Static and dynamic panel models: Which is better? (Case study: Poverty data in Indonesia 2012-2019)

P R Sihombing¹ and A M Arsani²,³

¹ Departemen of Statistics, IPB University, Bogor Indonesia
² Applied Economics Master Program, Padjadjaran University, Bandung, Indonesia
³ Statistics Indonesia

E-mail: robinson@bps.go.id

Abstract. Indonesia's poverty rate continues to decline from year to year; however, the decline in the percentage of poor people is slowing down continuously, following the law of diminishing returns. Many factors influence poverty, including HDI, Gini ratio, and the open unemployment rate. This study model static and dynamic panel data on Indonesia's poverty cases in 2012-2019 to explain the relationship between HDI, Gini ratio, and the unemployment rate to poverty. It also compares poverty modeling with static and dynamic panel data regression. The results show that the Gini ratio has a significant and positive relationship to poverty. HDI has a significant and negative relationship to poverty. However, there is insufficient evidence to suggest that unemployment affects poverty. Using static panel data regression, the selected model is a fixed effect model but still experiences violations of the classic autocorrelation assumption. The dynamic panel data model gives better results than the static panel data regression model when viewed from the r-square value and the number of variables that significantly affect. From the results of this study, it can be implemented that an increase in economic growth without an increase in equity has no impact on poverty. So, it needs extra efforts by the government in economic equality for all regions of Indonesia. Also, there is a need for additional actions by the government and the community to improve education, health, purchasing power, and community competitiveness.

1. Introduction

As in other developing countries, the poverty is still one of Indonesia's problems. Currently, Indonesia's poverty rate has reduced significantly compared to two decades ago, from 19.14 percent in 2000 to only 9.78 percent in 2020. However, the decline in the percentage of poor people has slowed further, following the law of diminishing returns. The decrease in the rate of reduction of the poor was experienced by Indonesia and almost all over the world. In previous decades, economic growth was relied on to reduce poverty. In their study, [1] emphasized that over the last few decades, poverty reduction has been determined mainly by economic growth and the redistribution of resources to the poor, both through domestic and foreign assistance. Unfortunately, when the remaining poverty is extreme, economic growth no longer plays a significant role in reducing poverty. Therefore, steps are needed so that the government's programs can meet the needs of the poor quickly. However, to find out what is best required by the poor is not easy. Thus, the programs that can be carried out by the government before knowing the specific needs of the poor are to meet basic needs that have long-term effects such as education and health.

To create right programs, it is essential to find out the most important factors of poverty by modelling determinant of poverty in a right way. Poverty in Indonesia has been studied thoroughly,
but the bulk of these research—concentrate on static poverty and examine the amount of the population over time underneath the income threshold [2]. Although many studies examine the poverty problems as a static problem, in fact, poverty is not just a static phenomenon since there is a chance to people escape from poverty as well as fall to poverty in a short time [3]. There are several factors that can shift the people’s poverty status such as education, employment status, and the infrastructure condition around them [4, 5, and 6]. Not only these variables, but other variables such as human development index and government policy also affect the people poverty status [7]. As quoted by [8], the human development index (HDI) explains how the population can access development outcomes in obtaining income, health, education, etc. HDI is an important indicator of success in building the quality of human life (society/population). As reflected in the HDI, the quality of human resources plays a role in reducing the poverty rate, poverty depth, and poverty severity in almost all community groups [9]. Evaluation of HDI figures in each region will be used as one of the bases for development planning to determine policy formulation [10].

Not only a matter of access to education and health, to ensure that a group of people can succeed in staying out of poverty, adequate employment opportunities with decent wages are necessary. The absence of decent work opportunities will result in the poor remaining poor and the poor vulnerable to becoming poor. We cannot unemployment wholly eradicated in both developing and developed countries. However, if unemployment is far above the natural unemployment rate, economic and social problems will arise. High unemployment will trigger the vulnerability in various forms, including poverty [11]. The imbalance between the level of demand for labour in the modern industrial sector and the rapid growth rate of urban labour supply from rural areas has led to the emergence of unemployment [12].

