The Influence of Village Funds, HDI, GRDP, and Unemployment on Poverty in Sulawesi 2017-2024 Using Panel Data Regression

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Abstract. Poverty in Indonesia remains a significant problem. Generally, rural poverty is higher than urban poverty. Therefore, the government has enacted a village fund policy through. Law Number 6 of 2024 to assist development efforts that can reduce rural poverty. However, despite a decline in national poverty, the poverty rate in Sulawesi has fluctuated. In addition to village funds, other variables influence poverty, such as human development index (HDI), gross regional domestic product (GRDP) per capita, and unemployment rate. The purpose of this study is to determine the effect of village funds, HDI, GRDP per capita, and unemployment on poverty rates in 70 districts in Sulawesi from 2017 to 2024. Data used are sourced from directorate general of fiscal balance (DJPK) for village funds and BPS for other variables. Panel data regression analysis is used to identify variables that influence poverty rates. Based on FEM, it is known that HDI and GRDP per capita have a negative and significant effect on poverty rates in Sulawesi Island. Village funds are insignificant in reducing poverty due to differences in development levels across regions. Therefore, equitable development and increased utilization of village funds for community empowerment and access to capital are needed.
Keyword: Panel Data Regression, Poverty, Village Funds

1. Introduction

Poverty is the economic inability to meet basic food and non-food needs, that measured from the expenditure side [1]. One of the significant concerns that the United Nations (UN) addresses is poverty. This is demonstrated by the fact that Goal 1 (No Poverty), one of the Sustainable Development Goals (SDGs), includes poverty reduction as one of its objectives. The SDGs are a shared goal agreed upon by all UN member states, including Indonesia, to address various global challenges and achieve sustainable development. The National Medium-Term Development Plan (RPJMN) for 2025–2029 includes eradication of poverty as one of its objectives. It aims to reduce poverty to 7-8 percent in 2024 and 4.5–5 percent in 2029. Based on the RPJMN, poverty alleviation is carried out through a direct approach by reducing the expenditure burden on the poor, as well as an indirect approach by improving infrastructure quality and economic growth. These poverty alleviation policies are focused on poverty pockets, including the 3T (underdeveloped, frontier, and outermost) regions.

Poverty in Indonesia remains a priority to address. However, each region in Indonesia has different conditions. BPS data shows that most of eastern Indonesia has a higher poverty rate than western Indonesia. If this data is categorized by rural and urban poverty, it can be seen that most of the province in eastern Indonesia has a much higher rural poverty rate than urban poverty. According to BPS data, rural poverty in Indonesia tends to be higher than urban poverty as seen in Table 1

Table 1. Urban and rural poverty rates in 2024 by Eastern province of Indonesia.

Province Name	Poverty rate (%) in 2024		
	Urban	Rural	Difference
Papua	5.93	36.57	30.64
Central Papua	5.27	34.86	29.59
South Papua	3.65	28.47	24.82
Maluku	4.59	25.08	20.49
Papua Mountains	12.11	31.00	18.89
Southwest Papua	8.03	25.90	17.87
West Papua	9.50	26.34	16.84
Gorontalo	4.99	21.62	16.63
East Nusa Tenggara	8.11	23.02	14.91
Southeast Sulawesi	6.78	13.07	6.29
North Sulawesi	4.07	10.14	6.07
Central Sulawesi	7.34	12.9	5.56
South Sulawesi	5.21	10.11	4.90
East Kalimantan	4.41	8.00	3.59
West Sulawesi	8.33	11.32	2.99
West Kalimantan	4.62	7.26	2.64
North Kalimantan	5.07	5.96	0.89
South Kalimantan	3.59	4.46	0.87
West Nusa Tenggara	11.64	12.21	0.57
Central Kalimantan	5.22	5.29	0.07
North Maluku	6.27	5.93	-0.34
Indonesia	**6.66**	**11.34**	**4.68**

Table 1 shows that rural poverty rates tend to be higher than urban poverty rates, with particularly significant differences occurring in the provinces of eastern Indonesia. The data also shows that five of the six provinces in Sulawesi Island have rural-urban poverty ratios exceeding Indonesia's poverty rate of 4.68%. Meanwhile, in Papua, all provinces have poverty ratios exceeding Indonesia's rural-urban poverty ratio. Poor people generally live in rural areas and rely on the agricultural sector [2]. A similar point was also made by [3] which states that high levels of poverty in rural areas can be caused by the fact that many people work as farmers so that their income tends to be low, there is a development gap between rural and urban areas, and there is a large urbanization of the productive age population so that villages experience a shortage of labor.

Poverty can be caused by various factors, including the low quality of human resources [4]. One indicator that can be used to measure the quality of human resources in a region is Human Development Index (HDI). Based on data from BPS, average HDI in Sulawesi in 2024 was 72.26, or in the high category. This contrasts with other eastern Indonesian regions, such as Papua, which had an HDI of 64.95, which falls into the medium category. However, despite Sulawesi's high human resource quality, its poverty rate is also high.This condition is depicted in Figure 1, which shows that the development of HDI in Sulawesi from 2017 to 2024 consistently showed a positive trend.

