International Journal of Latest Research in Humanities and Social Science (IJLRHSS)
Volume 07 - Issue 06, 2024
www.ijlrhss.com || PP. 19-39

Analysis on Income Distribution Inequality: A Case Study of Regencies and Cities in West Java, Indonesia

Anggie AlnurinPrasetya[1],Anindya Nitisari[1],Restu Arisanti[2,*]
[1]*Bachelor Programme of Statistics Department,*
Faculty of Mathematics and Natural Science,
Padjadjaran University, Indonesia
[2]*Department of Statistics,*
Faculty of Mathematics and Natural Science,
Padjadjaran University, Indonesia
[*]*Correspondence Author: r.arisanti@unpad.ac.id*

Abstract: Income inequality stems from differences in the allocation of production components, resulting in regional imbalances. This imbalance can lead to social inequities, restricted access to high-quality education and healthcare, a diminished quality of life due to unfulfilled fundamental requirements, and economic instability. The objective of this study is to analyzed the impact of various factors on income distribution disparity, as assessed by the Gini Ratio, in order to provide valuable insights for more effective policy formulation towards the country's future progress. The study employs secondary data, specifically social and population data from the Central Statistics Agency of West Java Province and analyzed it using panel data regression modeling. Using the Random Effects Model (REM), the analysis shows that the education index and regional minimum wage (RMW) have a noteworthy and detrimental impact on income inequality in West Java. In contrast, the labor force participation rate (LFPR) has a notable and meaningful impact on income inequality throughout the same time frame. During the study period, population density had a negative effect on income inequality, although this effect was not statistically significant. The unique aspect of this study is its thorough analysis of many socio-economic elements within a recent time period, specifically focusing on West Java, an area characterized by a wide range of economic situations. The findings enhance the existing body of knowledge by emphasizing particular factors that policymakers should take into account when dealing with income distribution inequality. This will assist in developing economic policies that are more efficient and focused.
Keywords: Education index, Regional Minimum Wage, Labor Force Participation Rate, Population density,Income inequality, Panel data regression.

1. Introduction

Income distribution is a concept related to the distribution of income between people or between households in society. Income distribution is often measured using two main concepts which are the concepts of absolute inequality and relative inequality. Absolute inequality is a concept that measures inequality based on absolute values. Meanwhile, relative inequality is a concept that measures inequality in income distribution by comparing the amount of income received by a person or group with the total income received by the community in a region in general (Ahluwalia, 1976) (Sukirno, 2006). Income inequality is a concept that explains the differences in wealth, living standards, and income that exist in society. Income inequality occurs due to the existence of production factors from different resources, resulting in inequality between regions. Measuring the level of inequality can use several methods, one of them is the Gini Ratio. The Gini Ratio can be used to measure the level of inequality in the distribution of people's income in various sectors and countries. In addition, the Gini Ratio can show changes in income distribution in a country over a while with a value between 0 and 1. A value of 0 indicates perfect equity and the closer it is to zero, the more equitable the income distribution is. Meanwhile, a value of 1 indicates the highest inequality and the closer it is to one, the more inequality in income distribution has occurred (Riani, 2016). The Gini Ratio calculation can use the formula

$$GR = 1 - \sum_{i=1}^{n} |fp_i(Fc_i + Fc_{i-1})|$$

GR : Gini Coefficient (Gini Ratio)
fp_i : Frequency of population in the i-th expenditure class
Fc_i : Cumulative frequency of total expenditure in the i-th expenditure class
Fc_{i-1} : Cumulative frequency of total expenditure in expenditure class (i-1)

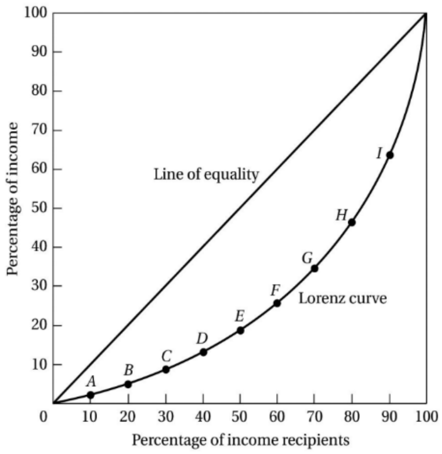

Figure 1: Gini Ratio Curve

According to Sastra (2017), the Gini Ratio divides the level of income inequality into five levels:

- Very high inequality (0.80 - 1.00)
- High inequality (0.60 - 0.79)
- Moderate inequality (0.40 - 0.59)
- Low inequality (0.20 - 0.39)
- Very low inequality (0.00 - 0.19)

The following diagram shows data on the development of income distribution inequality calculated using the Gini Ratio in Indonesia from 2005 to 2022.