Modelling the determinant of poverty is not easy. Since poverty is not a static problem, one-time data is not sufficient to analyse poverty’s determinant. Hence, the panel data are better to use. In panel data regression analysis, many studies often use static panel data regression; there is often a violation of the autocorrelation assumption. This violation usually occurs because of the dependent variable's influence in the previous period in the next period. The model that is often used to accommodate the dependent variable's effects in the past period is known as dynamic panel data analysis. Regarding the research in poverty, several previous studies use ordinary panel data regression, such as [13, 14, and 15]. Other studies use dynamic panel data regression, such as [16 and 17]. The use of ordinary panel or dynamic panel are depended on several considerations. Hence, it is important to examine the best model that suitable to use.

Based on the above problems, the author wants to know how to model static and dynamic panel data on poverty cases in Indonesia in 2012-2019, with the following research objectives:

a. Explain the relationship between HDI, Gini ratio, and unemployment to poverty.
b. Comparing poverty modelling with static and dynamic panel data regression

2. Method

2.1. Data

This study uses macro-socio-economic variables in 34 Provinces in Indonesia 2012-2019 released by BPS-Statistics Indonesia. The operational definition of each variable is as below:

The percentage of poor people using the Head Count Index (HCI-P0) represents the population below the poverty line (PL).

\[ P_{\alpha} = \frac{1}{n} \sum_{i=1}^{n} \left( \frac{z-y_{i}}{z} \right)^{\alpha} \]  

where:
\[ \alpha = 0 \]
\[ z = \text{poverty line.} \]
\[ y_{i} = \text{average monthly per capita expenditure of people who are below the poverty line} \]
\[(i=1, 2, 3, ..., q), y_{i} < z \]
The number of people who are below the poverty line.

The Human Development Index (HDI) explains how residents can access development outcomes in terms of income, health, education, etc. HDI was introduced by the United Nations Development Program (UNDP) in 1990 and is published regularly in the annual Human Development Report (HDR).

\[
HDI = \sqrt[3]{\frac{1}{\text{health}} \times \frac{1}{\text{education}} \times \frac{1}{\text{expenditure}}} \times 100
\]

The Unemployment Rate is the percentage of the total unemployed against the full labour force. Then, the Gini ratio or coefficient is a tool to measure the degree of inequality of population distribution. It is based on the Lorenz curve, a cumulative expenditure curve that compares the issuance of a particular variable (e.g., income) with a uniform distribution representing the population’s cumulative percentage.

2.2. Statistics Model

2.2.1 Panel Data Model. Panel data is a combination of cross-section and time-series data. In other words, panel data is data from the same number of observed individuals over a certain period. If we have a T period (t = 1, 2, ..., T) and N the number of individuals (i = 1, 2, ..., N), then with panel data, we will have NT total observation units. If the number of time companies is the same for each individual, the data is called a balanced panel. On the other hand, the number of time units is different for each individual; it is called an unbalanced panel. There are two main methods in the panel data regression model, namely static panel data analysis and dynamic panel data analysis.

In panel data analysis [18], there are three approach models used, namely the Common Effects Model, the Fixed Effects Model (FEM), and the Random Effects Model (REM) / Error Components Model (ECM).

2.2.1.1 Common Effects Model. This approach does not pay attention to individual or time dimensions, also known as Pooled Regression. The estimation method uses the Ordinary Least Squares (OLS). The regression equation model is as below:

\[
Y_{it} = \beta_0 + \beta_1 X_{1it} + \cdots + \beta_p X_{pit} + u_{it}
\]

2.2.1.2 Fixed Effects Model (FEM). This model assumes that, over time, the characteristics of each individual are different. This difference is reflected by the value of the intercept in the estimation model, which is different for each individual.