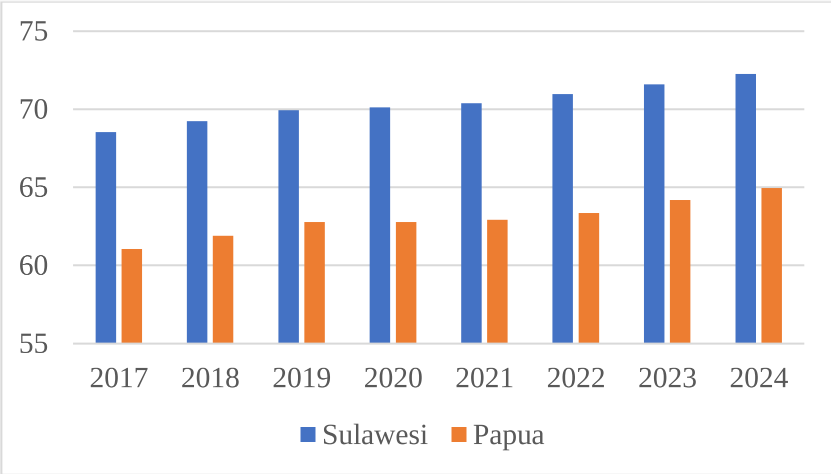

Figure 1. Human Development Index in Sulawesi and Papua 2017-2024.

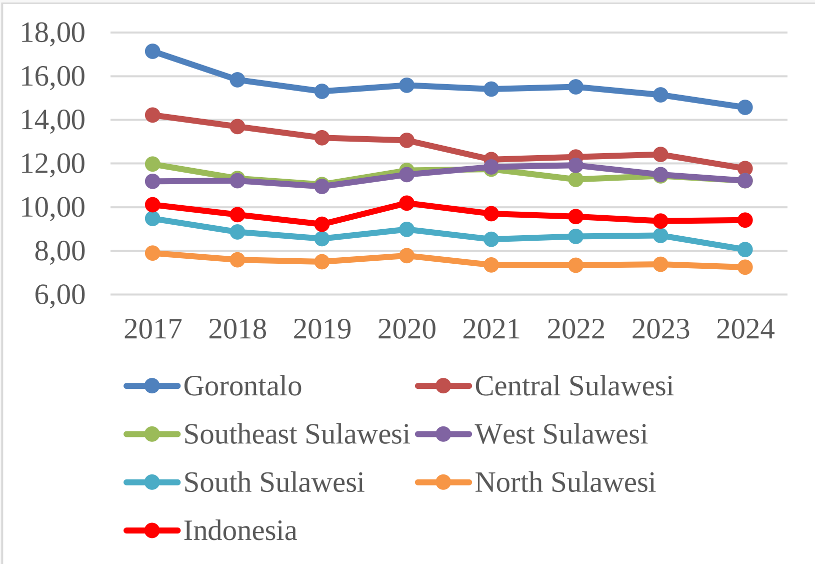

Figure 2. Percentage of poverty in Sulawesi 2017-2024.

Figure 2 shows a general overview of poverty rates across Sulawesi Island by province. In general, poverty rates on Sulawesi Island tended to fluctuate until 2024. For example, in 2022, Gorontalo, Central Sulawesi, West Sulawesi, and South Sulawesi experienced increases, despite a decline in the national poverty rate. Meanwhile, in 2024, all provinces in Sulawesi experienced a decline in poverty rates, in contrast to the increase in the national poverty rate. Gorontalo Province had highest poverty rate in Sulawesi. In 2024, the poverty rate in the region reached 14.57%. The province with the lowest poverty rate was North Sulawesi Province. In 2024, the poverty rate in that region was 7.25%. Based on the graph, only South Sulawesi and North Sulawesi had poverty rates below the national poverty rate, while Gorontalo, Central Sulawesi, Southeast Sulawesi, and West Sulawesi still had poverty rates above the national poverty rate.

House of Representatives (DPR) ratified Law Number 6 of 2014 concerning villages to increase development and decrease poverty in rural areas. As a follow-up to this law, Village Fund program was enacted. According to [5] concerning villages, village funds are defined as funds sourced from the State Budget (APBN) allocated for villages, transferred through APBD. That vilage funds are used to finance governance, implementation of development, community, and empowerment. The purpose of allocating these village funds is for comprehensive village development and construction, infrastructure development, improving the quality of resources, and poverty alleviation in rural areas. The allocation of village funds for regencies/cities in Sulawesi is as follows:

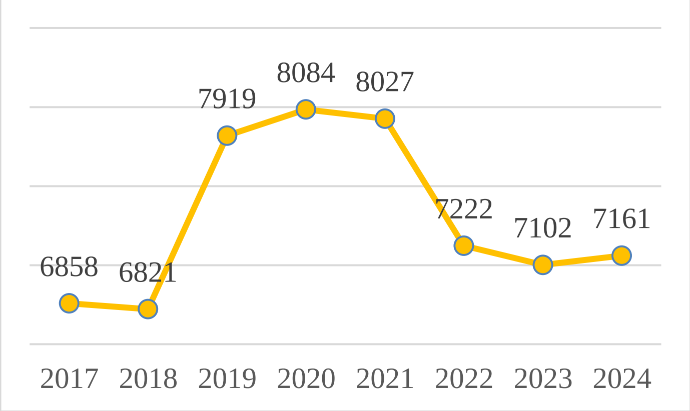

Figure 3. Village funds in Sulawesi 2017-2024 (in billions of rupiah).

Based on Figure 3, the village fund budget tends to increase until 2020, then decreases until 2023 and then increases again in 2024. As the village fund is implemented, there are still areas with a large difference between urban and rural poverty above the Indonesian poverty rate as shown in Table 1. Poverty rates still tend to fluctuate, as shown in Figure 2, despite an increase in village funds and HDI, as shown in Figures 1 and 3. Considering one of the objectives of village funds, which is to decrease poverty and inequality, this situation indicates that the objectives of village funds are not achieved yet. The occurrence of poverty between urban and rural areas in certain provinces, despite the tendency for village funds to increase annually, may indicate that village funds have not been effective in reducing poverty rates.

