International Journal of
Economics Development Research, Volume 5(5), 2024
pp. 3975-3992

# Monetary Child Poverty Analysis in Indonesia: Empirical Evidence with Panel Data

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***Abstract:***

*The monetary child poverty gap in Indonesia shows significant disparities between provinces, especially in eastern Indonesia. This phenomenon hinders the achievement of SDGs and has implications for the quality of long-term human development. This study aims to analyze the factors that influence the level of monetary child poverty in Indonesia using panel data from 34 provinces for the period 2019-2022. The analysis method uses panel data regression with the Fixed Effect Model (FEM) approach, based on secondary data from BPS, by analyzing eleven covariates to identify significant determinants of monetary child poverty. The estimation results show five variables that have a significant effect: birth certificate ownership, internet use for school, Human Development Index, regional economic growth, and labor force participation. Meanwhile, the variables of child labor, Gini ratio, out-of-school rate for 7-12 year olds, preschool level, and PIP recipients at elementary and junior high school levels do not show a significant effect. These findings imply the need for an integrated reformulation of child poverty alleviation policies, focusing on strengthening the population administration system, digital transformation of education, improving the quality of human development, and optimizing inclusive economic growth.*

***Keywords:*** *monetary child poverty, panel data, fixed effect model, public policy, Indonesia*

Sumbitted: 28 September 2024, Accepted: 3 November 2024, Published: 7 November 2024

## 1. Introduction

Child poverty is considered an important component of poverty by development economists and policy makers.(Kandapan et al., 2023). Poverty is seen as a barrier for children to develop and achieve their full potential. Living in a poor family can affect the availability of material resources available to children to meet their nutritional, health care, and education needs. Child poverty at birth has a negative and significant impact on children's readiness to enter school age. In addition, poverty that is continuously experienced by children also affects lower cognitive test results.(Dickerson & Popli, 2016). In children with low health conditions, poverty will worsen health conditions, accumulating throughout later life, causing them to have

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low educational attainment, which can then affect their ability to work in the future.(Case et al., 2002).

Child poverty is important, not only because of the high number of children affected, but also because of the negative impact on their cognitive and physical development both now and in the future.(Bandyopadhyay et al., 2023; Bessell, 2022; Makhalima, 2020; Pac et al., 2023). One of the causes of poverty in children could be due to the increasing proportion of single mothers in the family.(Bostic, 2023). Another study found that increasing child dependency significantly reduces consumption and worsens poverty.(Irfan et al., 2023).

Addressing child poverty is seen as a form of investment for the country to develop its human resource capacity in an effort to improve the economy. Research in the United States shows that poverty in childhood each year can reduce economic productivity equivalent to 1.30 percent of Gross Domestic Product (GDP)(Holzer et al., 2008). Studies also show that conditions of poverty experienced by children over a long period of time will increase the tendency to become poor as adults, which is increasingly high.(Fass et al., 2009).

Children from large families experience poverty rates up to twice as high as children from small families, yet they are often overlooked in financial assistance programs aimed at low-income households. While child benefits are a key form of income support provided to large families, their interaction with means-tested assistance policies limits access, particularly for middle-income families, leaving many in need unsupported.(Köppe et al., 2024). Therefore, various policies in order to address child and adolescent poverty are efforts to end poverty and prevent intergenerational losses.(The Global Coalition to End Child Poverty, 2017)one of which is through targeted fiscal policy(Ambel et al., 2024).

Nakray (2015)defines child poverty as the result of early exposure to a range of interrelated physical, social, economic and cultural risks. These factors significantly affect children's life expectancy and reduce their quality of well-being. Furthermore, at a societal scale, this problem significantly exacerbates both intra- and intergenerational poverty.

Efforts to eradicate poverty, including among children, are one of the agendas in the Sustainable Development Goals (SDGs) Goal 1, which is to end poverty in all its forms everywhere. Monetary child poverty is in line with SDGs Indicator 1.2.1, which is the percentage of the population living below the national poverty line by sex and age group. Monitoring child poverty, both in monetary and multidimensional terms, is an effort to implement various policies to eradicate child poverty and see the progress that has been achieved. But attention to children goes beyond the first goal because addressing children's vulnerability to poverty also has a positive relationship with outcomes in various SDGs. For example, combating child poverty means addressing multiple pathways of deprivation related to personal livelihoods, such as nutrition in SDG 2, or access to services and utilities such as health and clean water in SDGs 3 and 6. Fostering quality education for children (SDG 4) is key to breaking the intergenerational cycle of exclusion, as well as offering them the best possible employment opportunities in SDG 8 and greater choice about cleaner and less polluted living conditions in SDGs 7 and 12.(Sánchez et al., 2024).