The regression equation model is as below:

\[
Y_{it} = \beta_{0i} + \beta_1 X_{1it} + \cdots + \beta_p X_{pit} + u_{it}
\]

The model above is usually written in the form of a dummy variable to replace the existing intercept differences, so it can be written as follows:

\[
Y_{it} = \beta_0 + \alpha_2 D_{2i} + \alpha_3 D_{3i} + \cdots + \alpha_N D_{Ni} + \beta_1 X_{1it} + \cdots + \beta_p X_{pit} + u_{it}
\]

2.2.1.3 Random Effects Model (REM). This model also assumes that over time, the characteristics of each individual are different. However, in REM, this difference is reflected by the error of the model.

The regression equation model is as below:

\[
Y_{it} = \beta_0i + \beta_1 X_{1it} + \cdots + \beta_p X_{pit} + u_{it}
\]

with: \(\beta_{0i} = \beta_0 + \varepsilon_i\)

So that the model can also be written as follows:

\[
Y_{it} = \beta_0 + \beta_1 X_{1it} + \cdots + \beta_p X_{pit} + (\varepsilon_i + u_{it})
\]

or \(Y_{it} = \beta_0 + \beta_1 X_{1it} + \cdots + \beta_p X_{pit} + w_{it}\)

where: \(w_{it} = \varepsilon_i + u_{it}\)
The way to choose one of the three approaches listed above is as follows:

A. Choose between Common Effects VS Fixed Effects models.
To choose which model is more suitable between Common Effects or Fixed Effects, we can use the Chow Test or Restricted F-Test as follows:

Ho: Common Effects Model is better than Fixed Effects
H1: Fixed Effects Model is better than Common Effects

Significance level: $\alpha$

Test Statistics:

$$F_{obs} = \frac{(R^2_{UR} - R^2_R) / (N-1)}{(1-R^2_R) / (NT-k)}$$

(8)

Where: $N =$ number of individuals
$T =$ number of series (years), $k =$ number of parameters, including intercept
$R^2_{UR} =$ the coefficient of determination ($R^2$) of unrestricted/ Fixed Effects
$R^2_R =$ the coefficient of determination ($R^2$) of the restricted / Common Effects model

Decision Making Criteria: Reject Ho if $F_{obs} > F_{\alpha;(N-1),(NT-k)}$ or if $Prob. value \leq \alpha$

B. Choose between Common Effects VS Random Effects models.
To choose which model is more suitable between Common Effects or Random Effects, we can use the Lagrange Multiplier Test (LM Test), which is as follows:

Ho: $\sigma^2 = 0$ (the intercept is not random or stochastic)
H1: $\sigma^2 \neq 0$ (the intercept is random or stochastic)

Significance level: $\alpha$

Test Statistics:

$$LM = \frac{NT}{2(T-1)} \left[ \frac{\sum_{i=1}^{N} (\sum_{t=1}^{T} e_{it})^2}{\sum_{i=1}^{N} \sum_{t=1}^{T} e_{it}^2} - 1 \right]^2$$

(9)

Decision Making Criteria: Reject Ho if $LM > \chi^2_{\alpha;1}$ or if $Prob.-value \leq \alpha$

C. Choose between Fixed Effects VS Random Effects models.
To choose which model is more suitable between Fixed Effects or Random Effects, we can use the Hausman Test, which is as follows:

Ho: Random Effects model is better than Fixed Effects
H1: Fixed Effects model is better than Random Effects

Significance level: $\alpha$

Test Statistics: $\chi^2_{obs} = (\hat{\beta} - \hat{\beta}_{GLS})' \hat{\Psi}^{-1} (\hat{\beta} - \hat{\beta}_{GLS})$

(10)

Decision Making Criteria: Reject Ho if $\chi^2_{obs} > \chi^2_{\alpha;p}$ or if $Prob.-value \leq \alpha$