Poverty can be caused by differences in resource ownership patterns, differences in human resource quality, and differences in access to capital [4]. This implies that differences in human resource quality and the use of village funds can influence poverty in a region. According to the study [6], [7], and [8], the use of village funds can significantly reduce poverty rates. Besides village funds, several other factors influence poverty. [9] shows that GRDP, life expectancy, education, and unemployment influence poverty. The research [10] shows that education, GRDP per capita, and population influence poverty. The research from [6] also shows that village funds and unemployment rates have an impact on poverty. Research from [11] also shows that unemployement, HDI, ZIS, and GRDP per capita have an effect on poverty. In this study from [12] stated that village funds, HDI, population and unemployment rate, and GRDP influence poverty. Based on these research findings, various factors influence poverty, resulting in varying effects of village funds on poverty rates.

Based on previous research, there has been no research explaining the influence of village funds, HDI, GRDP per capita, and unemployment on poverty in Sulawesi until 2024. In addition, there is a need for research on the development of village funds and poverty in Sulawesi until 2024. This study aims to examine how Sulawesi Island's district-level poverty rates are impacted by village funds, human development index, GRDP per capita, and unemployment rate. Another objective of this study is to obtain a general overview of district poverty rates on Sulawesi Island. The unit of analysis is districts in Sulawesi because it is based on data on transfer funds from the Directorate General of Fiscal Balance, village funds are only transferred to districts because they have rural areas. The influence of village funds and village development on the percentage of rural poverty can be used to review the effectiveness of village fund use in decrease rural poverty in Sulawesi.

2. Research Method

2.1. Theoretical Basis

According to World Bank [13], poverty is a condition where a person cannot enjoy all kinds of choices and opportunities to fulfill their basic needs such as health, a decent standard of living, self-esteem, and a sense of respect like others. A person will be considered poor if their per capita expenditure per day is below the international poverty line of USD 2.15 PPP per capita per day. According to BPS [1], poverty is a condition of the population's economic inability to fulfill basic living needs in the form of food or non-food items, which is measured in terms of expenditure. Residents can be categorized as poor if their average expenditure is below the poverty line.

The factors causing poverty are differences in resource ownership patterns, differences in quality of human resources, and differences in access to capital [4]. The causes of poverty in rural areas include regional conditions, low economic growth, low education, inequality, dependency, and comfort in the zone [14]. Therefore, human resource development is necessary to manage natural resources so that productivity and income can increase and reduce poverty in rural communities. The ability of a community to manage natural resources can be determined by evaluating the quality of its human resources. The unemployment rate can be used to gauge the productivity of rural communities and their capacity to manage natural resources. GRDP per capita can be used to determine the level of community income. Meanwhile, village funds can be said to be capital for communities in managing natural resources which ultimately can reduce poverty.

Village funds are funds that sourced from APBN allocated for villages transferred through the APBD and used to finance the implementation of government, implementation of development, guidance and empowerment [5]. Based on PP No. 60 of 2014 , Village Funds sourced from the APBN, allocated fairly based on basic allocation (90%), and calculated allocation takes from population, area, poverty rate, and level of geographical difficulty (10%). Each village receives the same basic allocation of village funds so that the village funds received by the district depend on the number of villages.

Human resource quality indicators can be measured through human development indicators, namely the Human Development Index (HDI). HDI reflects the quality of life of human resources in a region. Based on the BPS indicator adopted from the UNDP concept, the HDI value is calculated using a dimension approach of longevity and healthy living, knowledge, and a decent standard of living [15].

Gross Regional Domestic Product (GRDP) per capita is the GRDP value divided by the population in a region over a given period. GRDP per capita reflects the average income of each resident in a region over a year. GRDP per capita at current prices can be used to determine the economic resource capacity, shifts, and economic structure of each resident in a region. The higher the regional income level (GRDP), the lower the poverty rate in that region [2].

Unemployed is a person who is included in the workforce and is actively looking for work at a certain wage level, but does not get the job he wants [16]. To measure the level of unemployment in a region, BPS uses the Open Unemployment Rate (UOR) indicator. UOR is the percentage of the unemployed compared to the labor force. Labor force is the working-age population (15-64 years old) who are employed, have jobs but are temporarily unemployed, and are unemployed.

2.2. Analysis Method

The scope of this study is all 70 districts on Sulawesi Island. The data period used in the study is 2017 to 2024. Dependent variable that used in this study is poverty rate, while independent variables are village funds, HDI, GRDP per capita, and unemployment rate. The method used is panel data regression analysis. Panel data is a combination of cross-sectional and time series data. Panel data regression is an estimation technique that combines time series and cross-sectional data to provide more observations [17]. Panel data analysis is used because it can account for heterogeneity by combining cross-sectional and time series data, allowing for more complex analyses. Furthermore, it minimizes bias and provides more degrees of freedom due to the larger number of observation units [17]. The software used for analysis is Eviews. The common effect model (CEM), fixed effect model (FEM), and random effect model (REM) are the three models in panel data regression models. In carrying out the modeling, data transformation was carried out using natural logarithms (ln) on the dependent variable of poverty percentage and the independent variables, namely village funds, HDI, GRDP per capita, and UOR with

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the aim of overcoming the problem of normality assumptions which will be violated if data transformation is not carried out on the variables. This transformation was applied because the data used had high variance and was not normally distributed [18].