In 2020, the percentage of poor people in Indonesia reached 9.78 percent, an increase of 0.37 percentage points from 2019. Research conducted by UNICEF, UNDP, Prospera, and SMERU to see the impact of the COVID-19 pandemic on households showed a reduction in income across all expenditure groups at the end of 2020 compared to the beginning of 2020 due to changes in behavior and economic activity due to COVID-19. There are around 40 percent of households that experienced a reduction in income of around 25 percent(UNICEF et al., 2021).

The economic shock is possible due to the large number of layoffs and rising prices of goods during the pandemic. The results of the BPS Labor Force Survey (Sakernas) show that there are 29.12 million (14.28 percent) of the working age population (population aged 15 years and over) in Indonesia who are affected by COVID-19. The highest impact of COVID-19 on the workforce is the reduction in working hours and unemployment.(BPS RI, 2021).

In line with the general poverty pattern, the percentage of poor children also increased from 2019 to 2020 and peaked in 2021 (Figure 1). The pandemic has increased deprivation not only in terms of the economy, but also children's opportunities to obtain health services and education.(UNICEF et al., 2021). The increase in the percentage of poor children due to the pandemic was slightly higher than the increase in poverty in general. In 2019-2020, the increase in the percentage of the poor population in Indonesia was 0.37 percentage points, while the percentage of poor children was 0.47 percent. The same increase also occurred in the 2020-2021 period. The pandemic situation which is starting to subside also appears to have an impact on the decrease in the percentage of poor children to 9.54 percent in 2022.

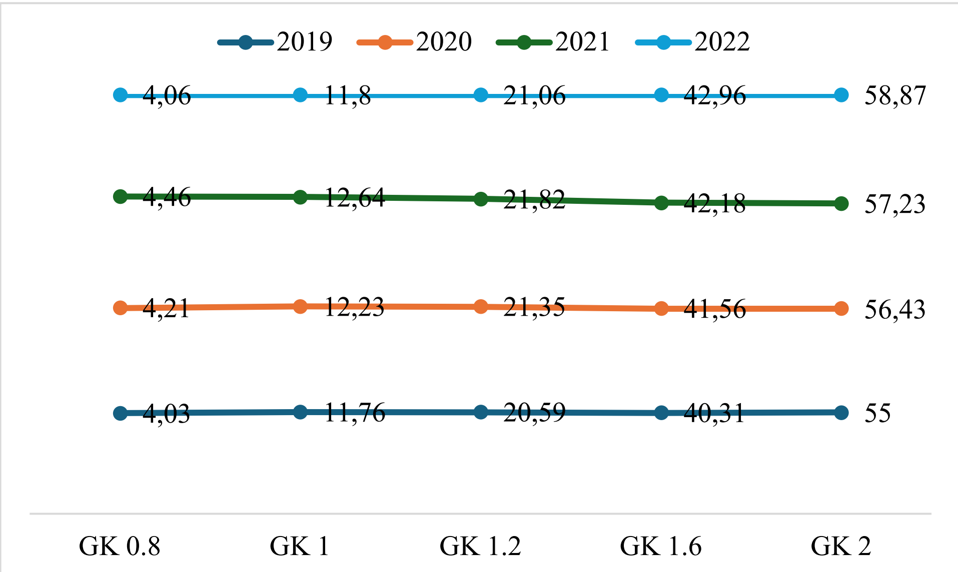


**Figure 1. Percentage of Poor Children According to Several Poverty Lines**
Source: Central Bureau of Statistics, 2022

Figure 1 shows the percentage of poor children in Indonesia as seen from several Poverty Lines (PWL). When the poverty line is increased to 1.2 PWL, the percentage of poor children almost doubles. This shows that many children are vulnerable to poverty or have an economy that is very close to poverty. Furthermore, when the poverty line is increased to 2 PWL, more than half of the children in Indonesia are categorized as poor.
In addition to the percentage of poor people, the severity and depth of poverty in the child age group are also higher than poverty in general. The higher the poverty depth index indicates that the average expenditure is further from the poverty line, while the higher the poverty severity index indicates the inequality of expenditure between poor children. Furthermore, the data pattern also shows that the percentage of poor adolescents is also consistently higher than poverty in general. Efforts to reduce child and adolescent poverty need to be equally prioritized. Poverty at an early age will form a foundation that traps children in poverty, while adolescent poverty can worsen the situation which, when continued, can become the basis for inheriting poverty to the next generation.(United Nations Children's Fund (UNICEF), 2020).