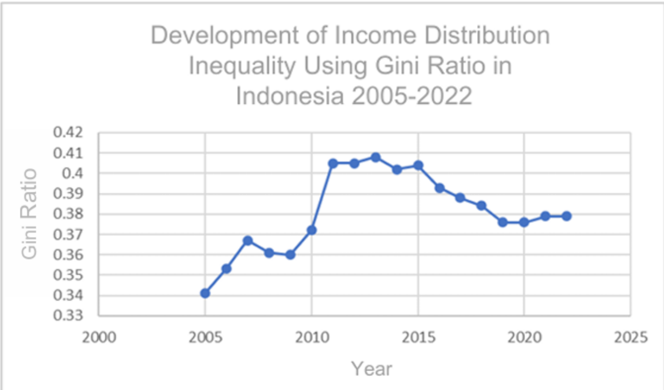

Figure 2: Development of Indonesia's Income Distribution Inequality 2005 - 2022

Based on data from The World Bank Data, it can be seen that the Gini Ratio in Indonesia is fluctuating. However, it can also be seen in Figure 2 that the Gini Ratio has increased in the last 3 years. This shows that the inequality of income distribution in Indonesia still has the possibility of continuing to increase every year so it must still be endeavored so that inequality is not as sharp as possible. However, efforts to create equality or reduce inequality cannot be achieved easily. Especially if this is due to the trade-off between economic growth and income inequality. As explained in Kuznet's theory in Todaro (2004), in the short run, strong economic growth will lead to an increase in income inequality in a region or country.

Table 1. 10 Provinces with the Largest Gini Ratio in Indonesia

Number	Province Name	Points (scale 0-1)
1.	Special Region of Yogyakarta	0.439
2.	Special Capital Region of Jakarta	0.423
3.	Gorontalo	0.418
4.	West Java	0.417
5.	Papua	0.406

6.	Southeast Sulawesi	0.387
7.	South Sulawesi	0.377
8.	Central Java	0.374
9.	West Nusa Tenggara	0.373
10.	East Java	0.371

Based on data from the Central Statistics Agency in March 2022, there are 10 provinces with the highest level of inequality in Indonesia, one of them is West Java Province which occupies position number 4 with a Gini Ratio of 0.417. This should certainly be a concern for West Java residents because the Gini Ratio above shows a considerable inequality in the income distribution in West Java.

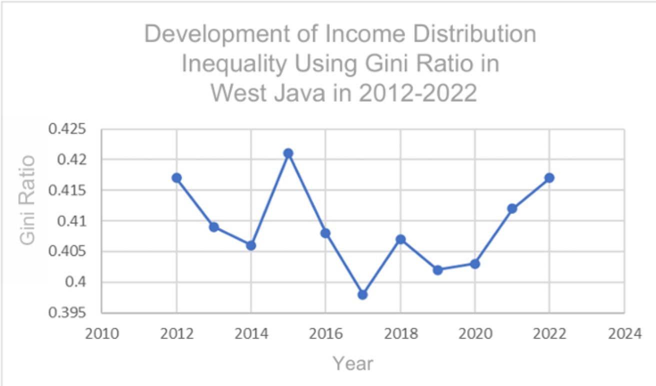

Figure 3: Development of Inequality in Income Distribution Equity of West Java 2012-2022

Based on data from Central Statistics Agency,the Gini Ratio in West Java fluctuates and tends to increase in the last 3 years. This shows that there is a possibility that the inequality of income distribution in the West Java region is getting worse every year. Therefore, special attention is needed from the relevant parties regarding the decline in income distribution equity occurring in West Java.

Inequality in income distribution can have several significant impacts on the economic conditions of the people in a country. The impacts that can be felt include social inequality, difficulties in accessing quality education and healthcare services, a low quality of life due to challenges in meeting basic needs, and economic instability where the economy becomes vulnerable to fluctuations and recessions that reduce people's purchasing power and decrease consumer demand. Social inequality in society due to unequal income distribution can cause a sense of dissatisfaction, injustice, and affect relationships between individuals or groups in society, thus leading to social tension. In addition, inequality in income distribution, especially among families or individuals with low incomes, can lead to difficulties in accessing education, health, and fulfillment of quality of life, which can affect human development, social mobility, and the physical and mental well-being of individuals.

This study aims to determine the influence of several factors on income distribution inequality in the Gini Ratio so it can help determine better policies for the future development of the country. This research is expected to enrich academic knowledge and develop a deeper theoretical understanding of the things that contribute to increasing income distribution inequality in each regency/city in West Java. Further, this research is expected to provide information on the things that can contribute to increasing income distribution inequality in each regency/city in West Java and can be used as a reference for related parties in designing, evaluating, and taking policies that can improve community welfare by equalizing income distribution in each regency/city in West Java.

