vice versa, the secondary school education level has a negative effect on income inequality.

The other research was conducted by Shahpari and Davoudi (2014). This research was conducted in Iran, which studied the effect of human resources on income inequality. The method was used in this research was ARDL with the indicators of human resource, economic growth, and unemployment. The estimation results show that human resource has a negative and significant effect on income inequality in the short run and long run. However, for economic growth and unemployment, it was found that there is a positive and significant effect on income inequality both in the short run and in the long run.

Vincens and Stafström (2015) researched income inequality in Brazil which used economic growth and urban population indicators. The data used was panel data from 2002 to 2009. Whereas the method used was Random Effect Model (REM). The results show that economic growth and urban population have a positive and significant effect on income inequality in Brazil. Yang and Huang (2017) studied the impact of human resources and urbanization on income inequality in rural and urban areas in China. The period of analysis was from 1997 to 2008. The method used in this research was GMM. Based on the results, it was found that investment in human resources has a positive and significant effect on income inequality. In comparison, the growth of the urban population has a negative effect but is not significant in income inequality. The study on urbanization and income inequality was conducted again by Ha et al. (2019). This study was undertaken in Vietnam from 2002 to 2016. The method used was also GMM. The results found that the urbanization with the proxy of urban population has a negative but not significant effect on income inequality. The control variable used was education that has a negative and significant effect on income inequality.

In other panel data analysis, Bucevska (2019) studied income inequality in the candidate countries of Europe. The estimation was conducted using the Fixed Effect Model (FEM) from 2005 to 2017. The variables used in this research were economic growth, unemployment, population, and education. The results found that unemployment, population, and economic growth affect income inequality. At the same time, education has a negative and significant effect on income inequality.

The current study was conducted by Sehrawat and Singh (2019) with an asymmetric approach. This research was conducted in India. The asymmetry used was education because the improvement and degradation in education have different impacts. The asymmetric method used was Non-Linear ARDL from 1970 to 2016. The results found that education has a positive impact on decreasing income inequality. In contrast, the degradation in education quality has a negative impact on income inequality.

Further research conducted by Odoardi et al. (2020) in Italy used the technique of two-stage least square (2SLS). Indicators used are human resources, unemployment, and economic growth from 2004-2016. The results showed human resources had a significant negative effect on inequality. However, unemployment and economic growth have positive but insignificant effects on inequality.

Suhendra et al. (2020) studied income inequality in Indonesia using indicators such as human resources, economic growth, and unemployment. The data used is panel data with 34 provinces from 2013 to 2019. The method used is the FEM method. Results show that human resources, economic growth, and unemployment significantly negatively affect inequality. Kavya and Shijin (2020) reviewed inequality but with the scale of the country's division based on income. The research indicator used were education and population. The method used was GMM. Results showed that education had a significant negative effect in all regions. While the population has a positive but insignificant effect in the region except for high-income countries.

Recent research by Alamanda (2021) analyzed the effects of economic growth and unemployment on income inequality in 50 countries. The analysis used was PLS, FEM, and REM. The results showed that the model that corresponded to the study was FEM. Economic growth has a positive and significant effect on income inequality. For example, increasing economic growth by 1% will increase the income inequality 0.082%. But unemployment has a bigger effect on income inequality that is 0.294%.

3. Materials and Methods

3.1. Materials

This study aims to analyze the impact of economic growth, urban population, unemployment, and human resources on inequality dynamically. The data used is annual data from 1984-2019 with a total of 36 samples. All data is obtained from the World Development Indicator (WDI) published by the World Bank. The Gini ratio is measured by the estimated inequality figures from the World Bank with a measurement of 0-1. Economic growth is the rate of economic growth on the basis of constant prices in the year 2010 as measured by percent. An urban population is a community living in a city area measured by units of life. Unemployment is the percentage of the workforce that is not working and is looking for work, and human resources is an index of human resources based on the length of the school and return to education.

3.2. Methods

The Autoregressive Distributed Lag (ARDL) model was used to achieve this research objective. This model includes using a variety of lag from bound variables and explanatory variables. This model was invented and developed by Pesaran et al. (2001); we can see the short-term and long-term dynamic influence. The general functions of this study follow the studies of Bucevska (2019), Kavya and Shijin (2020), and Alamanda (2021) where:

$$GINI = f(GGDP, URBAN, UN, HC) \tag{1}$$

GINI is the Gini Index, GGDP is the economic growth rate, URBAN is the urban population, UN is the open unemployment rate, and HC is a human resource. These four variables are important variables used in looking at inequality.