**Table 1. Percentage of Poor Population (P0), Poverty Depth (P1), and Poverty Severity (P2) by Age Group, 2022**

| Age Group | Percentage of Poor Population (P0) | Depth of Poverty (P1) | Poverty Severity (P2) |
|---|---|---|---|
| All ages | 9.54 | 1.59 | 0.39 |
| **Toddlers (0-4 years)** | **12.93** | **2.2** | **0.55** |
| **Children (0-17 years)** | **11.8** | **2.01** | **0.51** |
| **Teenagers (10-19 years)** | **10.67** | **1.82** | **0.46** |
| **Youth (16-30 years)** | **8.82** | **1.46** | **0.36** |
| Productive age (15-64 years) | 8.47 | 1.39 | 0.34 |
| Pre-Elderly (45-59 years) | 7.26 | 1.16 | 0.28 |
| Elderly (60 years+) | 10.15 | 1.67 | 0.41 |

Source: BPS, Susenas March 2022

After looking at the general trend of the percentage of poor children, Table 1 then shows the percentage of poverty by age group. The percentage of poor children in the toddler age group (0-4 years) is higher compared to poverty in general. Around 13 out of 100 children, both in the infant and toddler age groups, are included in the poor category. Furthermore, the decline in the percentage of poverty in this age group in the 2021-2022 period showed the smallest value compared to poverty in general.

Data from 2022 shows that the highest percentage of poor children is in Papua and West Papua Provinces. The data pattern also shows a tendency for the percentage of poor children to be higher in eastern Indonesia compared to western Indonesia. From Figure 1, information can also be obtained regarding the condition of child poverty by province and based on several GK. When the poverty determinant is increased to 1.6

GK or 2 GK, North Kalimantan Province shows the highest increase in the percentage of poor children, while Papua Province is the lowest.

Based on the above conditions, this research is important to be conducted as a contribution to the literature on the development of science, especially development economics, to view child poverty as a serious study material in order to make appropriate and targeted policies and programs so that the problem of child poverty will be reduced sustainably and evenly.

The monetary calculation of child poverty also shows that the risk of poverty in children increases with the increasing number of household members. Likewise with the level of depth of child poverty. Children with a larger number of household members will have a harder time escaping poverty than children in households with fewer members.

In 2022, half of the provinces in Indonesia will have a higher percentage of poor children than the national percentage. As mentioned in Figure 4.3, the percentage of poor children tends to be higher in eastern Indonesia. This condition is likely related to inequality between provinces in Indonesia. In 2022, the percentage of child poverty in Papua was five times higher than in the provinces of South Kalimantan, Bangka Belitung Islands, DKI Jakarta, and Bali. The condition of child poverty in West Papua and Papua needs more attention, this is because more than a quarter of children in these provinces are categorized as poor.

## 2. Methodology

The object of this research is 34 provinces in Indonesia using data for the period 2019-2022.

The type of data used in this study is secondary data, namely the type of data collected by related institutions and published to data users. Secondary data includes research data that has been published by the Central Statistics Agency and as literature related to the research title. The data used is time series data in the period 2019-2022. The data in this study were obtained from the Central Statistics Agency and various other journals related to the research title.

Data collection in a study is intended to obtain relevant materials. The data collection method used in this method is the documentation method. The documentation method is a method of collecting data from related institutions, namely the Central Statistics Agency and other libraries used as a complement to the problems related to the title of this study.

The research used in this study is a quantitative approach. This approach uses a regression analysis tool with a regression model used to test hypotheses from measurable data so that the effect of changes in a macroeconomic variable on child poverty in Indonesia is obtained.

The analysis tool in this study uses a panel data model. Panel data is defined as a collection of time series and cross section (individual) data.