2. Research Methodology

Education Index

Education plays a very important role in the progress of a nation, which is capable of directing society for the better. By getting a good education, people are expected to be able to compete in this era of globalization. In addition, education is also an important factor in obtaining employment status. The higher a person's level of education, the higher the employment status obtained. Seeing the cost of education increasing every year makes less affluent people receive lower education compared to those who can afford it. This reinforces that education can lead to income inequality (Nadya and Syafitri, 2019). Therefore, it is necessary to improve access and quality of education to reduce the education gap.

Labor Force Participation Rate

The labor force participation rate is the ratio of the labor force to the population of working age (Sukirno, 2010). The labor force is the population that is working and looking for work. The labor force consists of 2 groups, which are the working group and the unemployed group. However, some groups are not counted in the labor force category, which are people who are still going to school, people who take care of the household, and people who receive income (Masruri, 2016). There is a positive relationship between the labor force participation rate and the number of working-age people, which means that if the labor force participation rate increases, the number of working-age people will also increase.

Regional Minimum Wage

Minimum wage is the lowest or minimum monthly payment from an employer to employees for work or services they have performed based on statutory regulations and is paid based on a work agreement between employees and employers. Meanwhile, the regional minimum wage is the minimum standard used by an employer to provide wages to employees within the scope of business or work located in the region in a certain year. This is stated in the Minister of Manpower Regulation No. 05/Men/1989 dated May 29, 1989. In addition, based on Government Regulation No. 8/1981, it is said that minimum wages can be determined in regional, regional sectoral, and sub-sectoral minimums. Meanwhile, based on Law No. 13 of 2003, it is said that the minimum wage can only be addressed to workers with a working period of zero to one year (Sutama, Asmini, and Astika 2019).

Percentage of Poor Population

Poverty is the inability to fulfill basic needs, both food and non-food needs. The poor population consists of individuals whose average monthly per capita expenditure falls below the poverty line. The determination of the poverty line calculation includes food and non-food needs with the criteriabeing individuals whose income is below 7,057 Rupiah per person per day. In the calculation, food needs are equal to 2,100 kilo calories per capita per day. Meanwhile, the non-food poverty line represents the minimum needs for housing, health, and education (Sari, Soleh, and Wafiaziza, 2021).

Population Density

Population density is the ratio between the number of people living in an area and the area occupied (Samadi, 2007). The measurement commonly used is the number of people per one Km^2 or one mile. According to Samidi (Subekti and Islamiyah, 2017), several factors affect population density:

a. Residents moving out
Population movement is one of the basic factors that affect population density. If there are residents of an area who move, the area left behind will experience a population reduction.
b. Population arrives
The number of people who come to an area is a factor that affects population density. People who come will increase the number of previous residents so that population density will increase.
c. Deceased population
Every death that occurs in an area will reduce the population of the area. The population reduction will lead to a decrease in the population density of an area.
d. Population born
Every birth that occurs in an area will increase the population of that area. Indonesia implements population control with the Family Planning program which is considered successful in suppressing the population growth rate in Indonesia.
e. Area (Km^2)
The area has an influence on population density because the larger the area in a region, the greater the opportunity for people to occupy the area.

Income Inequality

Income inequality can be defined as the difference in economic prosperity between the rich and the poor. The real income of the wealthy grows faster compared to that of the poor. Based on the previous explanation, it can be concluded that income inequality is the difference in the amount of income received by the society, resulting in greater income disparities among different groups within the society. The result of this difference is that the rich will get richer and the poor will get poorer. According to Myrdall, income inequality occurs due to strong reverse effects and weak dispersion effects in developing countries. Meanwhile, according to Parvez Hasan, income inequality causes less opportunity to obtain or fulfill basic needs (Hernaningsih, 2018).

Panel Data Regression

Panel data regression is a combination of cross-section data and time series data, where the same cross section unit is measured at different times commonly referred to as panel data. Panel data is data from several individuals that are the same and observed over a certain period. If there are T periods and N number of individuals, then with panel data the total observation units are NT. If the number of time units is the same for each individual, then the data is called a balanced panel. If on the contrary, the number of time units is different for each individual, then the data is called unbalance panel.