$p =$ number of independent variables

2.2.2 Dynamic Panel Data Regression Model. The second-panel model is a dynamic panel regression model, a regression method that adds the dependent variable lag to serve as an independent variable.
The dynamic model equation is defined as follows:

$$y_{i,t} = \delta y_{i,t-1} + \beta x'_{i,t} + u_{it}$$

(11)

where:
$y_{i,t}$: The dependent variable which is the ith observations of the cross-section unit for the time period $t$
$\delta$: The intercept, which is the group / individual effect of the ith unit cross-section for time $t$
$\beta$: constant vector of size $K \times 1$ where $K$ is the number of independent variables
$x'_{i,t}$: The independent variable vector which is the ith observations of the unit cross-section for the time $t$ with size $1 \times K$
u_{it}: error component
In dynamic panel data regression, the Arellano-Bond GMM estimation method produces unbiased, consistent, and efficient parameter estimates. The following are the estimation results of the GMM Arellano-Bond one-step estimator.

\[
\begin{align*}
\delta &= \left[ N^{-1} \sum_{i=1}^{N} (\Delta y_{i,t-1}, \Delta x_{i})' Z_i \right] \hat{W} \left[ N^{-1} \sum_{i=1}^{N} Z_i' (\Delta y_{i,t-1}, \Delta x_{i}) \right]^{-1} \\
&= \left[ \left( N^{-1} \sum_{i=1}^{N} (\Delta y_{i,t-1}, \Delta x_{i})' Z_i \right) \hat{W} \left( N^{-1} \sum_{i=1}^{N} Z_i' \Delta y_i \right) \right]^{-1}
\end{align*}
\]

The results of the twostep estimator estimation by substituting the weight of \( \hat{W} \) with \( \nabla^{-1} \) o that the estimation results of the GMM Arellano-Bond are as follows:

\[
\begin{align*}
\delta &= \left[ \left( N^{-1} \sum_{i=1}^{N} (\Delta y_{i,t-1}, \Delta x_{i})' Z_i \right) \hat{W} \left( N^{-1} \sum_{i=1}^{N} Z_i' (\Delta y_{i,t-1}, \Delta x_{i}) \right) \right]^{-1} \\
&= \left[ \left( N^{-1} \sum_{i=1}^{N} (\Delta y_{i,t-1}, \Delta x_{i})' Z_i \right) \hat{W} \left( N^{-1} \sum_{i=1}^{N} Z_i' \Delta y_i \right) \right]^{-1}
\end{align*}
\]

where:
\( \hat{W} \) is a functional weight matrix of the GMM method with the order \( L \times L \) where \( L \) is the number of instrument variables and \( \nabla^{-1} \) s the optimal weight matrix with the formula:

\[
\nabla^{-1} = N^{-1} \sum_{i=1}^{N} z_i' \Delta v_i \Delta v_i' z_i
\]

Furthermore, the specification test is performed on the dynamic model. The first test is the Sargan test, to determine the validity of the use of instrument variables whose number exceeds the number of expected parameters (overidentifying conditions); the hypothesis is as follows:

H0: The overidentifying restriction condition in estimating the model is valid (instrument variables are not correlated with errors so that the instrument variables are valid)

H1: The overidentifying restriction condition in estimating the model is not valid

Sargan test statistics are as follows:

\[
S = \bar{v} Z \left( \sum_{i=1}^{N} Z_i' \bar{v}_i v_i' z_i \right)^{-1} Z' \bar{v} \sim \chi^2_{L-(k+1)}
\]

Noted:
Z: Instrument variable matrix
\( \bar{v} \): Error component of the model estimate
Decision: H0 is rejected if the p-value is in the test statistic \( < \alpha \) (\( \alpha = 0.05 \)).

Furthermore, the Arellano-Bond test (1991) was used to test the consistency of estimates obtained from the GMM process, with the following hypothesis.

H0: There is no autocorrelation in the 2nd order first difference error.