2.2.1. Selection of estimations model.
The model for panel data regression proposed in this study is as follows:

1. CEM: $lnPo_{it} = \alpha + \beta_1 lnVF_{it} + \beta_2 lnHDI_{it} + \beta_3 lnGRDP_{it} + \beta_4 lnUOR_{it} + v_{it}$ (1)
2. FEM : $lnPo_{it} = (\alpha + \mu_i) + \beta_1 lnVF_{it} + \beta_2 lnHDI_{it} + \beta_3 lnGRDP_{it} + \beta_4 lnUOR_{it} + v_{it}$ (2)
3. REM: $lnPo_{it} = \alpha + \beta_1 lnVF_{it} + \beta_2 lnHDI_{it} + \beta_3 lnGRDP_{it} + \beta_4 lnUOR_{it} + u_{it}$ (3)
$; u_{it} = \mu_i + v_{it}$

where

$lnPo_{it}$	:	Poverty percentage of i-th district and t-th period in natural logarithm
$lnVF_{it}$	:	Village Funds of i-th district and t-th period in natural logarithm
$lnHDI_{it}$	:	HDI of i-th district and t-th period in natural logarithm
$lnGRDP_{it}$	:	GRDP per capita of i-th district and t-th period in natural logarithm
$lnUOR_{it}$	:	Open unemployment rate of i-th district and t-th period in natural logarithm
u_{it}	:	error component of i-th district and t-th period
μ_i	:	specific error of individual effect of i-th district without being influenced by t-th period
v_{it}	:	other errors are in the form of interaction effects between individual effects and time effects simultaneously
i	:	1, 2, 3, … , 70 ; Districts on the Sulawesi
t	:	1, 2, 3, 4, 5, 6, 7, 8; Research period 2017-2024

The difference between the three models effects lies in the presence of individual-specific effects (μ_{it}) and their correlation with the observed explanatory variables ($\boldsymbol{x'}_{it}$). The next step is to select the best model from the three panel data regression models. The first step is to conduct a Chow test to determine between CEM and FEM. The hypothesis of the Chow test are below.

$H_0 : \alpha_1 = \alpha_2 = \cdots = \alpha_{70} ; i = 1, 2, \ldots, 70$ (CEM is better than FEM)
H_1 : At least one $\alpha_i \neq \alpha_j$; $i \neq j$ (FEM is better than CEM)

Test statistics:

$$F_{hit} = \frac{(R^2_{FEM} - R^2_{CEM})/(69)}{(1 - R^2_{FEM})/(486)} \sim F_{(69,486)} \quad (4)$$

Decision: Reject null hypothesis if $F_{hit} > F_{(69,486)}$

The second step is to conduct a Hausman test to choose between FEM and REM. The hypothesis of Hausman test are below.

$H_0 : E(u_{it}|\boldsymbol{x}_{it}) = 0$ (REM is better than FEM)
$H_1 : E(u_{it}|\boldsymbol{x}_{it}) \neq 0$ (FEM is better than REM)

Test statistics:

$$W = [\boldsymbol{b} - \widehat{\boldsymbol{\beta}}]' \widehat{\boldsymbol{\Psi}}^{-1} [\boldsymbol{b} - \widehat{\boldsymbol{\beta}}] \sim \chi^2_K ; \boldsymbol{\Psi} = var(\boldsymbol{b}) - var(\widehat{\boldsymbol{\beta}}) \quad (5)$$

Decision: Reject null hypothesis if $W > \chi^2_K$

The next step is to perform the Breusch-Pagan LM test to determine whether CEM or REM is appropriate. Hypothesis of this test are below.

$H_0 : \sigma^2_u = 0$ (CEM is better than REM)
$H_1 : \sigma^2_u \neq 0$ (REM is better than CEM)

Test statistics:

$$LM = \frac{560}{14} \left[\frac{\sum_{i=1}^{N} [\sum_{t=1}^{T} u_{it}]^2}{\sum_{i=1}^{N} \sum_{t=1}^{T} u_{it}^2} - 1 \right]^2 \sim \chi^2_1 \quad (6)$$

Decision: Reject null hypothesis if $LM > \chi^2_1$

2.2.2. Testing the residual variance-covariance structure.

If the best model is FEM, then a residual variance-covariance structure test is performed. This test is used to determine the best parameter estimation method. The residual variance-covariance structure test is Lagrange Multiplier (LM) test and λ_{LM} test. Lagrange Multiplier (LM) test is conducted to determine whether the residual variance-covariance structure. The hypothesis and test statistics are as follows:

$H_0 : \sigma_i^2 = \sigma^2$ (Homoscedastic residual covariance variance structure)

$H_1 : \sigma_i^2 \neq \sigma^2$ (Heteroscedastic residual covariance variance structure)

Test statistics:

$$LM = \frac{8}{2}\sum_{i=1}^{70}\left[\frac{\hat{\sigma}_i^2}{\hat{\sigma}^2} - 1\right]^2 \sim\chi^2_{(69)} \tag{7}$$

Decision: Reject null hypothesis if $LM > \chi^2_{(69)}$

If the residual variance-covariance structure is heteroscedastic, λ_{LM} test is performed to determine the correlation between individuals. The hypothesis and test statistics are as follows:

$H_0 : E(u_{it}u_{jt}) = 0$ (There is no cross sectional correlation)

$H_1 : E(u_{it}u_{jt}) \neq 0$ (There is cross sectional correlation)

Test statistics:

$$\lambda_{LM} = 8\sum_{i=2}^{70}\sum_{j=1}^{i-1} r_{ij}^2 \sim\chi^2_{(2415)} \tag{8}$$

Decision: Reject null hypothesis if $\lambda_{LM} > \chi^2_{(2415)}$

2.2.3. Classical Assumption Test.

Once the best model and estimation method are identified, assumption testing is performed. If the best model selected is CEM, REM, or FEM with a homoscedastic variance-covariance structure, then the assumptions tested are normality, homoscedasticity, non-autocorrelation, and the non-multicollinearity requirement. If the best model selected is FEM with a heteroscedastic variance-covariance structure, then the assumptions tested are normality and the non-multicollinearity requirement.