This study uses regional panel data in Indonesia from 2019 to 2022. This study then uses panel data analysis with the Fixed Effect Model (FEM) or Random Effect Model (REM) based on the best modeling results. Some of the estimates that have been developed, show what assumptions underlie the estimates, how well the estimates work relative to each other and how to test the validity of the assumptions behind the estimates to choose the most appropriate estimate for the data used in the study.

In estimating child poverty in Indonesia, this study uses variables of child birth certificate ownership rate, child labor, internet usage rate for school, Human Development Index (HDI), economic growth, income inequality, labor force participation, out-of-school rate for children aged 7-12 years, number of children who complete pre-school education, number of recipients of Smart Indonesia Program (PIP) for elementary school, and number of recipients of PIP for junior high school. The data in this study were obtained from the Central Bureau of Statistics of Indonesia.

**Table 2. Operational Definition of Variables**

| Variables | Definition | Measurement Scale | Source |
|---|---|---|---|
| Monetary Child Poverty (childpov) | The calculation of monetary poverty is carried out by referring to the value of income (or expenditure) as the main benchmark in determining poor individuals. | Percentage | Central Bureau of Statistics of the Republic of Indonesia |
| Ownership of Birth Certificate (birth certificate) | Ownership of a birth certificate is a form of fulfilling a child's right to identity as stated in the Convention on the Rights of the Child. | Percentage | Central Bureau of Statistics of the Republic of Indonesia |
| Child labor rate (Childlabor) | The proportion of child workers is child workers that include the population (i) all children aged 5-12 years who work; (ii) the population aged 13-14 years who work more than 15 hours per week; (iii) and the population aged 15-17 years | Percentage | Central Bureau of Statistics of the Republic of Indonesia |

| | | | |
|---|---|---|---|
| | who work more than 40 hours per week against the total population aged 5-17 years. | | |
| Internet Usage Rate for Schools (internetforschool) | Percentage of Population Aged 5 Years and Over Who Have Accessed the Internet in the Last 3 Months by Province and School Participation (Percent), 2023 | Percentage | Central Bureau of Statistics of the Republic of Indonesia |
| Human Development Index (HDI) | IPM explains how people can access development results in terms of income, health, education, and so on. | Percentage | Central Bureau of Statistics of the Republic of Indonesia |
| Economic Growth (Growth) | Economic growth is an increase in the production of goods and services in an economy in a region. | Percentage | Central Bureau of Statistics of the Republic of Indonesia |
| Income Inequality (Gini Ratio) | The Gini Ratio or Gini Coefficient is a coefficient used to measure the degree of inequality in population distribution, which is displayed using the Lorenz curve. | Percentage | Central Bureau of Statistics of the Republic of Indonesia |
| Labor Force Participation (workparticip) | The Labor Force Participation Rate is defined as the ratio of the labor force to the total working age population. | Percentage | Central Bureau of Statistics of the Republic of Indonesia |
| Out of School Rate 7-12 years old (ORS) | Children Not in School is the percentage of the population of a certain educational age who are not | Percentage | Central Bureau of Statistics of the Republic of Indonesia |

| | | | |
|---|---|---|---|
| | currently attending school. Residents who are in preschool are considered to be attending school. Residents aged 16-18 years who are no longer in school but have a high school diploma or above are considered to be attending school. The age used in calculating this indicator is the age at the beginning of the school year. | | |
| Preschool | Percentage of Children by Preschool Education Participation (Percent) | Percentage | Central Bureau of Statistics of the Republic of Indonesia |
| Recipients of the Smart Indonesia Program for Elementary and Middle Schools (LogPIPSD and LogPIPSMP) | This is assistance in the form of cash, expanded access, and learning opportunities from the government which is given to students who come from poor or vulnerable families to finance their education. | Number of Recipients | Ministry of Education and Culture of the Republic of Indonesia |

The empirical model of this research is constructed as follows:

$$\begin{aligned} Childpov_{i,t} = \beta_0 &+ \beta_1 Birthcertif_{i,t} + \beta_2 Childlabor_{i,t} + \beta_3 Internetforschool_{i,t} \\ &+ \beta_4 HDI_{i,t} + \beta_5 Growth_{i,t} + \beta_6 Giniratio_{i,t} + \beta_7 Workparticip_{i,t} \\ &+ \beta_8 OSR_{i,t} + \beta_9 Preschool_{i,t} + \beta_{10} Log(PIPSD)_{i,t} \\ &+ \beta_{11} Log(PIPSMP)_{i,t} \\ &+ \varepsilon_{i,t} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.. (1) \end{aligned}$$