H1: There is autocorrelation in the 2nd order first difference error.

The Arellano-Bond test statistics are as follows.

\[
m_2 = \frac{v_i' v_i}{v_i'^2} \sim N(0,1)
\]

Decision: H0 is rejected if the p-value is in the test statistic \( m_2 < \alpha \) (\( \alpha = 0.05 \)).

The two tests above and seeing model specifications, can also be used to test classical assumptions. The Sargan test can be used for the heteroscedasticity test, while the Arellano-Bond test is used for the autocorrelation test.

3. Result and Discussion
3.1. Descriptive Statistics
This section describes several descriptive statistical measures of the research variables. Several statistical measures are displayed in the form of minimum, maximum, and average values. Before analysing the data, the first thing to do is to do a descriptive analysis to see how the data can be described briefly. The following shows a descriptive analysis of the research variables:
### Table 1. Descriptive Analysis of Research Variables (Percent)

| Indicator | Variable | Poverty | HDI | Gini | Unemployment |
|-----------|----------|---------|-----|------|--------------|
| Min.      |          | 3.47    | 55.55 | 0.27 | 1.37         |
| 1st Qu.   |          | 6.60    | 66.74 | 0.34 | 3.81         |
| Median    |          | 9.80    | 68.92 | 0.36 | 4.83         |
| Mean      |          | 11.52   | 68.92 | 0.37 | 5.26         |
| 3rd Qu.   |          | 14.93   | 71.13 | 0.40 | 6.38         |
| Max.      |          | 31.13   | 80.76 | 0.44 | 10.51        |

Table 1 above shows that the average poverty scores for Provinces in Indonesia during the study period was 11.52 percent. Nationally, the percentage of poverty in Indonesia continues to decline until 2019 is below 10 percent. The highest rate of poverty was in Papua Province, amounting to 31.13 percent in 2013; the pattern of poverty fluctuates in line with the infrastructure conditions in Papua. The province with the lowest poverty score of 3.47 percent was DKI Jakarta Province. This condition is natural because the economic center is in Jakarta as the national capital. The average HDI of Provinces in Indonesia during the study period was 68.92. Nationally, Indonesia's HDI continues to increase from year to year. If viewed per province during the research period, the highest HDI was 80.76 in the DKI Jakarta Province in 2019. This condition is reasonable because DKI Jakarta is the capital of a country with good facilities and infrastructure.

Meanwhile, the lowest HDI was 55.55 in Papua Province in 2012. It is also reasonable to say that Papua still does not have optimal facilities and infrastructure. However, Papua starts to change every year along with the increase in builders and infrastructure; HDI's value continues to increase every year. When viewed from the income distribution side, the Gini ratio, on average, the Gini coefficient for provinces in Indonesia is 0.37, which indicates that there are still disparities in the distribution of income in Indonesia. In Yogyakarta, Gorontalo, West Papua, and Papua have the largest Gini coefficient values. In these four provinces, we can say that income distribution is very unequal; only asset owners who benefit from the economy.

Meanwhile, the lowest Gini ratio was 0.27 in Bangka Belitung Province in 2019. On average, the provincial open unemployment rate in Indonesia is 5.26 percent. The province with the largest TPT was Maluku Province in 2014, amounting to 10.51. Meanwhile, the lowest was Bali Province, amounting to 1.37 in 2018. This condition is natural because Bali is the center of foreign tourism in Indonesia, which can absorb many workforces, mostly informal workers in the MSME sector.