Normality

Normality is a condition where each residual value is normally distributed with a mean of 0 and constant variance [17]. The normality assumption was tested using the Jarque-Bera test. This test measures skewness and kurtosis. The hypothesis of the Jarque-Bera test is as follows:

$H_0 : u_{it} \sim N(0, \sigma^2)$ (residuals have a normal distribution)

$H_1 : u_{it} \nsim N(0, \sigma^2)$ (residuals do not have a normal distribution)

The Jarque-Bera test statistic is as follows [17]:

$$JB = 70\left[\frac{S^2}{6} + \frac{(K-3)^2}{24}\right] \sim\chi^2_2 \tag{9}$$

where

K : Coefficient of sharpness (kurtosis)

S : Skewness coefficient

If the result or p-value is greater than 0.05, the decision is to fail to reject H_0 so that the residuals are normally distributed and the normality assumption is met $JB < \chi^2_2$

Homoscedasticity

The assumption of homoscedasticity is a condition where the residual values have the same or constant variance [17]. The homoscedasticity assumption test uses the same test as the residual variance covariance matrix test, namely the LM test method. The hypothesis in this test is as follows:

$H_0 : \sigma_i^2 = \sigma^2$ (Constant residual variance)

$H_1 : \sigma_i^2 \neq \sigma^2$ (Residual variance is not constant)

LM test statistics according to[19] are as follows:

$$LM = \frac{8}{2}\sum_{i=1}^{70}\left[\frac{\hat{\sigma}_i^2}{\hat{\sigma}^2} - 1\right]^2 \sim\chi^2_{(69)} \tag{10}$$

With :

$\hat{\sigma}_i^2$: Estimate of residual variance of i-th individual
$\hat{\sigma}^2$: Estimation of residual variance of the model

If the result is then the decision is to reject H_0. So it can be concluded that the residual variance is not constant or the residual covariance structure is heteroscedastic $LM > \chi^2_{(69)}$

Non-autocorrelation

The non-autocorrelation assumption is a condition where an observation has a temporal correlation with the same observation. The non-autocorrelation assumption is tested using the Durbin-Watson test with the following hypothesis:

$H_0: \rho\left(u_{it}, u_{js}\right) = 0$ (no autocorrelation)

$H_1: \rho\left(u_{it}, u_{js}\right) \neq 0$ (there is autocorrelation)

Durbin-Watson test statistics in [20] are as follows:

$$DW = \frac{\sum_{i=1}^{70}\sum_{t=2}^{8} (\hat{v}_{i,t} - \hat{v}_{i,t-1})^2}{\sum_{i=1}^{70}\sum_{t=1}^{8} \hat{v}_{i,t}{}^2} \tag{11}$$

with:

$\hat{v}_{i,t}$: Residual of each it-th panel

The statistical results of the Durbin-Watson test will be compared with the dU (limit value) and dW (lower limit value) values according to the Durbin-Watson table. If the result is 4-dL < DW < 4 or Reject H_0 or 0 < DW < DL, the conclusion is Reject H_0 (autocorrelation occurs). If the result is dU < DW < 4-dU the conclusion is no autocorrelation occurs.

Conditions for non-multicollinearity

Multicollinearity is a condition where there is a strong correlation between independent variables in a model [17]. Variance Inflation Factor (VIF) measure are used to check mulcollinearity with the following formula [17]:

$$VIF_j = \frac{1}{1-R_j^2} \tag{12}$$

With :

VIF_j : VIF calculated value
R_j^2 : The coefficient of determination of the j-th independent variable with other variables

If the VIF value is > 10, there is high collinearity between the independent variables. Consequently, the non-multicollinearity assumption is violated.

2.2.4 Goodness of fit test.

Next, model estimation can be carried out which is then continued by testing the significance of the model with three criteria, namely simultaneous regression coefficient testing, partial regression coefficient testing, and coefficient of determination.

Simultaneous regression coefficient test (F-test)

Simultaneous regression coefficient testing using the F-test aims to examine the effect of the regression coefficients used in the model simultaneously or jointly on the dependent variable. This test has the following hypotheses:

$H_0 :\ \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$

H_1 :there is at least one $\beta_j \neq 0,\ j = 1,2,3,4$

The test statistics are as follows:

$$F_{hit} = \frac{R^2/(73)}{(1-R^2)/(486)} \sim F_{(73,486)} \tag{13}$$

With:

R^2 : Coefficient of determination

If the result is $F_{hit} > F_{(0.05;73,486)}$, then the decision is to reject H_0. So it can be concluded that at the significance level α, there is at least one independent variable that significantly together or simultaneously influences the dependent variable

Partial regression coefficient test (t-test)

Partial regression coefficient testing using the T-test aims to determine the effect of the regression coefficients used in the model, either independently or partially, on the dependent variable. This test has the following hypotheses:

$H_0 : \beta_j = 0$

$H_1 : \beta_j \neq 0, \ j = 1,2,3,4$

With the test statistics as follows:

$$t_{hit} = \frac{\hat{\beta}_j}{se(\hat{\beta}_j)} \sim t_{(486)} \tag{14}$$

With:

$\hat{\beta}_i$: The estimated value of the parameterj

$se(\hat{\beta}_j)$:*Standard error* from the estimated value of the j-th parameter

If the result is $|t_{hit}| > t_{(0.05;486)}$, then the decision is to reject H_0. So it can be concluded that at the significance level α, the independent variable significantly influences the dependent variable.

Coefficient of determination

Coefficient of determination is a measure of the variation in dependent variable that can be explained by independent variables. Increasing the number of independent variables used in a regression model can affect the coefficient of determination. Therefore, a measure called adjusted R-square ($R^2 adj$) is used to eliminate the influence of the independent variables. The formula for adjusted R-square is as follows:

$$R^2_{adj} = 1 - (1 - R^2)\frac{559}{486} \tag{15}$$

With:

R^2 : Coefficient of determination

3. Result and Discussion

3.1 Overview of Poverty Rate and Village Funds

General overview of poverty in each district in Sulawesi Island is seen using the percentage of the poor population (P0) indicator. This overview and thematic maps are available for 2017 in Figure 4 and 2024 in Figure 5. The average village fund allocation for each district can be seen in the thematic maps in Figure 6.