## 3. Empirical Findings/Result

In a study, presenting descriptive statistics is an important initial step to provide an overview of the data that has been collected. Descriptive statistics serve to summarize and simplify raw data, making it easier for researchers and readers to understand the patterns, characteristics, and distribution of the variables being measured. In this section, a descriptive statistics table will be presented that includes information such as the average (mean), standard deviation, minimum value, maximum value and number of observations. This data is expected to provide initial insight related to the main findings in this study. The Descriptive Statistics of this study are summarized in the following table:

**Tabel 3. Descriptive Statistics**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Childpov | 136 | 13.165 | 6.443 | 4.58 | 33.9 |
| Birthcertif | 136 | 87.873 | 9.681 | 45.19 | 98.36 |
| Childlabor | 136 | 3.174 | 1.48 | .61 | 8.05 |
| Internetforschool | 136 | 71.625 | 15.656 | 30.54 | 98.49 |
| HDI | 136 | 71.363 | 3.887 | 60.44 | 81.65 |
| Growth | 136 | 3.357 | 4.351 | -15.74 | 22.94 |
| Giniratio | 136 | .346 | .041 | .247 | .459 |
| Workparticip | 136 | 5.301 | 1.811 | 1.57 | 10.95 |
| ORS712tahun | 136 | .95 | 2.184 | 0 | 15.92 |
| Preschool | 136 | 25.904 | 6.186 | 8.5 | 47.72 |
| PIP SD | 136 | 12.057 | 1.024 | 9.891 | 14.464 |
| PIP SMP | 136 | 11.224 | .996 | 9.288 | 13.599 |

*Source : Data Processed Result, 2024.*

Based on the descriptive statistics table, the research data includes several important variables that provide an overview of social, economic, and educational conditions. The childpov variable or child poverty has an average of 13.165 with a standard deviation of 6.443, indicating significant variation in the level of child poverty, with a minimum value of 4.58 and a maximum of 33.9. The level of birth certificate ownership shows an average of 87.873, with a standard deviation of 9.681, indicating that most of the population has a birth certificate, although there are areas with the lowest coverage of 45.19%.

In terms of childworkers, the average was recorded at 3,174 with a standard deviation of 1.48, indicating inequality, with a minimum of 0.61 and a maximum of 8.05. Internet access for schools (internetforschool) had an average of 71,625 with a standard deviation of 15,656, with a variation between 30.54 and 98.49, reflecting inequality of access.

The human development index (hdi) has an average of 71.363 with a standard deviation of 3.887, with a minimum value of 60.44 and a maximum of 81.65. Economic growth shows an average of 3.357 with a standard deviation of 4.351, indicating that there are regions that experience economic contraction of up to -15.74, while others record growth of up to 22.94.

Income inequality measured by the Gini ratio (giniratio) has an average of 0.346 with a fairly small variation, namely a standard deviation of 0.041. Labor force participation (workparticip) has an average of 5.301, indicating a distribution of participation with a variation between 1.57 and 10.95.

Education indicators such as ats712tahun (number of out-of-school children aged 7-12 years) have a low average of 0.95, but with a standard deviation of 2.184, indicating variation between regions. Preschool participation is recorded at an average of 25.904 with a standard deviation of 6.186. In the primary and secondary education indicators, the average value of lpipsd (primary school exam score) is 12.057, while lpipsmp (junior high school exam score) is 11.224, with relatively small variations between the regions observed.

**Selecting the Best Panel Data Model**

**a. Selection of Pooled Least Squares or Fixed Effect Model (FEM)**

In panel data analysis, selecting the right model is an important step to obtain accurate estimates. Two common approaches that are often used are the Pooled Least Squares (PLS) model and the Fixed Effect Model (FEM). To determine the best model between the two, the Chow Test is used, which aims to test whether the FEM model is more appropriate than PLS. This test checks whether there are significant differences between groups or entities in the data, so if the test results are significant, FEM is chosen because it is able to capture differences between individuals or entities that cannot be handled by PLS.