Previous Research

Critical review is a review of previous studies that have relevance to the problem to be studied. Research on the effect of education index, labor force participation rate, region minimum wage, percentage of poor people, and population density on income distribution inequality has been conducted previously and the analysis of these studies is presented below:

Table 2: Previous Research Related to the Variables Used

Researcher	Research Title	Research Results
Maruri, M. (2016)	Analysis of the Effect of Economic Growth, HDI, Labor Force Participation Rate, and Open Unemployment on Inter-Regional Income Inequality in Central Java Province 2011 - 2014	This study uses multiple linear regression analysis. The results of this study are as follows. The economic growth variable in the study has a role in inhibiting the decline in income inequality in Central Java Province. The Human Development Index has a role in reducing income inequality in Central Java Province. An increasing labor force participation rate has no impact on income inequality in Central Java Province. Open Unemployment Rate influences income inequality in Central Java Province.
Wahyuni, R. N. T., & Monika, A. K. (2017)	The Effect of Education on Labor Income Inequality in Indonesia	This study uses quantile regression analysis. The result of this study is that the effect of education on income increases as income distribution increases. In other words, the additional income due to education is higher at the top of the income distribution. As a result, income inequality occurs.
Nadya, A. & Syafri. (2019)	The Effect of Economic Growth, Education, and Unemployment Factors on Income Distribution Inequality in Indonesia	This study uses panel data regression analysis. The result of this study is that the economic growth variable shows a positive sign but has no significant effect on inequality in Indonesia. Meanwhile, the education variable and the unemployment variable show a positive and significant sign of inequality in Indonesia.
Rahman, R. & Putri, D. Z. (2021)	Analysis of the Effect of Minimum Wage, Economic Growth, Population, and Inflation on Provincial Income Inequality in Sumatera Island	The analysis used in this study uses a panel regression model. The results of this study show that the minimum wage variable has a negative and significant effect on income inequality, economic growth has a positive and insignificant effect on income inequality, and population has a positive and insignificant effect on income inequality.
Sari, Y., Soleh, A., & Wafiaziza, W. (2021)	Analysis of the Effect of Education and the Poor on Income Inequality in Jambi Province	The analysis used in this study is quantitative descriptive analysis and multiple linear regression analysis. The results of this study, namely the variables of education and the poor population showed a significant effect simultaneously on income inequality in Jambi Province.
Humairo, M. (2021)	Analysis of Socioeconomic Factors Affecting Income Inequality in Realizing Poverty Alleviation in Indonesia	The per capita income and population variables show a positive and significant influence on income inequality in Indonesia. Meanwhile, the variables of the unemployment rate and human development index show a negative and significant influence on income inequality

		in Indonesia.
Oktaviani, N., Rengganis, S. P., & Desmawan, D. (2022)	The Effect of Income Distribution Inequality and Economic Growth on Poverty Levels in Central Java Province for the Period 2017 - 2021	This research uses the Ordinary Least Square method. The result of the research is that there is a positive relationship between the variable of income distribution inequality and changes in the poverty rate, that is, when the Income Distribution Inequality increases, the poverty rate also increases. Meanwhile, the poverty rate and growth variables are not significant.
Nilasari, A. & Amelia, R. (2022)	The Effect of GRDP Per Capita, Human Development Index, and Labor Force Participation Rate on Income Distribution Inequality in Indonesia	The analysis in this study uses the panel data regression method with the following results. GDP per capita and the labor force participation rate have a negative and significant effect on income inequality in Indonesia. HDI has a positive and significant effect on income inequality in Indonesia.

Data Description

This research data is secondary: Social and Population data in West Java from 2019 to 2022 obtained from the Central Bureau of Statistics of West Java Province. The following are the variables used in this study.

Table 3: Research Variables

Variable	Notation
Gini index for each regency/city in West Java Province	Y
Education index for each regency/city in West Java Province	X_1
Labor force participation rate of each regency/city in West Java Province	X_2
Minimum wage for each regency/city in West Java Province	X_3
Percentage of poor people in each regency/city in West Java Province	X_4
Population density of each regency/city in West Java Province	X_5

Common-Effect Model (CEM)

Common Effect Model (CEM), also known as the pooled regression model, is a panel data regression model that combines cross-sectional and time-series data into one unit (pooled data) and is estimated using OLS techniques. This results in unobserved inter-individual and inter-time differences. In other words, this approach does not take into account the individual dimension or the time dimension. The data behavior is assumed to be the same among individuals in various periods. The pool model equation can be written as follows.

$$y_{it} = \alpha + \beta_1 x_{1it} + \beta_2 x_{2it} + \cdots + \beta_k x_{kit} + \varepsilon_{it} \quad (1)$$

i=1,2, ... ,n; t=1,2, ...,T; *k=1,2, ...,K*. y_{it} is the dependent variable of the i-th individual and the t-th time. a is the intercept, x_{kit} is the k-th independent variable of the i-th individual and the t-th time. β_k is the coefficient of the independent variable, and ε_{it} is the error of the i-th individual and the t-th time.

Fixed-Effect Model (FEM)

Fixed-Effect Model is a type of panel data regression model that takes into account individual and time effects. In this model, there is an assumption that there is variation in intercepts between individuals and time but the regression coefficients for individual and time effects are constant. Models that influence either individuals or time are called one-way lagged models, and models that are influenced by both are called two-way lagged models. Estimation in this model is usually done using the Within or Least Square Dummy Variable (LSDV) model.

