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Regression Analysis of Panel Data on Gross Enrolment Rate (GER) At Junior High School and Equivalent Education Levels in South Sulawesi Province in 2018-2022

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Abstract

Panel data regression is a combination of time series and cross section data. This research aims to determine the factors that influence the gross participation rate in South Sulawesi Province using panel data regression analysis. The data used is data from 24 districts/cities in South Sulawesi province from 2018 to 2022 which was obtained through the website of the South Sulawesi Provincial Central Statistics Agency. There are three models in panel data regression analysis, namely the Common Effect Model (CEM), Fixed Effect Model (FEM) and Random Effect Model (REM). Based on the model selection carried out by carrying out the Chow Test, Hausman Test, and Lagrange Multiplier Test, the best model was obtained, namely the Random Effect Model. The equation of this model is $Y_{it} = 82{,}818 + 0{,}1485X_{1it} - 0{,}0784X_{2it} + 0{,}0053X_{3it} + 0{,}0011X_{4it}$. Based on the results of panel data regression analysis, it was found that the variables that had a significant effect on the Gross Enrollment Rate in South Sulawesi province were the student to teacher ratio (X_2), and population density (X_4).

Keywords: panel data regression, random effect model , gross participation rate (APK)

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1. Introduction

Regression analysis is one of the most widely used statistical methods for data analysis and serves as a fundamental tool in decision-making, particularly in constructing mathematical models (Nurdin et al., 2018). A more advanced form of regression modelling that incorporates both time-series and cross-sectional data is known as panel data regression analysis. Panel data combines multiple observations over time for several individuals, thus offering a richer dataset. There are several advantages of using panel data: (1) it explicitly accounts for individual heterogeneity by allowing individual-specific variables; (2) it supports the testing, development, and evaluation of complex behavioural models; (3) it provides more informative and varied data with reduced multicollinearity and increased degrees of freedom, leading to more efficient estimation; (4) it minimizes bias caused by the aggregation of individual-level data; and (5) it enables better detection and measurement of effects that may not be observable when using either time-series or cross-sectional data alone (Basuki & Prawoto, 2017).

In the field of education, one of the key indicators used to evaluate educational outcomes is the Gross Enrolment Ratio (GER). According to Statistics Indonesia (BPS), GER is defined as the ratio between the number of students enrolled at a certain level of education regardless of their age and the number of individuals in the official age group for that education level. GER reflects the overall level of participation in education and also indicates the capacity of the education system to accommodate students within the designated age group (Naharin et al., 2023). As such, GER serves as an important benchmark for assessing the success of government policies aimed at expanding educational access (Mukhaiyar et al., 2022).

In South Sulawesi Province, the GER at the junior secondary education level (equivalent to lower secondary school or SMP) provides insights into student participation in this level of education. To enhance GER, it is essential to identify

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and analyse the key determinants that influence enrolment rates. Therefore, this study aims to examine the factors affecting the GER for junior secondary education in South Sulawesi using panel data regression analysis.

2. Literature Review

2.1. Panel Data Regression Analysis

Panel data regression is a statistical method that combines features of both time series and cross-sectional data. Data collected at a single point in time across multiple observational units is referred to as cross-sectional data, whereas data collected over multiple time periods for a single or limited number of observational units is known as time series data (Madany et al., 2022). A panel regression model is built using panel data, which essentially merges both time series and cross-sectional dimensions.

In a time series dataset, one or more variables are observed repeatedly over a specified period for a single unit of analysis. In contrast, cross-sectional data involves observations of several units at a single point in time (Arum, 2019). The use of panel data allows researchers to capture both temporal dynamics and individual heterogeneity within the same analytical framework.

The general form of the panel data regression model is expressed as follows (Firdaus, 2004):

$$Y_{it} = \propto + \beta X_{it} + \varepsilon_{it} \tag{1}$$

Where: Y_{it} is the dependent variable for individual i at time t; α is the intercept; β is the coefficient vector; X_{it} is the independent variable(s) for individual i at time t; ε_{it} is the error term. This model serves as the foundation for more advanced specifications, such as fixed effects and random effects models, which are widely used in panel data analysis to account for unobserved heterogeneity.

2.2. Estimation Models in Panel Data Regression

In panel data regression analysis, there are three commonly used estimation approaches: the Common Effect Model (CEM), the Fixed Effect Model (FEM), and the Random Effect Model (REM). Each of these approaches offers different assumptions regarding the heterogeneity of the observational units and the treatment of the error components.