**Table 4. Chow Test Results**

| | | |
|---|---|---|
| sigma_u | 4.834353 | |
| sigma_e | .49908329 | |
| rho | .98945455 | (fraction of variance due to u_i) |

F test that all u_i=0: F(33, 91) = 252.78 Prob > F = 0.0000

*Source : Data Processed Result, 2024.*

In the selection of PLS or FEM is based on the value of Prob > F, if the value of Prob > F is more than 0.05 then the best model chosen is PLS, but if Prob > F is less than 0.05 then the best model is FEM. Based on the estimation results using Stata that the value of Prob > F from the chow test results is 0.0000 which indicates that the model to be selected is the Fixed Effect Model (FEM).

**b. Selection of Fixed Effect Model (FEM) or Random Effect Model (REM)**

In panel data analysis, one of the main challenges is choosing the most appropriate model between the Fixed Effect Model (FEM) and the Random Effect Model (REM). These two models have different approaches in handling inter-individual or entity variability. To determine the best model between FEM and REM, the Hausman Test is used. This test functions to evaluate whether the correlation between independent variables and individual effects is significant. If the test results show that there is a significant correlation, then the FEM model is more appropriate because it is able to overcome individual heterogeneity. However, if there is no significant correlation, REM is considered more efficient and appropriate to use because the assumption of unrelatedness is met.

**Table 5. Hausman Test Results**

| | Coefficients (b) FEM | (B) REM | (b-B) Difference | sqrt(diag(V_b-V_B)) S.E. |
|---|---|---|---|---|
| birthcertif | -.0816698 | -.0937722 | .0121024 | . |
| childworkers | .0292634 | .0257463 | .003517 | . |
| internetfo~l | .0364187 | .0422408 | -.0058221 | .0025681 |
| hdi | -.8270584 | -.9272616 | .1002032 | .1203759 |
| growth | .0402533 | .0394065 | .0008468 | . |
| giniratio | 4.59264 | 8.247576 | -3.654936 | .337121 |
| workparticip | .2059715 | .1886567 | .0173148 | . |
| ats712tahun | .0063937 | .0477497 | -.041356 | . |
| prasekolah | -.0284097 | -.0114524 | -.0169573 | .0167292 |
| lpipsd | .565212 | .4219203 | .1432918 | .1212024 |
| lpipsmp | .3086475 | .2309118 | .0777357 | . |

```
                  b = consistent under Ho and Ha; obtained from xtreg
   B = inconsistent under Ha, efficient under Ho; obtained from xtreg

Test:  Ho:  difference in coefficients not systematic

             chi2(11) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                      =       28.66
            Prob>chi2 =      0.0026
            (V_b-V_B is not positive definite)
```

*Source : Data Processed Result, 2024.*

The Hausman test is determined by the value of Prob>chi2. The best FEM model if the Prob>chi2 value is less than 0.05 while the best REM model if the Prob>chi2 value is more than 0.05. From the test results, it can be seen that the Prob>chi2 value is 0.0026 which is still smaller than 0.05 so the best model to be selected is the Fixed Effect Model (FEM).

**Panel Data Estimation Results**

Based on the results of the model selection test, the Fixed Effect Model (FEM) was identified as the best model for panel data analysis in this study. FEM was chosen because it is able to capture specific variations between individuals or entities that are fixed and affect the dependent variable. By using FEM, we can control for the unique characteristics that do not change from each entity, thus allowing for more accurate and consistent estimates. The following section will show the estimation results using FEM, which describe the relationship between the independent and dependent variables after controlling for the fixed effects of each entity. These results provide deeper insight into the factors that influence the observed variables.

**Table 6. Panel Data Estimation Results**

| Variable | PooledLeast~e | FEM | REM |
|---|---|---|---|
| Childpov | -.20188447* | -.08166984* | -.09377221* |
| Birthcertif | -0.447 | 0.029 | 0.026 |
| Childlabor | -0.023 | .03641872*** | .0422408*** |
| Internetforschool | -.79808959*** | -.82705841*** | -.92726162*** |
| HDI | -0.080 | .04025327* | .0394065* |
| Growth | 47.210662*** | 4.593 | 8.248 |
| Giniratio | -0.370 | .20597153* | .18865671* |
| Workparticip | -0.005 | 0.006 | 0.048 |
| ORS712tahun | 0.069 | -0.028 | -0.011 |
| Preschool | -0.307 | 0.565 | 0.422 |
| PIP SD | 0.117 | 0.309 | 0.231 |
| _cons | 77.382012*** | 64.293508*** | 73.051923*** |