The FEM model equation can be written as follows:

- Individual Effect

$$y_{it} = \alpha + f_i + \beta_1 x_{1it} + \beta_2 x_{2it} + \cdots + \beta_k x_{kit} + \varepsilon_{it} \quad (2)$$

- Time Effect

$$y_{it} = \alpha + \lambda_t + \beta_1 x_{1it} + \beta_2 x_{2it} + \cdots + \beta_k x_{kit} + \varepsilon_{it} \quad (3)$$

- Two-way Model (individual and time effect)

$$y_{it} = \alpha + f_i + \lambda_t + \beta_1 x_{1it} + \beta_2 x_{2it} + \cdots + \beta_k x_{kit} + \varepsilon_{it} \quad (4)$$

Chow Test

Chow test is a test conducted to see if there are individual specific effects and time-specific effects on panel data. In this analysis, the Chow test is also used to determine the best model between CEM and FEM.
H_0: The CEM model is the best
H_1: The FEM model is the best
Level of significance: α = 5%
Test Statistics: Chow Test
Test Criteria: Reject H_0 if p-value < significance level.

Individual Effect Test

H_0: there is no individual-specific effect
H_1: there is an individual-specific effect
Significance level: α =5%
Test Statistic: $F = \frac{SSE_{MG} - SSE_{MPTI}}{SSE_{MPTI}} \cdot \frac{NT-N-K}{N-1}$
Test Criteria: Reject H_0 if p-value < significance level.

Time Effect Test

H_0: there is no time-specific effect
H_1: there is a time-specific effect
Significance level: α =5%
Test Statistic: $F = \frac{SSE_{MG} - SSE_{MPTW}}{SSE_{MPTW}} \cdot \frac{N-T-K}{T-1}$
Test Criteria: Reject H_0 if p-value < significance level.

Random-Effect Model (REM)

Random-Effect Model assumes that there is no correlation between individual-specific effects and time-specific effects with independent variables. This assumption allows the residual components of individual-specific effects and time-specific effects to be included in the residuals. The model for one-way residuals is

- Individual Effect

$$y_{it} = \alpha + \beta_1 x_{1it} + \beta_2 x_{2it} + \cdots + \beta_k x_{kit} + f_i + \varepsilon_{it} \quad (5)$$

- Time Effect

$$y_{it} = \alpha + \beta_1 x_{1it} + \beta_2 x_{2it} + \cdots + \beta_k x_{kit} + \lambda_t + \varepsilon_{it} \quad (6)$$

- For the two-way lags model, it can be written as follows.

$$y_{it} = \alpha + \beta_1 x_{1it} + \beta_2 x_{2it} + \cdots + \beta_k x_{kit} + f_i + \lambda_t + \varepsilon_{it} \quad (7)$$

With α is the intercept of the model and f_i and λ_t are the random effects of each individual and time. Parameter estimation for the Random-Effect Model (REM) is done using Generalized Least Square (GLS) (Baltagi, 2008). GLS is used as an estimator for panel data analysis with system equations because heterogeneity information between individuals and time is used as important information to produce $\hat{\beta}$parameters. The GLS parameter estimation equation is written as follows.

$$\hat{\boldsymbol{\beta}} = (\boldsymbol{X}'(\Sigma)^{-1}\boldsymbol{X})^{-1}\boldsymbol{X}'(\Sigma)^{-1}\boldsymbol{y} \quad (8)$$

The GLS method incorporates the structure of the residual variance matrix in the $\hat{\boldsymbol{\beta}}$ parameters (Ekananda, 2016). In the REM model it is assumed that the value of the individual effect is random.

Significance of Individual and Time Effects

Examination of the effect of individuals and time is carried out using the Breusch-Pagan Test with the following hypothesis.

H_0: The effect is not significant to the model
H_1: Significant influence on the model
Significance level: α =5%
Test Statistics: Breusch-Pagan Test
Test Criteria: Reject H_0 if p-value < significance level.
If both effects have significant test results, it means that the two-way model is appropriate for the REM model.

Haussman Test

The Haussman test is used to compare the FEM model with the REM model. This test is conducted to determine the best model between models that have a fixed effect or models with random effects. The Haussman test is based on the difference between the $\hat{\beta}_{MPT}$ fixed effect model estimator and the $\hat{\beta}_{MPA}$ random effect model estimator. Both estimators are consistent at H_0, but $\hat{\beta}_{MPA}$ will be biased and inconsistent at H_1. The hypothesis for this test is written as follows.