2.2.1. Common Effect Model (CEM)

The Common Effect Model (CEM), also known as the pooled ordinary least squares (pooled OLS) model, is the simplest technique for estimating panel data regression parameters. This model assumes that there are no individual-specific effects across observational units or over time. In other words, it treats the data as if they are homogeneous by simply combining time series and cross-sectional observations into a single dataset (Basuki & Prawoto, 2017).

The general form of the Common Effect Model can be written as follows (Porter, 2013):

$$Y_{it} = \propto + \beta X_{it} + \varepsilon_{it} \tag{2}$$

Where: Y_{it} is the dependent variable for individual i at time t; α is the intercept term (assumed constant across all units and time periods); β is the vector of slope coefficients; X_{it} is represents the independent variable(s); ε_{it} is the error term, which captures the unexplained variation. Since the CEM does not account for unobserved heterogeneity across individuals or time, it may produce biased estimates if such heterogeneity exists. Nevertheless, it serves as a useful baseline model for comparison with more complex specifications such as FEM and REM.

2.2.2. Fixed Effect Model

The Fixed Effect Model (FEM) assumes that each observational unit (individual, region, etc.) has its own unique intercept that does not vary over time. In this approach, the differences across units are captured by allowing for individual-specific intercepts, while assuming that these effects remain constant over the observation period (Ghozali, 2018).

FEM is particularly useful when the unobserved individual heterogeneity is correlated with the independent variables. To estimate the parameters under this model, the Least Squares Dummy Variable (LSDV) method is typically employed. This technique introduces dummy variables for each observational unit to control for the fixed effects.

The general form of the Fixed Effect Model is as follows (Porter, 2013):

$$Y_{it} = \propto_i + \beta X_{it} + \varepsilon_{it} \tag{3}$$

Where: Y_{it} is the dependent variable for unit iii at time t; $\propto_i$ is the individual-specific intercept that varies across units but is constant over time; β is the slope coefficient vector (assumed constant across individuals and time); X_{it} is the independent variable(s); $\varepsilon_{it}$is the error term.

2.2.3. Random Effect Model (REM)

The Random Effect Model (REM) is an estimation technique that incorporates error components to account for variability across both time and individuals. Unlike the Fixed Effect Model (FEM), which uses dummy variables to capture individual-specific effects, REM treats these effects as random variables that are uncorrelated with the explanatory variables in the model. This approach is particularly advantageous in overcoming the limitations of FEM, especially the issue of degrees of freedom consumed by dummy variables.

REM is typically appropriate when the cross-sectional dimension (number of individuals or units) is greater than the number of explanatory variables, and when the unobserved individual-specific effects are assumed to be random and uncorrelated with the regressors (Nandita et al., 2019).

The general form of the Random Effect Model is expressed as follows (Widarjono, 2009):

$$Y_{it} = \propto + \beta X_{it} + u_i + \varepsilon_{it} \tag{4}$$

Where: Y_{it} is the dependent variable for individual i at time t; α is the intercept term; β is the vector of slope coefficients; X_{it} is represents the independent variable(s); u_i is the individual-specific random error component, constant over time but varying across units; ε_{it} is the idiosyncratic error term. The random effects component uiu_iui captures unobserved heterogeneity across units, while the assumption of no correlation between u_i and X_{it} is essential for obtaining consistent and efficient estimates. If this assumption is violated, REM may lead to biased results, in which case FEM would be the more appropriate choice.

2.3. Model Selection Tests in Panel Data Regression

Several statistical tests are commonly used to determine the most appropriate estimation model in panel data regression. These tests help identify whether a pooled regression, fixed effects, or random effects model is most suitable for the data structure.

2.3.1. Chow Test

The Chow Test is employed to determine whether the Fixed Effect Model (FEM) provides a significantly better fit than the Common Effect Model (CEM)**.** This test essentially evaluates whether there are significant individual-specific intercepts across observational units. If the test favors the FEM over the CEM, the next step is to perform the Hausman Test to decide between FEM and the Random Effect Model (REM)**.** However, if the Chow Test indicates that the CEM is sufficient, the analysis proceeds with the Lagrange Multiplier (LM) Test to compare CEM and REM (Side, 2016).