There are several reasons this study uses the ARDL model, among others are: (1) This model can use a small number of samples, (2) Variables used may have different stationarities I(0) and I(1), (3) The lag used may differ or equal to different forms, (4) This model is a model that many researchers use and is very popular in recent years, (5) Linear regression using ordinary least square (OLS) estimates. The general form of the ARDL Cointegration Model is:

$$\Delta lnY_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i} \Delta lnY_{t-i} + \sum_{i=1}^{n} \alpha_2 \Delta lnX_{t-i} + \beta_1 \ln Y_{t-1} + \beta_2 lnX_{t-1} + \varepsilon_t \tag{2}$$

Where Y is dependent variable, X is independent variable, α_1 and α_2 are short run coefficient, β_1 and β_2 are long run coefficient, t is year, and i is lag sequence, and also ε is *error term.* Equation (3) is equation that was included into the variables observed.

$$\begin{aligned}\Delta lnGINI_t = {} & \alpha_0 + \sum_{i=1}^{n} \alpha_1 \Delta lnGINI_{t-i} + \sum_{i=1}^{n} \alpha_2 \Delta GGDP_{t-i} + \sum_{i=1}^{n} \alpha_3 \Delta lnURBAN_{t-i} \\ & + \sum_{i=1}^{n} \alpha_4 \Delta UN_{t-i} + \sum_{i=1}^{n} \alpha_5 \Delta lnHC_{t-i} + \beta_1 lnGINI_{t-1} + \beta_2 GGDP_{t-1} \\ & + \beta_3 lnURBAN_{t-1} + \beta_4 UN_{t-1} + \beta_5 lnHC_{t-1} + \varepsilon_t \end{aligned} \tag{3}$$

In order to test cointegration hypothesis, it can be conducted by using Bound F-test with the restriction of Wald F-statistic and it is compared to *upper band* and *lower band critical value* with null hypothesis are $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$ (Hye and Islam, 2013). Bound F-test is the means in testing cointegration of ARDL Model. Cointegration is aimed to see the short run and long run existence. Based on Pesaran et al. (2001), there are three possibilities of Bound F-test results those are as follow:

1. If F-stat is obtained greater than *upper band* and *lower band critical value,* then there is cointegration and we reject H_0.
2. If F-stat is obtained smaller than *upper band* and *lower band critical value,* then we accept H_0.
3. If F-stat is obtained in between of *upper band* and *lower band critical value,* then there is no decision.

The critical value in Pesaran et al. (2001) was used in case studies that had a large sample. When using this critical value against a small sample it results in an incorrect estimate. Narayan (2004) recalculated this critical value for case studies that had a small finite sample. Because the sample of this study is not too large (36 samples), then we use critical value of Narayan (2004). Furthermore, the short run error correction model is also used in the goal of identifying short-term dynamic estimation. This correction requirement (ECM) is expected to have a negative and significant sign against dependent variables. The specifications of the short-term correction model in this study are as follows:

$$\begin{aligned}\Delta lnGINI_t = {} & \gamma_{0i} + \sum_{i=1}^{n} \gamma_1 \Delta lnGINI_{t-1} + \sum_{i=1}^{n} \gamma_2 \Delta GGDP_{t-1} + \sum_{i=1}^{n} \gamma_3 \Delta lnURBAN_{t-1} \\ & + \sum_{i=1}^{n} \gamma_4 \Delta UN_{t-1} + \sum_{i=1}^{n} \gamma_5 \Delta lnHC_{t-1} + ECM_{t-1} + \varepsilon_t \end{aligned} \tag{4}$$

4. Results and Discussion

4.1 Descriptive Statistic

Descriptive statistics are an early overview before entering into the analysis. Descriptive statistical measurements are seen from average, maximum, minimum, and standard deviations. Descriptive statistics shown in Table 1 describe the inequality figures in the Gini column have an average of 0.34 with the highest inequality value of 0.40. Meanwhile, Indonesia's economic growth rate has an average of 5.04. The average urban population in Indonesia reaches 93 million people with a standard error of 34 million people. It signifies a considerable population movement caused by urbanization and population growth. The average unemployment in Indonesia is 4.7%, and human resources are 2.14.