H_0: The REM model is the best
H_1: The FEM model is the best
Significance level: α =5%
Test Statistics: Haussman Test
Test Criteria: Reject H_0 if p-value < significance level

Residual Diagnostic Test

The residual diagnostic test is carried out to test whether the residuals meet all the necessary assumptions or not. The required assumptions include:

a. Normality Test

The normality test is used to determine whether the data is normally distributed or not (Nuryadi et al., 2017). In this study, the normality test was carried out using two methods, namely visualization using a histogram and using a statistical test, namely the Jarque-Bera Test with the following hypothesis.

H_0: residuals are normally distributed
H_1: residuals are not normally distributed
Significance level: α =5%
Test Statistics: Jarque-Bera Test
Test Criteria: Reject H_0 if p-value < significance level

b. Autocorrelation Test

The autocorrelation test is used to test whether in a linear model, there is a correlation between errors in period t and errors in period t-1 or the previous period (Ghozali, 2016: 107-108). The hypothesis for this test is:

H_0 : there is no autocorrelation in the residuals
H_0 : there is autocorrelation in the residuals
Significance level: α =5%
Test Statistics: Breusch-Godfrey Test
Test Criteria: Reject H_0 if p-value < significance level

c. Homogeneity Test

The homogeneity test is a statistical test used to check whether the samples used have the same variance or not (Nuryadi et al., 2017). The hypothesis used in this test is:

H_0: residuals have a homogeneous variance
H_1: residuals have heterogeneous variances
Significance level: α =5%
Test Statistics: Breusch-Pagan Test
Test Criteria: Reject H_0 if p-value < significance level

d. Multicollinearity Test

The multicollinearity test is used to test whether there is a high correlation or perfect correlation between independent variables (Ghozali, 2017: 71). If there is a high correlation between the independent variables, the relationship between the independent variables and the dependent variable will be disrupted. To see if there is multicollinearity in the independent variables, it can be done by looking at the Variance Inflation Factor (VIF) value with the following criteria (Priyatna, 2020: 53).

- VIF value < 10: there is no multicollinearity
- VIF value > 10: there is multicollinearity

e. Outlier Test

The outlier test is a test to see if there is one or more data that has unique characteristics that are very different from other data (Tileng, 2015). The outlier test can be done visually using a boxplot.

f. Linearity Test

According to Sugiyono and Susanto (2015: 323), the linearity test is a test that can be used to determine whether the dependent variable and the independent variable have a significant linear relationship or not. The linearity test can be done through visualization using the Q-Q Plot.

g. Cross-Section Unit Freedom Test

The cross-sectional unit freedom test is used to assess the relationship between two or more variables at one point in time (Zikmund, 1997). The hypothesis used in this test is:
H_0 : There are no dependencies between individual units
H_1: there are dependencies between individual units
Significance level: α =5%
Test Statistics: Breusch-Pagan LM test
Test Criteria: Reject H_0 if p-value < significance level

h. Coefficient of Determination

According to Sujarweni (2015: 164), to see how strong the relationship between the independent variable and the response variable is, it is seen through the coefficient of determination (R^2). The coefficient of determination is in the range of 0 to 1. The higher the R^2value, the better the ability of the independent variable to explain the dependent variable.

3. Results and Discussion

The data used in this study have an interval measurement scale. The results of the data description analysis of this study can be seen in Table 4.1 below

Table 4.1. Descriptive Statistics

	Minimum	Maximum	Median	Mean	Std. Deviation
Gini Index	0.284	0.489	0.3605	0.369	6.0417
Education Index	53.97	77.33	62.36	64.23	6.679
Labor Force Participation Rate	55.74	79.92	65.04	65.43	3.604
Regional Minimum Wage	1.69	4.82	2.84	2.951	0.959
Percentage of Poor Population	2.07	13.13	8.34	8.364	2.792
Population Density	383	15643	1458	3907	4601.965

A low standard deviation means that most values tend to be close to the average or the data is homogeneous. Based on table 4.1, it can be seen that the standard deviation of the Gini index and regional minimum wage variables is almost close to zero, which means that the data is homogeneous. Meanwhile, the population density variable has a high standard deviation, which means that the data is heterogeneous. The exploration data is used to see the inequality of income distribution in each regency/city in West Java Province in 2019-2022.