The general procedure for the Chow Test can be described as follows (Caraka, 2017):

$$F = \frac{(RSS_1 - RSS_2)/(N-1)}{RSS_2/[N(T-1)-k]} \tag{5}$$

Where: RSS_1 is Residual Sum of Squares from the CEM; RSS_2 is Residual Sum of Squares from the FEM; N is Number of cross-sectional units; T is Number of time periods; k is Number of independent variables. If the calculated F-statistic exceeds the critical value from the F-distribution at a specified significance level, then the null hypothesis (which states that CEM is adequate) is rejected in favor of FEM.

2.3.2. Hausman Test

The Hausman Test is used to determine the most appropriate panel data regression model between the Fixed Effect Model (FEM) and the Random Effect Model (REM). This test evaluates whether the unique errors (random effects) are correlated with the regressors in the model. If they are, the REM would produce biased estimates, and thus the FEM would be preferred. Conversely, if there is no correlation, REM provides efficient and consistent estimates and is therefore preferable (Gujarati, 2012):

$$H = (\beta_{REM} - \beta_{FEM})'[Var(\beta_{REM}) - Var(\beta_{FEM})]^{-1}(\beta_{REM} - \beta_{FEM}) \quad (6)$$

Where: H is the Hausman test statistic; β_{REM} and β_{FEM} are the vectors of estimated coefficients; $Var(\beta_{REM})$ and $Var(\beta_{FEM})$ are the corresponding variance-covariance matrices. The test statistic follows a chi-squared ($\chi 2$) distribution with degrees of freedom equal to the number of regressors. If the p-value is less than the significance level (e.g., 0.05), the null hypothesis that the REM is rejected in favour of the FEM. If the p-value is greater than the significance level, the REM is considered more suitable due to its greater efficiency.

2.3.3. Lagrange Multiplier (LM) Test

According to Widarjono (2007), the Lagrange Multiplier (LM) Test is used when the Chow Test indicates that the Common Effect Model (CEM) is appropriate, and the Hausman Test is used to compare Fixed Effect Model (FEM) with the Random Effect Model (REM)**.** In such cases, the LM Test helps determine the better model between the CEM and REM. This test is particularly important when deciding whether to account for random effects in the model structure. The general procedure for conducting the LM Test is as follows (Caraka, 2017):

$$LM = \frac{NT}{2(T-1)}\left(\frac{\sum_{i=1}^{N}(\bar{e}_i^2)}{\hat{\sigma}^2}\right)^2 \quad (7)$$

Where: N is number of cross-sectional units; T is number of time periods; $\bar{e}_i^2$ average residual for each cross-section unit; $\hat{\sigma}^2$ variance of the residuals from the CEM. The LM statistic follows a chi-squared distribution with one degree of freedom. If the p-value is less than the significance level (e.g., 0.05), the null hypothesis that the CEM is appropriate is rejected in favor of the REM. If the p-value is greater than the significance level, the CEM is considered adequate and more appropriate.

2.4. Gross Enrolment Rate (GER)

The Gross Enrollment Rate (GER) refers to the proportion of the population enrolled in a particular level of education, regardless of age, compared to the total population within the official age group for that level of education (Rahmadina et al., 2021). GER is one of the key indicators used to measure human resource development in the education sector. The GER at the junior high school level in South Sulawesi can serve as a focal point, as it provides insight into the level of student participation in secondary education within the province.

Efforts to improve the GER can be pursued by identifying and analyzing the factors that potentially influence or contribute to the increase in GER in South Sulawesi Province.

3. Research Method and Materials

The data used in this study are secondary data obtained from the official website of the Statistics Indonesia (Badan Pusat Statistik/BPS) of South Sulawesi Province. The dataset is structured as panel data, consisting of a total of 120 observations, combining time series data over five years (2018–2022) and cross-sectional data covering 24 regencies/cities within the province of South Sulawesi.

The analytical techniques employed in this study include:

a. Panel Regression Modelling, carried out through the following stages:

   (1) Estimating the model parameters using the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM).

   (2) Determining the appropriate estimation method for the panel regression model by conducting the following model selection with Chow Test, Hausman Test, and LM Test

   (3) Performing classical assumption tests on the selected model, including Normality Test, Heteroscedasticity Test, Multicollinearity Test, Autocorrelation Test

b. Identifying significant factors influencing the panel regression model and assessing the parameters with t-Test, F-Test, and Coefficient of Determination (R^2 interpretation)

c. Model interpretation, including an explanation of the panel regression model and the significant factors affecting the Gross Enrollment Ratio (GER) at the junior secondary education level in South Sulawesi Province from 2018 to 2022.