Table 1. Descriptive Statistic

Variable	Mean	Max	Min	Std. Error
GINI	0.34	0.40	0.286	0.034
GGDP	5.04	8.22	-13.12	3.43
URBAN	93,457,024	1.52E+08	40,774,954	34,026,771
UN	4.70	8.06	2.10	1.77
HC	2.14	2.41	1.68	0.22

4.2 Stationarity Test

Stationary testing is a key requirement in using time series models such as ARDL models. One of the advantages of the ARDL model is that it uses different stationary variables in the form of I(0) and I(1) integrations. The stationary testing in this study uses the Ng-Perron approach (2001) with intercept and trend equations. The test results are shown in Table 2.

Table 2. Results of Ng-Perron Stationarity Test

Variable	Mza	Mzt	MSB	MPT
GINI	-5.806	-1.703	0.299	15.694
DGINI	-21.363**	-3.268**	0.152**	4.265**
GGDP	-15.944	-2.823	0.177	5.716
DGGDP	-25.847***	-3.593***	0.139***	3.532***
URBAN	-87.555***	-6.558***	0.074***	1.267***
DURBAN				
UN	-1.083	-0.517	0.477	48.687
DUN	-20.638**	-3.166**	0.136**	4.435**
HC	-131.887***	-8.040***	0.060***	0.954***
DHC				

Source: Estimation Results (2021). D is difference, **Sig 5% ***sig1%.

Table 2 shows the first stationary testing conducted with level conditions on each of the variables studied. It is known that Gini, economic growth, and unemployment are not stationary at the level. Furthermore, this variable was tested at the first difference level, and the results found that Gini and unemployment were already stationary at the 5% level. While the economic growth is stationary at the level of 1%, for variables of urban population and human resources, results are stationary at a level with a significant rate of 1%. Based on these results, it is concluded that there are different stationery, which is very by the ARDL method. Therefore, the use of ARDL models in research has been fulfilled.

4.3 Optimal Lag

Optimal lag testing is essential on ARDL models. It is because lag serves to explain how long it affects a variable against another variable. Additionally, in the ARDL model, the lag between variables has a different amount of lag. It is what distinguishes ARDL models from VAR and VECM. Lag testing using Akaike Information Criterion (AIC). Optimal lag selection is based on the smallest value.

Table 3. Results of Optimal Lag With AIC

Lag ARDL	Number Model	AIC
(1,4,1,2,3)	87	-5.284^
(1,4,1,3,3)	82	-5.255
(1,4,3,2,3)	37	-5.249
(1,4,1,4,3)	77	-5.243
(1,4,2,2,3)	62	-5.229

Source: Estimation Results (2021). ^ is the optimal value.

Based on Table 3, the optimal lag used in this research is (1,4,1,2,3). The use of lag is as much as 1 for Gini, 4 for economic growth, 1 for human resource, 2 for unemployment, and 3 for urban population variable.

4.4 The Test of Bound Cointegration

Contingency testing on ARDL models is indispensable for looking at short-term to long-term relationships. Therefore, cointegration testing of ARDL models with Bound-test approaches on different integrations or small samples. Because the sample used is small, the Narayan approach (2004) is the critical value used. The test results are shown in Table 4.

Table 4. Results of Cointegration Test

Model	F-stat	Critical value I(0)	Critical value I(1)	Conclusion
GINI = f ($\boldsymbol{GGDP, URBAN, UN, HC}$)	9.98***	4.093	5.532	Cointegrated

Source: Estimation Results (2021). *** Sig at 1%.

Based on Table 4, the economic growth model has obtained an F-stat value of 9.98. According to Pesaran et al. (2001), it is said that there is a cointegration when the f-stat value is obtained greater than the critical values lower I(0) and upper I(0). Thus, the F-stat value is obtained greater than the lower and upper critical values, and it is concluded that there is a short-term cointegration into the long term.

4.5 Long Run Estimation

After cointegration testing and finding significance, the next step is to estimate the Gini equation in the long run. The long-term estimation results are presented in Table 5, where economic growth positively and significantly impacts inequality. For example, if the coefficient of economic growth increases by 1%, then inequality will increase by 0.045%. The study is similar to the findings made by Alamanda (2021) and Bucevska (2019).

Economic growth should be suppressed (Siami-Namini &Hudson, 2019), but this does not apply to countries with high inequality, such as Indonesia. Alamanda (2021) explains that inequality in Indonesia occurs because several people control the economy. As a result, the economy is more pronounced in the rich and poor cannot impact, and this causes a wider gap between the two groups. As is the case in Europe, each region competes for a high economy. Some regions already have advantages such as a reliable workforce and cutting-edge technology. The effect is that other regions cannot compete, causing a significant economic downturn and causing inequality (Bucevska, 2019).