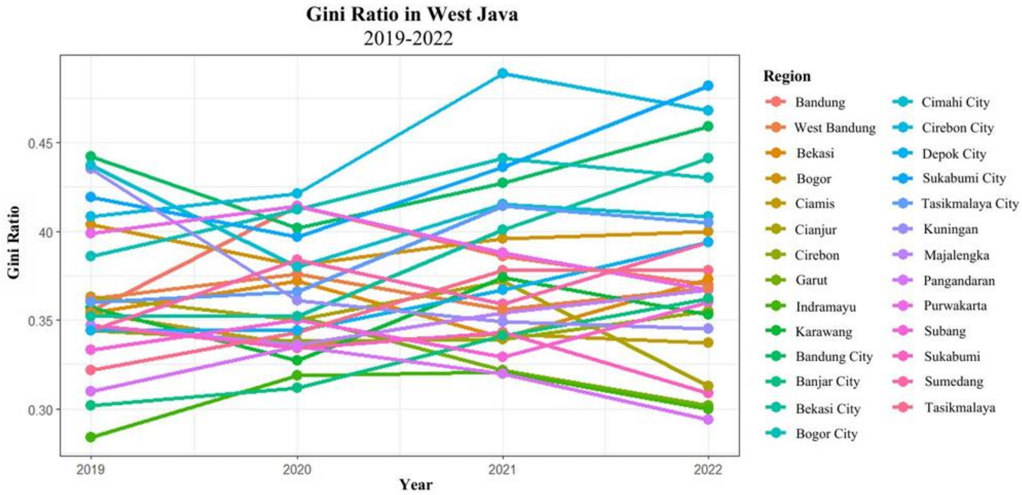

Figure 4: Line Chart of Gini Index for each Regency/City in West Java Province 2019-2022

The Line Chart above displays the distribution of income distribution levels of each regency/city in West Java Province from 2019 to 2023. It can be seen that Bandung City occupied the top position as the city with the highest inequality in 2019, Cirebon City occupies the top position as the city with the largest population inequality in 2020 and 2021, and Sukabumi City occupies the top position as the city with the largest population inequality in 2022. This indicates that there are differences for each individual.

Data Modeling Using CEM

Based on the modeling results, the CEM model results are as follows.

Table 4.2. Modeling Using CEM

	Estimate	Std. Error	t-value	Pr(> | t |)	
Intercept	3,2386E+03	9,2613E+02	3,4696	0,0006985	***
X1	3,2056E+01	9,9556E+00	3,2199	0,0017204	**
X2	-3,5554E+01	8,3552E+00	-4,2553	4,645E-05	***
X3	5,1148E+01	3,7111E+01	1,3782	0,1711474	
X4	5,7446E+01	1,5566E+01	3,6904	0,0003615	***
X5	2,2409E-02	1,3484E-02	1,6619	0,0995991	.

Based on model (1) and the table above, the CEM model is obtained, namely

$$y_{it} = 0.329 + 0.0032x_{1it} - 0.0036x_{2it} + 0.0051x_{3it} + 0.0036x_{4it} + 2.24(10)^{-6}x_{5it} + \varepsilon_{it}$$

- A one-unit increase in the education index causes income distribution inequality to increase by 0.0032 holding other variables constant.
- Each one-unit increase in LFPR causes income distribution inequality to decrease by 0.0036 holding other variables constant.
- Each one-unit increase in RMW causes income distribution inequality to increase by 0.0051 holding other variables constant.
- Each one-unit increase in the percentage of poor people causes income distribution inequality to increase by 0.0036 holding other variables constant.
- Every one-unit increase in population density causes income distribution inequality to increase by $2.24(10)^{-6}$holding other variables constant.
- The F-test p-value (5.4846e-15) < 5%. This means that we can say that the model is feasible.
- The T-test p-value for the education index, LFPR, and the percentage of poor people is <5%. This means that the variables have a significant effect on the model.
- R^2 in the model is 0.54264 or 54.264%, which indicates that the independent variables can explain the dependent variable by 54.264%.

FEM Model Formation

a. Individual Effect

Table 4.3. Modeling Using FEM for Individual Effects

	Estimate	Std. Error	t-value	Pr(>|t|)	
X_1	3.288E-03	1.1336E-03	2.9010	0.0048625	**
X_2	-3.0262E-03	8.8324E-04	-3.4262	0.0009904	***
X_3	7.1703E-03	4.6176E-03	1.5528	1.246E-01	
X_4	6.8254E-03	1.8186E-03	3.7531	0.0003395	***
X_5	2.0196E-06	1.4733E-06	1.3708	0.1744634	

Based on the model (2) and the table above, the FEM model for individual effects is obtained, namely

$$y_{it} = f_i + 0.0033x_{1it} - 0.0030x_{2it} + 0.0072x_{3it} + 0.0068x_{4it} + 2.02(10)^{-6}x_{5it} + \varepsilon_{it}$$

- A one-unit increase in the education index causes income distribution inequality to increase by 0.0033 holding other variables constant.
- Each one-unit increase in LFPR causes income distribution inequality to decrease by 0.0030 holding other variables constant.
- Each one-unit increase in RMW causes income distribution inequality to increase by 0.0072 holding other variables constant.
- Each one-unit increase in the percentage of poor people causes income distribution inequality to increase by 0.0068 holding other variables constant.
- Every one-unit increase in population density causes income distribution inequality to increase by $2.02(10)^{-6}$holding other variables constant.
- The F-test p-value (2.7914e-08) < 5%. This means that we can say that the model is feasible.
- The T-test p-value for the education index, LFPR, and the percentage of poor people is <5%. This means that the variables have a significant effect on the model.
- R^2 in the model is 0.43061 or 43.061%, which indicates that the independent variables can explain the dependent variable by 43.061%.