### 3.2. Inferential Analysis

Because the data used is in the form of panel data, namely data consisting of several individuals and several periods, one of the analyses used is by using regression analysis with panel data. In panel data regression analysis, there are three general models used, namely the pooled model (PLS), the fixed-effect model (FEM), and the random effect model (REM). In the first step, we must test to own the three models, namely the LM BP Test (to test between pooled and random models), Chow Test (to test between pooled and fixed models), and Hausman Test (to test between random models against fixed-effect models). The following shows the results of the three tests:

| Panel Test | F Stat | Chi Stat | P.value | Conclusion |
|------------|--------|----------|---------|------------|
| Chow Test  | 357.210| 0.000    |         | Fixed Effect is better than Pooled Model. |
| BP LM Test | 723.680| 0.000    |         | Random Effect is better than Pooled Model. |
| Hausman    | 14.208 | 0.003    |         | Fixed Effect is better than Random Model. |
From the three tests, we can say the model chosen is the Fixed model. Henceforth, from the selected model is subjected to a classical assumption test before interpreting the model. The assumptions tested consisted of normality assumptions using the Skewness and Geary Test. For the heteroscedasticity test, we use the Breusch Pagan test. Multicollinearity test by looking at the Variant Inflation Factor (VIF) value, and autocorrelation test by looking at the Durbin Watson value. We can see the results of the four classical assumption tests as follows:

### Table 3. Classical Assumption Test

| Classic Assumptions         | Prob. | Conclusion       |
|-----------------------------|-------|------------------|
| Normality (Skewness/Geary Test) | 0.087 | Normal distributed data |
| Heteroscedasticity (BP Test) | 0.201 | Non Heteroscedasticity |
| Multicollinearity (VIF)     | VIF < 5 | Non Multicollinearity |
| Autocorrelation (DW Panel Test) | 0.000 | Autocorrelation |

From the four tests conducted, it can be seen that three assumptions are met, one assumption is not met, namely the autocorrelation assumption. This condition often occurs in models containing time series data due to the dependent variable data lag's influence. Therefore, to overcome this autocorrelation problem, it is followed by dynamic panel data regression analysis, which includes the lag element from the dependent variable data known as the Arellano Bond Model. The following is the comparison of the regression model for static panel data and dynamic panel data:

### Table 4. Comparison of Static and Dynamic Panel Models

| Coefficients:              | Pooled/Common Estimate | Pr(>|z|) | Fixed Estimate | Pr(>|z|) | Random Estimate | Pr(>|z|) | Dynamic Panel Estimate | Pr(>|z|) |
|---------------------------|------------------------|---------|----------------|---------|-----------------|---------|------------------------|---------|
| lag(poverty,1:2)1         | -0.9404                | 0.0000  | -0.4482        | 0.0000  | -0.4620         | 0.0000  | 0.5292                 | 0.0000  |
| lag(poverty,1:2)2         | 45.9917                | 0.0000  | -1.7624        | 0.4963  | -1.5078         | 0.5669  | 0.1807                 | 0.0000  |
| HDI                       | 0.0188                 | 0.8911  | 0.0328         | 0.5298  | 0.0206          | 0.6975  | 3.6880                 | 0.0069  |
| Gini                      | 0.0188                 | 0.8911  | 0.0328         | 0.5298  | 0.0206          | 0.6975  | -0.0094                | 0.7388  |
| unemployment              | 0.51                   | 0.44    | 0.48           | 0.99    |                 |         |                        |         |
| F /Chi /Wald              | 94.65                  | 82.88   | 254.86         | 1249.90 |                 |         |                        |         |
| Prob.F /Chi/Wald          | 0.00                   | 0.00    | 0.00           | 0.00    |                 |         |                        |         |

If we look at the four models, three static models (pooled, fixed, and random) with dynamic models, all simultaneous tests are significant, meaning that the model is fit, and it is stated that at least one independent variable affects the dependent variable. When viewed from the journal, the independent variables that significantly affect the pooled and dynamic models have two significant variables. Meanwhile, if viewed from the adjusted r square side, it can be seen that the dynamic model is the best model with the largest r-square value. Furthermore, the suitability and assumption tests are carried out on the dynamic panel model, namely the Sargan test, to see whether the model is fit and test the heteroscedasticity assumption autocorrelation test on lag data.