4. Results and Discussion

4.1. Parameter Estimation of the Panel Regression Model

4.1.1. Common Effect Model (CEM)

The data were processed using the Common Effect Model (CEM) approach also known as the Pooled Effect Model as specified in Equation (2). This approach combines the time series and cross-sectional data into a single dataset and estimates the regression model using the Ordinary Least Squares (OLS) method. The results of the Common Effect Model estimation are presented in Table 1.

Table 1. Output of the Common Effect Model

Variabel	Estimate	p-value	Interpretation
(Intercept)	82.818	$2x10^{-16}$	Significant
X_1	0.1485	0.5916	Not Significant
X_2	-0.0784	0.0376	Significant
X_3	0.0053	0.0952	Not Significant
X_4	0.0011	0.0355	Significant

As shown in Table 1, variables X1 and X3 are statistically insignificant in the model because their p-values exceed the standard level of significance. Based on the estimation results, the panel regression equation for the Common Effect Model (CEM), as outlined in Equation (2), can be formulated as follows:

$$Y_{it} = 82.818 + 0.1485\ X1_{it} + 0.0784X2_{it} + 0.0053X3_{it} + 0.0011X4_{it}$$

4.1.2. Fixed Effect Model

The Fixed Effect Model (FEM) assumes that individual-specific and time-specific effects can be differentiated, and does not require the assumption that the error components are uncorrelated with the explanatory variables. Parameter estimation in this model is carried out using the Least Squares Dummy Variable (LSDV) method.

Table 2. Output of the Fixed Effect Model

Variabel	Estimate	p-value	Interpretation
X_1	0.0370	0.8985	Not Significant
X_2	-0.0854	0.0285	Significant
X_3	-0.0025	0.6933	Not Significant
X_4	0.0010	0.0396	Significant

Based on Table 2, variables X1 and X3 are not statistically significant in the model, as their p-values exceed the significance threshold (α = 5%). The estimated regression equation for the Fixed Effect Model (FEM), as specified in Equation (3), is formulated as follows:

$$Y_{it} = 0.0370\,X1_{it} + 0.0854X2_{it} + 0.0025X3_{it} + 0.0010X4_{it}$$

4.1.3. Random Effect Model

The Random Effect Model (REM) is an estimation technique that incorporates a disturbance term to account for potential correlations in the residuals across time and between cross-sectional units. This model assumes that the residuals may be correlated both temporally and across individuals.

Table 3. Output of Random Effect Model

Variabel	Estimate	p-value	Interpretation
(Intercept)	82.818	$2x10^{-16}$	Significant
X_1	0.1485	0.5906	Not Significant
X_2	-0.0784	0.0355	Significant
X_3	0.0053	0.0925	Not Significant
X_4	0.0011	0.0333	Significant

As presented in Table 3, variables X1 and X3 are not statistically significant within the model, as indicated by their p-values exceeding the 5% significance level (α = 0.05). The estimated regression equation for the Random Effect Model (REM), in accordance with Equation (4), is expressed as follows:

$$Y_{it} = 82.818 + 0.1485\,X1_{it} + 0.0784X2_{it} + 0.0053X3_{it} + 0.0011X4_{it}$$

4.2. Model Selection

4.2.1. Chow Test

The Chow test is employed to determine the best model between the Common Effect Model (CEM) and the Fixed Effect Model (FEM).

Table 4. Chow Test Results

p-value	Decision
0.5154	Fail to Reject H_0

As shown in Table 9, the p-value is greater than the significance level (p-value > 0.05), leading to the decision to fail to reject the null hypothesis (H_0). This indicates that the selected model is the Common Effect Model.

4.2.2. Hausmant Test

The Hausman test is used to determine the best model between the Random Effect Model (REM) and the Fixed Effect Model (FEM).

Table 5. Hausmant Test Result

p-value	Decision
0.7262	Fail to Reject H_0

Based on Table 5, the p-value exceeds the significance level (p-value > 0.05), so the null hypothesis (H_0) cannot be rejected. This implies that the Random Effect Model is the preferred model, and therefore, the test proceeds to the Lagrange Multiplier (LM) test.