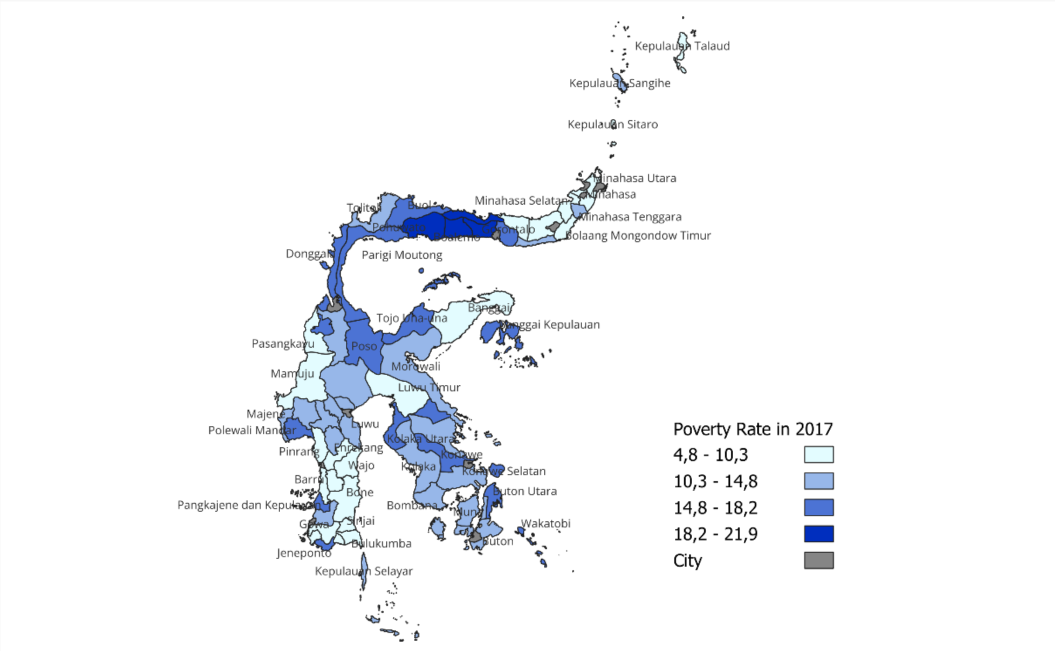

Figure 4. Poverty rate in Sulawesi on 2017.

Based on the map in Figure 4, it is known that in 2017 there were 9 districts with very high (18.2%-21.9%) poverty levels. These districts include Donggala and Tojo Una-Una in Central Sulawesi, Konawe Islands and Central Buton in Southeast Sulawesi, and Boalemo, Gorontalo, Pohuwato, Bone Bolango, and North Gorontalo in Gorontalo Province. There are 17 districts with high poverty levels (14.8%-18.2%), 21 districts with moderate poverty levels (10.3%-14.8%), and 23 districts with low poverty levels (4.8%-10.3%).

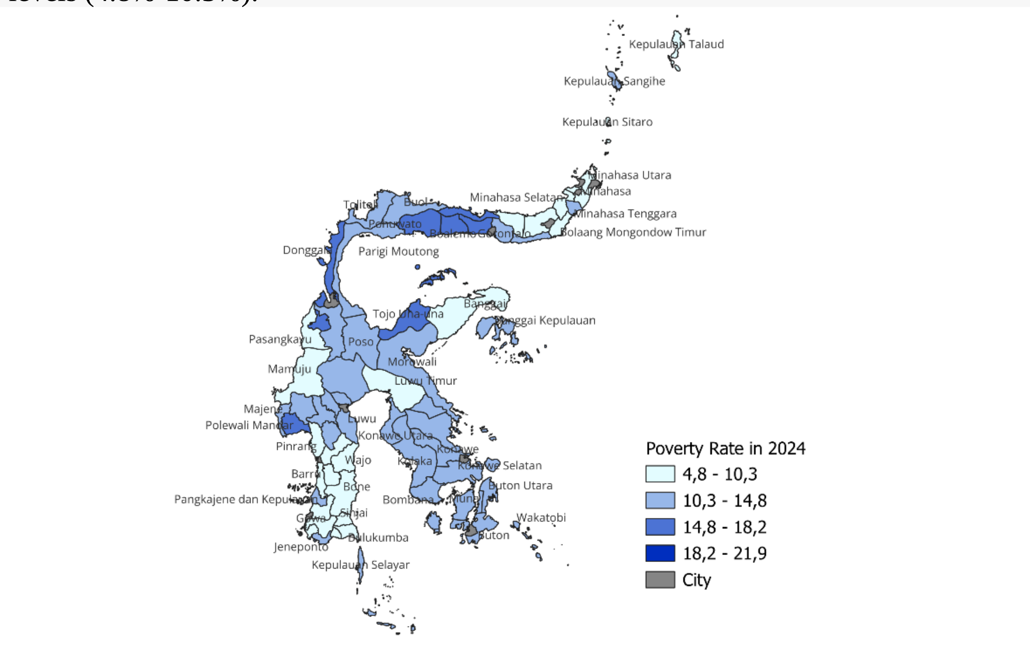

Figure 5. Poverty rate in Sulawesi on 2024

Based on the map in Figure 5, it is known that in 2024 there no districts with very high poverty rates (18.2%-21.9%), that decreased from 2017, which had 9 districts. In addition, there are 8 regencies with high poverty rates (14.8%-18.2%), a figure that decreased from 2017, which had 17 districts. There were

37 regencies with moderate poverty rates (10.3%-14.8%), an increase from 21 districts in 2017. There were 25 districts with low poverty rates (4.8%-10.3%), an increase from 23 districts in 2017. Based on these differences, it can be said that there was a decrease in poverty rates at the district level in Sulawesi in general between 2017 and 2024.