### Table 5. Sargan Test and Dynamic Model Autocorrelation

| Test                        | Chi Square | Prob.Value | Conclusion                        |
|-----------------------------|------------|------------|-----------------------------------|
| Sargan                      | 20.82455   | 0.28836    | Fit / Heteroscedasticity Free Model |
| Autocorrelation/ arrelano bond test |            |            |                                   |
| lag 1                       | -2.52905   | 0.011437   |                                   |
| lag 2                       | -1.27538   | 0.2022     | Non Autocorrelation               |
| lag 3                       | 0.96767    | 0.3332     |                                   |
From the above results, it can be seen that the value of the probability value Sargan test = 0.288 means that the model is fit and is free of heteroscedastic assumptions. While from the Arellano bond test on lag 2 and 3, the value of prob.value = 0.202 means that the model is free of autocorrelation assumptions.

3.3. Discussion

HDI has a significant effect on poverty with a negative coefficient. This result means that an increase in HDI reduces poverty. This result is in line with [19] which states that an increase in HDI will reduce poverty. The same result was also obtained by [20] research, which states that increasing HDI will reduce poverty. Similar results were also obtained by [21]. This result indicates that improving the quality of life through investment in health and education will drive poverty. This result can be explained by the relationship between health and education and the ability to increase income. Furthermore, this study also examined the relationship between the Gini ratio and poverty. Until now, the relationship between these two economic indicators is not clear. Some research states that there is no relationship between poverty and the Gini ratio. Meanwhile, some other research says that poverty and the Gini ratio are closely related. In this study, it was found that the Gini ratio has a significant effect on poverty with a positive coefficient. This result is in line with [22], who states that there is a relationship between the Gini ratio and poverty. The higher the Gini ratio (the gap), the poverty will increase. Several previous studies conducted in various parts of the world also showed similar results. These studies show that not only affects the level of poverty, the occurrence of inequality in income distribution will also affect the depth and severity of poverty [23].

Unlike the two previous variables, which showed a significant effect on poverty, this study has insufficient evidence that unemployment affects poverty. This result is similar to that of [24], which states that the number of unemployed has no significant effect on poverty. A similar thing was also found in [11], which also found that unemployment was not significantly associated with poverty levels in East Indonesia and Central Java. There are several arguments; for example, Maryono DS (2001) in [11] argues that in some areas, the unemployment that occurs is voluntary unemployment that happens because you choose to be unemployed rather than having to work but not in the field of work or compensation as expected.

4. Conclusion

As poverty is an important problem in developing countries like Indonesia, it is essential to modeling the determinant of poverty in the right ways. Based on the data and the model evaluations equipped in this study, static panel data regression, the selected model is a fixed effect model but still experiences violations of the classic autocorrelation assumption. Hence, the dynamic panel data model provides better results than the static panel data regression model. When viewed from the r-square value, the number of variables that have significant effects. Therefore, based on the selected model, the Gini ratio has a significant and positive relationship to poverty. In contrast, HDI has a significant and negative relationship to poverty. However, unlike the two previous variables, there is insufficient evidence to suggest that unemployment affects poverty.

References

[1] Page L and Pande R 2018 Ending global poverty: Why money isn’t enough Journal of Economic Perspectives 32 173-200.
[2] Dartanto T and Nurkholis 2013 The determinants of poverty dynamics in Indonesia: evidence from panel data Bulletin of Indonesian Economic Studies 49 61-84.
[3] Müller G P 2002 Explaining poverty: on the structural constraints of income mobility Social Indicators Research 59 301-319.
[4] Fields G, Cichello P, Freije S, Menéndez M, and Newhouse D 2003 Household income dynamics: a four-country story The Journal of Development Studies 40 30-54.
[5] Herrera J 1999 Ajuste económico, desigualdad y movilidad. Pobreza y Economía Social: Análisis de Una Encuesta ENNIV-1997 101–142.
[6] Sawada Y, Shoji M, Sugawara S, and Shinkai N 2014 The role of infrastructure in mitigating poverty dynamics: The case of an irrigation project in Sri Lanka. The BE Journal of Economic Analysis & Policy 14 1117-1144.