The urban population variable is found to have no significant effect on income inequality in the long run. It is seen from the probability value that is greater than 0.05. Meanwhile, the unemployment variable is found to have a positive and significant effect on inequality. It indicates that if unemployment increases by 1% in the long run, the gap will increase by 0.036%. This influence is very real because the probability value obtained is smaller than 5%. These results are consistent with the findings made by Alamanda (2021), Bucevska (2019), and Shapari and Davoudi (2014). In the long run, unemployment becomes a serious problem in increasing income inequality because those workers do not have jobs, then their incomes are lost, and those who are still working have incomes. Therefore, it can create new gaps in society. In the long run, the estimation results can be seen in Table 5.

Table 5. Estimation Results in The Long Run

Variable	Coefficient	Std. error	t-Stat	Prob.
GGDP	0.045***	0.007	6.227	0.000
URBAN	0.018	0.122	0.150	0.882
UN	0.036**	0.017	2.144	0.047
HC	-0.771	0.509	-1.512	0.149
C	3.545	2.135	1.660	0.116
R-squared	0.989			
Adj. R-squared	0.978			
DW	1.997			

Source: Estimation Results (2021). **, *** Sig. 5%, 1%.

Meanwhile, the human resources variable is found to have a negative but insignificant effect on income inequality. These findings differ from Kavya and Shinjin (2020), Odoardi et al. (2020), and Suhendra et al. (2020). It indicates that the development of human resources is believed to be a long-term investment is not a solution in reducing inequality in Indonesia.

4.6 Short Run Estimation

After estimating long-term equations, the next step is to estimate short-term equations. This requirement also requires cointegration. Short-term ECM estimation results are performed to determine the effect of variable lag and see equilibrium. In addition, ECM determines the speed of adjustment from the short-term balance to the long-term in case of shocks. The short-term model evaluates the relationship of variables studied and confirms the reliability of long-term estimates. Indications of ECM models should be negative and significant. Negative indicates convergence (towards the point of equilibrium). If the ECM obtained is positive, it is divergent (away from the equilibrium point).

Table 6. Estimation Results in the Short Run

Variable	Coefficient	Std. error	t-Stat	Prob.
DGGDP	0.006***	0.001	10.038	0.000
DGGDP(-1)	-0.020***	0.002	-7.448	0.000
DGGDP(-2)	-0.050***	0.002	-5.921	0.000
DGGDP(-3)	-0.003*	0.001	-2.064	0.055
DHC	-6.515***	0.804	-8.103	0.000
DUN	-0.001	0.004	-0.414	0.683
DUN(-1)	-0.031***	0.005	-6.127	0.000
DURBAN	-14.199***	2.729	-5.202	0.000
DURBAN(-1)	2.343	3.928	0.596	0.559
DURBAN(-2)	10.036***	2.466	4.069	0.000
ECM(-1)	-0.606***	0.068	-8.869	0.000
R-squared	0.923			
Adj. R-squared	0.886			
DW	1.997			

Source: Estimation Results (2021). D is difference ** 5% significance, *** 1% significance.

Table 6 describes the ECM coefficients showing negative and significant signs. The result of the sign is in accordance with the expected equilibrium point. The ECM coefficient of -0.606 means 60.6% to the equilibrium point. Short-term to long-term adjustments in the results of this study are relatively long. The coefficient of economic growth in the short term is found to have varying influences, and the influence is significant on income inequality. Furthermore, in the short term, human resources negatively and significantly affect income inequality. The increase in human resources by 1% will decrease income inequality by 6.515%. These results differ in the long run, which has no impact. The improvement of human resources in the short term is defined by skill training that is used quickly to be applied in work.

Lastly, urban populations have two impacts: positive and negative in the short term. The influence of 2 years ago had a positive effect that explained that a 1% increase in the urban population could be income inequality of 10.03%. This result is similar to the findings by Buscevka (2019). But over time, urban population increases could reduce the inequality rate by 14% if there is assumed to be a 1% increase. This result follows Ha et al. (2019) where those who work in the city are people who urbanize due to jobs in the village not being available either in limited employment skills. When a person is already working in the city, some income will be transferred to his home region. It means that rural and urban areas are experiencing income equilibrium. It is why urban populations can reduce income inequality.