legend: * p<0.05; ** p<0.01; *** p<0.001
*Source : Data Processed Result, 2024.*

Based on the results of panel data estimation with the best model is FEM, it can be seen that the variables involved as covariates are ownership of child birth certificates (birthcertif), child workers level (childworkers), internet use for school (internetforschool), Human Development Index (HDI), economic growth (growth), inequality level (giniratio), labor force participation (workparticip), number of children aged 7-12 years out of school (ats712years), preschool level (preschool), number of recipients of PIP SD (lpipsd), and number of recipients of PIP SMP (lpipsmp).

Eleven covariates involved in the model on the level of monetary child poverty in Indonesia, it shows that there are five variables that significantly influence the level of monetary child poverty.

## 4. Discussion

Based on the results of the model estimation, the variables that have a significant influence on child poverty (childpov) are birth certificate, internet for school, hdi, growth, and work participation, with the following details:

Birthcertif (ownership of birth certificate) has a coefficient of -0.0817, which means that every 1 point increase in birth certificate ownership is associated with a decrease in the child poverty rate of 0.0817 points. This effect is significant with a p value = 0.031, indicating that birth certificate ownership has a significant and negative effect on child poverty.

Having a birth certificate allows children to gain access to public services that can help them escape poverty. It also provides a legal identity that is essential for social protection and children's rights.

These findings highlight the importance of prioritizing efforts to accelerate birth registration, especially in rural areas and among marginalized or disadvantaged groups. Evidence suggests that integrating these efforts into services that children and families frequently access, such as health and education, can significantly increase registration rates. Persistent inequalities underscore the need for targeted interventions to ensure comprehensive coverage across all household groups. Such interventions require a thorough review of the legal framework governing the registration process and the operation of the civil registration system. Given that many unregistered children come from poor backgrounds, it is critical that birth registration, including late registration, is free of charge. In countries where registration fees or fines apply, policy and legal reforms should focus on removing these financial barriers.(Cappa et al., 2014).

The results of calculating child poverty in monetary terms in the last four years show that the poverty rate for children who do not have birth certificates is about twice as high as for children who do have birth certificates. In line with this, the risk of poverty and the level of poverty depth for children who do not have birth certificates are also the highest compared to other social protection categories calculated. This indicates that children whose identity rights (birth certificates) have not been fulfilled have a high risk of being poor and will find it more difficult to escape poverty.(BPS, 2023).

Internetforschool (internet access for schools) has a positive coefficient of 0.0364, meaning that every 1 point increase in internet access is associated with a 0.0364 point increase in child poverty. This effect is significant with a p value of 0.000, indicating that internet access is positively correlated with child poverty, which may be caused by other factors related to infrastructure.

Increasing internet access in schools may not directly reduce child poverty if it is not accompanied by improvements in digital skills and effective use. This positive correlation may also reflect a policy focus on improving infrastructure in poor areas, without addressing the root causes of poverty.

Empirical evidence shows a strong correlation between telecommunications infrastructure adoption metrics and reductions in socio-economic deprivation indices. Increased access to formal financial mechanisms shows a statistically significant inverse relationship with poverty indicators. Furthermore, data analysis reveals that informal sector economic activities demonstrate measurable efficacy in improving conditions of material deprivation, suggesting that unregistered commercial ventures serve as a viable pathway to economic advancement among disadvantaged populations.(Kelikume, 2021).

However, other evidence suggests that digitalization reduces poverty and income inequality in developing countries.(Kamalu & Wan Ibrahim, 2024)and productive use of the internet will lead to a reduction in poverty(Huang et al., 2023; Nguyen et al., 2022).

HDI (Human Development Index) has a coefficient of -0.8271, which means that every 1 point increase in HDI is associated with a decrease in child poverty by 0.8271 points. This effect is significant with a p value of 0.000, indicating that an increase in HDI is negatively correlated with child poverty, meaning that the higher the human development, the lower the child poverty rate.

A higher HDI reflects improvements in education, health, and living standards that directly contribute to reducing child poverty. This underscores the importance of investing in human resource development to address poverty. This research is supported by research conducted byMoyo et al., (2022), this study found that increasing human resources leads to a decrease in poverty rates.