[7] Jazid A I M, and Ibrahim P 2020 Persistent Poverty Based on Three Dimensions in HDI. In Charting a Sustainable Future of ASEAN in Business and Social Sciences (pp. 87–98). Springer.

[8] BPS 2013 Indeks Pembangunan Manusia. Retrieved October 11, 2020, from https://bps.go.id/subject/26/indeks-pembangunan-manusia.html#subjekViewTab1

[9] Sitepu, R. K., & Sinaga, B. M. (2007). Dampak investasi sumberdaya manusia terhadap pertumbuhan ekonomi dan kemiskinan di indonesia: pendekatan model computable general equilibrium SOCA: Jurnal Sosial Ekonomi Pertanian 7 2.

[10] Susanti S 2016 Pengaruh Produk Domestik Regional Bruto, Pengangguran dan Indeks Pembangunan Manusia terhadap Kemiskinan di Jawa Barat dengan Menggunakan Analisis Data Panel Jurnal Matematika Integrati 9 1-18

[11] Amalia F 2012 Pengaruh Pendidikan, Pengangguran dan Inflasi Terhadap Tingkat Kemiskinan di Kawasan Timur Indonesia (KTI) Periode 2001-2010 Jurnal Ilmiah Econosains 10 158-169.

[12] Todaro M P, and Smith S C 2004 Pembangunan ekonomi di dunia ketiga (8th ed.). Jakarta: Penerbit Erlangga.

[13] Imai K S, and Azam M S 2012 Does microfinance reduce poverty in Bangladesh? New evidence from household panel data Journal of Development Studies 48 633–653.

[14] Ucal M Ş 2014 Panel data analysis of foreign direct investment and poverty from the perspective of developing countries Procedia Social and Behavioral Sciences 109 1101–1105.

[15] Berhane G and Gardebroek C 2011 Does microfinance reduce rural poverty? Evidence based on household panel data from northern Ethiopia American Journal of Agricultural Economics 93 43-55.

[16] Negin V, Abd Rashid Z, and Nikopour H 2010 The causal relationship between corruption and poverty: A panel data analysis. MPRA Paper No. 24871

[17] Gujarati D 2006 Ekonometrik Dasar Jakarta Erlangga.

[18] Meriyanti N K, Haris I A, Artana M 2015 Pengaruh program indeks pembangunan manusia (ipm) terhadap pengentasan kemiskinan di kecamatan buleleng tahun 2011-2014 Jurnal Jurusan Pendidikan Ekonomi, 5 52-62

[19] Saeufuddin A, Setiabudi N A, and Fitrianto A 2012 On comparison between logistic regression and geographically weighted logistic regression: With application to Indonesian poverty data World Applied Sciences Journal 19 205–210

[20] Novianto S and Sudarsono H 2018 Analysis of poverty levelin districts/cities of central java Jurnal Ekonomi Pembangunan 16 1–12.

[21] Rizky P 2016 Faktor-faktor yang mempengaruhi tingkat kemiskinan di provinsi kalimantan timur Jurnal Ekonomi, Manajemen Dan Akuntansi 18 111-129.

[22] Naschold F 2002 Why inequality matters for poverty (Inequality briefing no. 2). London, UK: Overseas Development Institute.

[23] Nisbah F 2018 Analisis Pengaruh Tingkat Pengangguran dan Pertumbuhan Ekonomi Terhadap Tingkat Kemiskinan Di Kabupaten/Kota Medan, Binjai, Deli Serdang, Karo, Dan Langkat. Universitas Sumatera Utara.

[24] Rudsart R and Sebayang L K 2013 Faktor-faktor yang mempengaruhi tingkat kemiskinan di provinsi jawa tengah Jurnal Economia 9 1–9.