4.2.3. Lagrange Multiplier (LM) test

The Lagrange Multiplier test is used when the Chow test selects the Common Effect Model and the Hausman test favors the Random Effect Model. It is applied to determine the most appropriate model between the Common Effect Model and the Random Effect Model.

Table 6. LM Test Result

Test Type	p-value
Two-sided test	$2,2x10^{-16}$
Individual test	$2,2x10^{-16}$

According to the analysis in Table 11, the p-values are less than 0.05, indicating that the Random Effect Model is the most suitable model.

4.3. Assumption Testing of the Best Panel Data Regression Model

4.3.1. Normality Test

The Anderson-Darling method was used to assess whether the residuals follow a normal distribution.

Table 7. Normality Test Results

Anderson-Darling	p-value
0,72482	0.05722

Based on Table 7, the p-value is greater than the significance level (0.05722 > 0.05), therefore the null hypothesis (H_0) cannot be rejected. This indicates that at the 5% significance level, the residuals are normally distributed.

4.3.2. Homoskedasticity Test

Homoscedasticity testing was conducted to ensure that the variance of residuals remains constant across observations.

Table 8. Homoskedasticity Test Results

p-value	Decision
0.2598	Fail to Reject H_0

As shown in Table 8, the p-value exceeds the significance level (0.2598 > 0.05), thus failing to reject H_0, which indicates homoscedasticity (constant variance).

4.3.3. Multicollinearity Test

This test detects whether there is inter-correlation or collinearity among the independent variables in the regression model.

Table 9. Multicollinearity Test Results

Variable	VIF Value	Interpretation
X_1	1.209085	No multicollinearity detected
X_2	1.611214	No multicollinearity detected
X_3	1.625723	No multicollinearity detected
X_4	1.186119	No multicollinearity detected

Since all VIF values are less than 10 (VIF < 10), it can be concluded that multicollinearity is not present among the independent variables.

4.3.4. Autocorrelation Test

The autocorrelation test examines whether residuals from one observation correlate with residuals from another.

Table 10. Autocorrelation Test Results

p-value	Decision
0.2598	Fail to Reject H_0

From Table 14, the p-value is greater than 0.05, indicating no autocorrelation exists in the regression model residuals.

4.4. Panel Data Regression Evaluation

4.4.1. Partial Test (T-Test)

The T-test is applied to determine whether each independent variable individually has a significant effect on the dependent variable.

Table 11. Partial Test (T-Test) Results

Variable	estimate	p-value	Interpretation
(Intercept)	82.8177	$2.2\text{x}10^{-16}$	Significant
X_1	0.1485	0.59055	Not Significant
X_2	-0.0784	0.03545	Significant
X_3	0.0053	0.09253	Not Significant
X_4	0.0011	0.03339	Significant

According to Table 15, the intercept, X2, and X4 variables have a significant impact on the dependent variable APK (Gross Enrollment Rate) since their p-values are less than 0.05.

4.4.2. Simultaneous Test (F-Test)

The F-test is used to examine whether the independent variables collectively influence the dependent variable.

Table 12. Simultaneous Test (T-Test) Results

p-value	Decision
0.0455	Reject H_0

Based on Table 16, the p-value is less than the significance level (p-value < 0.05), so the null hypothesis is rejected, indicating that the independent variables jointly have a significant effect on the dependent variable under the Random Effect Model.

4.4.3. Coefficient of Determination (R^2)

The coefficient of determination measures the proportion of variance in the dependent variable explained by the independent variables. The R^2 value of the panel data regression model using the Random Effect approach is 0.078, indicating that approximately 7.8% of the variation in the dependent variable is explained by the independent variables, while the remaining 92.2% is influenced by other factors outside the model.

5. Conclusion

Based on the results of the analysis conducted, the following conclusions can be drawn:

– After passing the significance tests and regression model assumption tests, the best model used in this study to analyze factors influencing the Gross Enrollment Rate (GER) at the junior high school (SMP) level in South Sulawesi Province during 2018–2022 is the Random Effect Model. The panel data regression model using REM is expressed as follows:

  ○ $Y_{it} = 82.818 + 0.1485\, X1_{it} + 0.0784X2_{it} + 0.0053X3_{it} + 0.0011X4_{it}$

- From the Random Effect Model, it is identified that the variables significantly affecting the Gross Enrollment Rate (GER) at the junior high school level in South Sulawesi Province are the student-to-teacher ratio (X2) and population density (X4).

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