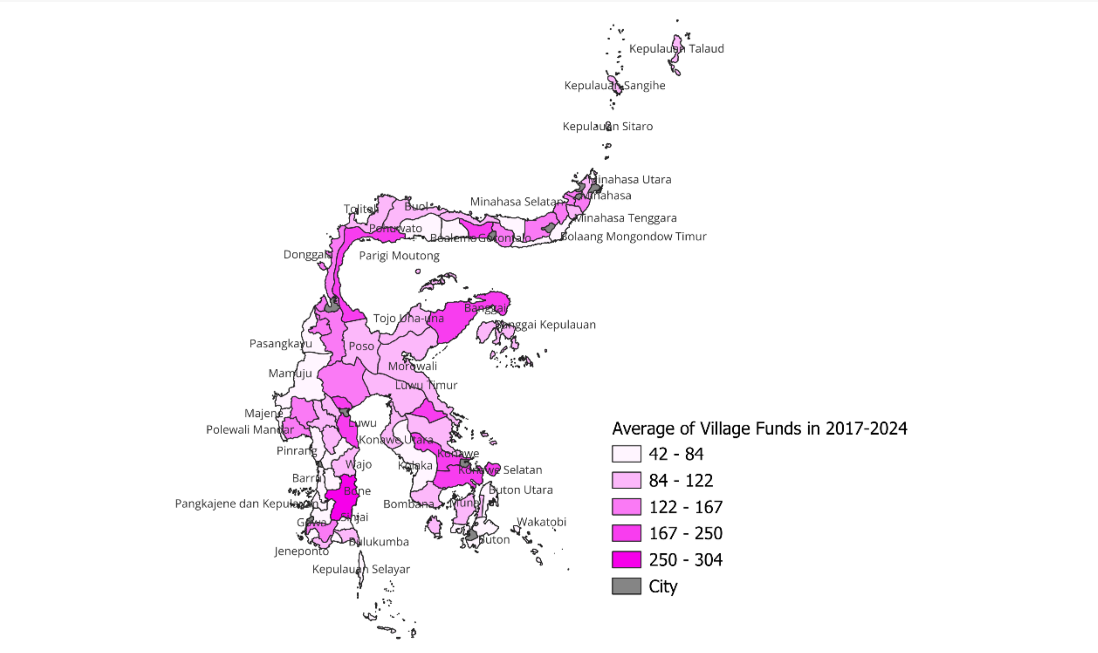

Figure 6. Average of village funds in Sulawesi 2017-2024 (in billions of rupiah).

The district with the largest village fund allocation is Bone in South Sulawesi, with an average of 310.96 billion rupiah received from 2017 to 2024. Meanwhile, the district with the smallest village fund allocation is Bantaeng in South Sulawesi, with an average of 42.06 billion rupiah received from 2017 to 2024. The differences in village fund budgets for each district are influenced by the number of villages in each district. Districts with more villages receive a larger village fund budget. This is because government-provided village funds are allocated based on population, poverty, area, and geographic difficulty of each village.

3.2 Selection of Estimations Model

The inferential analysis method used was panel data regression. In modeling, data was transformed using the natural logarithm (ln) on the dependent variable, the poverty percentage, and the independent variables, namely village funds, HDI, GRDP per capita, and unemployment rate. The first step is selecting the best panel data estimation model. Available models include CEM, FEM, and REM. The results of testing the best model are shown in Table 2 below:

Table 2. Best model selection.

Test	*p-value*	Decision	Selected Model
Chow	0.000	Reject H_0	FEM
Hausman	0.000	Reject H_0	FEM

Based on the Chow Test and the Hausman Test in Table 1 and referring to equations (4) and (5), the results are rejecting the null hypothesis at a significance level of 5% or α = 0.05. That means the best model selected is FEM.

3.3 Testing the Residual Variance-Covariance Structure

Because the selected model is FEM, before conducting the classical assumption test, it is necessary to examine the residual variance-covariance structure. The test results from the LM test and λ_{LM} referring to equations (7) and (8) show the results that have p-values <0.05 each so null hypothesis is rejected. This means that the model has a residual variance-covariance structure that is heteroscedastic and there is cross-section correlation. Therefore, the appropriate estimation method to use is Feasible Generalized Square (FGLS) with Seemingly Unrelated Correlation (SUR).

3.4 Classical Assumption Test

Classical assumtion test on this model only tested the assumptions of normality and non-multicollinearity. This is because the estimation method used is the FGLS-SUR estimation in FEM. The results of the normality assumption test using the Jarque-Bera test refer to equation (9) which shows the results *p-value* = 0.082 which is greater than $\alpha = 0.05$ so that the result fails to reject the null hypothesis which means the normality assumption is met. Next, a non-multicollinearity check is carried out using the VIF value referring to equation (12) with a summary in the following table 3:

Table 3. Results of non-multicollinearity examination with VIF.