4.7 Stability Model

The stability of estimates in ARDL models is an important concern throughout the year used. Stability testing is with CUSUM and CUSUMQ. It is said to receive H_0, which is a stable estimate if it does not cross the 5% significance line. The CUSUM and CUSUMQ images can be seen in Figure 1. The estimated model does not cross the 5% significance level based on the figure. Therefore, the ARDL regression model of this research is stable in the long run.

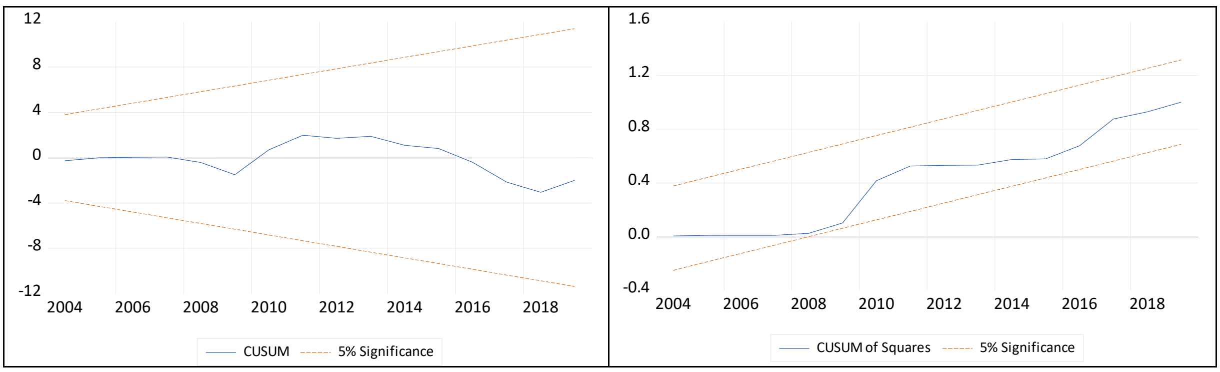

Figure 1. Stability Model CUSUM and CUSUMQ

4.8 Diagnostic of Estimation Model

The last stage in ARDL model testing is to diagnose model estimation. ARDL model uses OLS estimation techniques. Therefore, OLS estimation is required to test classic assumptions to obtain efficient estimation (Gujarati and Porter, 2009). Classic assumption testing in the form of normality, autocorrelation, heteroskedasticity, and model specification tests.

Table 7. Results of Classic Assumption Testing

Testing	Statistic	Prob.
Normality	0.242	0.885
Autocorrelation	1.201	0.359
Heteroskedasticity	2.195	0.148
RESET	0.869	0.420

Table 7 show that all classic assumption tests receive H_0 so that the estimates obtained from the ARDL model are consistent and efficient.

5. Conclusion

From the results of the analysis and discussion in this study, it can be concluded that there is a cointegration in the model of income inequality due to variables of economic growth, urban population, unemployment, and human resources. It also shows that all four variables have long-term relationships. Therefore, economic growth in the short and long term has a positive and significant effect on income inequality in Indonesia.

The urban population variable has a negative effect on income inequality in Indonesia in the short term. But in the long-term, it does not affect income inequality. Unemployment is found to have a positive and significant influence on income inequality in the long run. Rising unemployment will increase income inequality. Human resources have a significant effect on reducing income inequality in the short term. At the same time, the effect of human resource variables on income inequality is not found in the long run.

Based on the previous conclusions and analysis, the recommendations can be advised: variable economic growth, urban population, unemployment, and human resources become an important component in looking at income inequality in Indonesia, especially in dynamic analysis. The government can take some policies from those variables. Seeing economic growth effects, the increase in income inequality, the government can use progressive tax regulation to control income inequality because the increase in growth also affects the rich and poor to increase their welfare. But the welfare of the rich will be higher than the poor. Through these policies, income inequality can be reduced due to the suppression of wealth and distribution to the poor.

The government has emphasized urbanization so as not to detonate population growth in urban areas. But the short-term estimates have the effect of decreasing income inequality. In addition, the government can socialize the concept of commuter work. In the long run, unemployment is known to impact income inequality significantly.

From these results, the government can reduce the unemployment rate by creating appropriate jobs and providing training under the current conditions. The increase in human resources plays a vital role in reducing the inequality rate but in the short term but not in the long term. Through these results, it is recommended that the government conduct more programs in the form of soft skills training than formal education improvement because such education takes a very long time to be used, especially receiving high incomes.

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