In addition, in terms of the channels used to improve children's cognitive outcomes, it significantly promotes internet access in low-income families, extends children's learning time, and improves children's mental health conditions, thereby enhancing their human capital accumulation.(Qi et al., 2024).

Growth has a coefficient of 0.0403, meaning that every 1 point increase in economic growth is associated with a 0.0403 point increase in child poverty. Although significant at $p = 0.026$, this relationship appears contradictory and may be influenced by other factors that require further analysis. Economic growth does not automatically reduce child poverty if its benefits are not evenly distributed. This highlights the importance of policies that ensure inclusive growth and effective redistribution to reduce child poverty. Does economic growth always benefit the poor? Perhaps in some circumstances, yes, but to treat it as a universal principle is an oversimplification. Addressing poverty requires more than just economic growth. If economic growth alone were enough to eradicate poverty, the problem would have been solved long ago. Oversimplified approaches to complex problems often do more harm than good. (Vandemoortele & Delamonica, 2023).

Another finding revealed that economic growth did not significantly reduce poverty.(Pham & Riedel, 2019). MeanwhileKheir, (2018)confirms the existence of a two-way relationship between economic growth and poverty.

The results of this study also contradict the findings put forward byNana Djomo et al., (2024); Ngubane et al., (2023); Saidi et al., (2024)about economic growth can reduce poverty levels both in positive and negative shock situations in economic growth. However, there are quite important findings put forward byJanjua et al., (2023)which provides important evidence that economic growth is not reflected in poverty reduction in the current economic systems of SSA countries, due to the fact that poverty is closely related to income distribution.

Workparticip has a positive coefficient of 0.206, indicating that every 1 point increase in labor force participation is associated with a 0.206 point increase in child poverty. This effect is significant at $p = 0.013$, indicating that higher labor force participation is correlated with higher child poverty, either due to job quality or low wage levels. This could be because the unaccounted for poverty exposure among workers in nonstandard jobs varies widely across the labor market, and that this variation has implications for political inclusion.(Marinova, 2022).

The study revealed that the level of work poverty problem is in line with the overall poverty level, although the poverty rate in the workplace is lower compared to the general poverty rate in all provinces. The results of the logistic regression indicate that three key factors of individual-level variables, work-related variables, and household-level variables significantly affect the prevalence of work poverty in Indonesia.(Faharuddin & Endrawati, 2022). Work participation, especially for women, is also able to reduce poverty levels.(Mulugeta, 2021; Paul, 2023).

Other variables such as childworkers, giniratio, ats712years, preschool, lpipsd, and lpipsmp do not show a significant influence on child poverty because the p value > 0.05, so their influence in this model is considered insignificant.

## 5. Conclusions

Based on the results of panel data estimation with the Fixed Effect Model (FEM), it was found that the dynamics of monetary child poverty in Indonesia have complex and multidimensional characteristics. Of the eleven covariates analyzed in the model, five variables were identified that had a statistically significant effect on the level of monetary child poverty, while the other six variables did not show a significant effect. This indicates that birth certificate ownership, internet use for school, Human Development Index (HDI), economic growth, and workforce participation are key determinants that need to be the focus in efforts to eradicate child poverty in Indonesia.

The statistical significance found in the five variables confirms the importance of a comprehensive approach in addressing child poverty that considers administrative aspects of population, accessibility of educational technology, human development, economic growth, and work participation. This finding also confirms that policy interventions need to be designed by considering spatial and temporal heterogeneity at the provincial level, considering the different characteristics and challenges in each region.

On the other hand, the insignificance of the variables of child labor, inequality, out-of-school rates, preschool levels, and PIP recipients at both elementary and junior high school levels indicates that the effectiveness of programs related to these variables needs to be evaluated and reformulated. This does not mean that these variables are not important, but may require a more integrated approach and be tailored to the local context to be able to provide a significant impact on reducing child poverty.

The results of this analysis provide a strong empirical basis for developing more targeted and effective child poverty alleviation policies. The findings also highlight the importance of strengthening an adaptive and sustainable social protection system, as well as the need for better coordination between stakeholders in implementing child poverty alleviation programs in Indonesia. In the future, further research is needed to explore the causal mechanisms and interactions between variables in more depth, as well as ongoing evaluation of program impacts to ensure the effectiveness of interventions in reducing child poverty in Indonesia.

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