Variables	VIF	Non-multicollinearity (VIF < 10)
ln(VF)	1.0367	Fulfilled
ln(HDI)	1.5119	Fulfilled
ln(GRDP)	1.4155	Fulfilled
ln(UOR)	1.0497	Fulfilled

3.5 Estimation Result

Coefficients of determination, partial tests, and simultaneous tests can be used to assess the significance of the regression coefficients once the non-multicollinearity conditions and the assumption of normality have been fulfilled. The first test is a simultaneous coefficient test. Referring to equation (13), the test statistic results are found to be 421.9658 with an F table of 1.3168, so the decision is to reject the null hypothesis. This means that the independent variables together significantly influence the dependent variable, namely the percentage of poverty. The results of the partial test are summarized in Table 4 below:

Table 4. Summary table of partial t-test

Variables	Coefficient	*Standard error*	Test statistic (t)	*p-value*	Decision
Constant	9.2944	1.1347	8.1914	0.0000	Reject H_0
ln(VF)	-0.0894	0.0523	-1.7105	0.0878	Failed to Reject H_0
ln(HDI)	-1.2570	0.2640	-4.7609	0.0000	Reject H_0
ln(GRDP)	-0.1049	0.0155	-6.7841	0.0000	Reject H_0
ln(UOR)	-0.0206	0.0124	-1.6627	0.0970	Failed to Reject H_0

Based on the results in Table 4 and referring to equation (14), it was found that the variables ln(HDI) and ln(GRDP) had absolute values of t-test statistics more than t-table = ±1.9648 so that the decision was to reject the null hypothesis. This means that the variables ln(HDI) and ln(GRDP) partially had a significant effect on the dependent variable. Meanwhile, the variables ln(VF) and ln(UOR) did not have a significant effect because they had absolute values of t-test statistics less than t-table = ±1.9648 so that the decision failed to reject the null hypothesis.

For the village fund variable, these results differ from research conducted by [8] also shows that village funds can reduce poverty in East Java in 2015-2016. [12] research also showed that village funds had no impact on poverty in NTT between 2016 and 2022. This was due to the low performance of village officials, indications of misuse of village funds, and the low quality of rural infrastructure. These results also differ from previous research. [7] which states that village funds are effective in reducing the number of poor people at the district/city level in Indonesia. According to [21], village funds do not have an impact on reducing poverty because there is no equitable distribution of development and the perception of village funds as a means of utilization in various sectors. Strategies such as community empowerment to increase income through increased access to capital and human resource development, as proposed by Sabuna [12].

The low quality of human resources is one of the factors causing poverty. For the HDI variable, these results are in similar with research by Sabuna & Ruslan (2023) [12] which states that the HDI has a negative and significant influence on poverty rates in NTT and research conducted by Baihaqi and Puspitasari (2020) [11] which also states that the HDI has a negative and significant effect on poverty rates in Aceh. The results of these studies show that the higher the quality of human resources as measured by the HDI, the lower the poverty rate will be.

For GRDP per capita, these results are in accordance with research conducted by [11] also shows that GRDP per capita has a significant negative influence on poverty rates in Aceh and research by Azizah et al (2018) [10] also stated that GRDP per capita had a negative and significant effect on poverty rates in East Java. As the income level of each resident of the region increases, it can be indicated that the poverty rate in the region will decrease.

For UOR, these results differ from the research Bintang & Woyanti (2018) [9] and Ritonga et al (2021) [6] which states that UOR has a significant influence on poverty. According to Todaro [2], there are working residents who work in the informal sector so their income remains low. Unemployment is one of the factors contributing to poverty. The greater the unemployment rate, the greater the number of people without sufficient income, which increases poverty rates.

For the results of the determination coefficient test, referring to equation (15), the value obtained is adjusted R-square of 0.985. This means that the poverty percentage variable can be explained by the lnDD, lnIPM, lnGRDP, and lnUOR variables in 70 districts on Sulawesi Island in 2017-2024 by 98.4%. Meanwhile, 0.16% of the poverty percentage variable is explained by other variables not included in the model. The obtained equation model is as follows:

$$\widehat{lnP0_{it}} = (9{,}2944 + \mu_i) - 0{,}0894 lnVF_{it} - 1{,}257 lnHDI^*_{it} - 0{,}1049 lnGRDP^*_{it} - 0{,}0206 lnUOR_{it} + v_{it} \quad (16)$$

with :

$lnPo_{it}$	:	Poverty percentage of i-th district and t-th period in natural logarithm
$lnVF_{it}$	:	Village Funds of i-th district and t-th period in natural logarithm
$lnHDI_{it}$	:	HDI of i-th district and t-th period in natural logarithm
$lnGRDP_{it}$	:	GRDP per capita of i-th district and t-th period in natural logarithm
$lnUOR_{it}$	:	Open unemployment rate of i-th district and t-th period in natural logarithm
u_{it}	:	error component of i-th district and t-th period
μ_i	:	specific error of individual effect of i-th district without being influenced by t-th period
v_{it}	:	other errors are in the form of interaction effects between individual effects and time effects simultaneously
i	:	1, 2, 3, … , 70 ; Districts on the Sulawesi
t	:	1, 2, 3, 4, 5, 6, 7, 8; Research period 2017-2024
$*$	:	Significant at α = 0.05

The model in equation (16) explains that a 1 percent growth in the HDI will reduce the growth in poverty rates in Sulawesi by 1.257 percent, assuming other independent variables remain constant. In addition, if the value 1 percent increase in per capita GRDP will reduce the poverty rate in Sulawesi by 0.1049 percent, assuming other independent variables remain constant. Of the two significantly influential variables, the per capita HDI has the greatest impact on poverty rates, while the GRDP has the smallest impact compared to per capita GRDP.

4. Conclusion

In general, the poverty rate in the Sulawesi Island region decreased from 2017 to 2019, increased from 2021 to 2023, and decreased again in 2024. In 2020, the Covid-19 pandemic occurred, resulting in an increase in the poverty rate in Indonesia, including Sulawesi. Afterward, the poverty rate in each province in Sulawesi tended to fluctuate until 2024. Based on the results of the panel data regression analysis, it can be concluded that the HDI and GRDP per capita variables significantly negatively affected the poverty rate in Sulawesi in 2017-2024. Meanwhile, other variables, namely village funds and TPT, did not have a significant effect on the poverty rate. The results of this study indicate that village funds do not significantly affect poverty in Sulawesi Island. Village funds are insignificant in reducing poverty due to differences in development levels across regions. Therefore, equitable development and increased utilization of village funds for community empowerment and access to capital are needed.

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