The intercept value for each individual can be seen in the following table.

Table 4.4. Intercept Value for Each Region in West Java Province

Region	Estimate	Std. Error	t-value	Pr(> | t |)	
Bandung	0.29401	0.10572	2.781	0.006829	**
West Bandung	0.28785	0.1058	2.7207	0.008071	**
Bekasi	0.2529	0.10688	2.3661	0.020526	*
Bogor	0.2834	0.10652	2.6606	0.009511	**
Ciamis	0.27569	0.10926	2.5233	0.013714	*
Cianjur	0.25981	0.11118	2.3369	0.022079	*
Cirebon	0.26274	0.11015	2.3852	0.01956	*
Garut	0.27923	0.10581	2.6389	0.010086	*
Indramayu	0.2598	0.10937	2.3754	0.050049	*
Karawang	0.26806	0.11076	2.4201	0.017905	*
Bandung City	0.27134	0.10857	2.4992	0.014605	*
Banjar City	0.27093	0.11048	2.4522	0.016494	*
Bekasi City	0.23813	0.11238	2.1189	0.037362	*
Bogor City	0.25873	0.11037	2.3441	0.021685	*
Cimahi City	0.27749	0.10936	2.5374	0.013215	*
Cirebon City	0.25314	0.11051	2.2907	0.024756	*
Depok City	0.25887	0.11103	2.3316	0.022375	*
Sukabumi City	0.25612	0.11126	2.302	0.024075	*
Tasikmalaya City	0.30339	0.11186	2.7122	0.008261	**
Kuningan	0.25573	0.11446	2.2343	0.028401	*
Majalengka	0.2627	0.10896	2.4111	0.01832	*
Pangandaran	0.26245	0.11106	2.3631	0.020679	*
Purwakarta	0.26127	0.11058	2.3626	0.020705	*
Subang	0.25977	0.11057	2.3495	0.021399	*
Sukabumi	0.27066	0.11384	2.3776	0.019943	*
Sumedang	0.3268	0.11479	2.8469	0.005674	**
Tasikmalaya	0.26994	0.11344	2.3769	0.019842	*

The value above is the constant effect value of each individual which in the model can be written as f_i.

Time Effect

Table 4.5. Modeling Using FEM for Time Effect

	Estimate	Std. Error	t-value	Pr(>|t|)	
X_1	3.2134E-03	9.9581E-04	3.2182	0.0017443	**
X_2	-3.5238E-03	8.4327E-04	-4.1787	6.33E-05	***
X_3	5.1581E-03	3.7208E-03	1.3863	1.688E-01	
X_4	5.7532E-03	1.5603E-03	3.6873	0.0003703	***
X_5	2.2313E-06	1.3522E-06	1.6502	0.1020752	

Based on the model (3) and the table above, the FEM model for the effect of time is obtained, namely

$$y_{it} = \lambda_t + 0.0032x_{1it} - 0.0035x_{2it} + 0.0052x_{3it} + 0.0058x_{4it} + 2.23(10)^{-6}x_{5it} + \varepsilon_{it}$$

- A one-unit increase in the education index causes income distribution inequality to increase by 0.0032 holding other variables constant.
- Each one-unit increase in LFPR causes income distribution inequality to decrease by 0.0035 holding other variables constant.
- Each one-unit increase in RMW causes income distribution inequality to increase by 0.0052 holding other variables constant.
- Each one-unit increase in the percentage of poor people causes income distribution inequality to increase by 0.0058 holding other variables constant.
- Every one-unit increase in population density causes income distribution inequality to increase by $2.23(10)^{-6}$holding other variables constant.
- The F-test p-value (21.0466e-15) < 5%. This means that we can say that the model is feasible.
- The T-test p-value for the education index, LFPR, and the percentage of poor people is <5%. This means that the variables have a significant effect on the model.
- R^2 in the model is 0.5472 or 54.72%, which indicates that the independent variables can explain the dependent variable by 54.72%.

The intercept value for each individual can be seen in the following table.

Table 4.6. Intercept Value for Time from 2019 – 2022

Year	Estimate	Std. Error	t-value	Pr(>|t|)	
2019	0.326701	0.093406	3.4976	0.0007046	***
2020	0.218432	0.093773	3.3958	9.86E-04	***
2021	0.315433	0.093224	3.3836	0.0010262	**
2022	0.323962	0.093062	3.4811	0.0007444	***

The value above is the constant effect value of each time which in the model can be written as λ_t.

Individual and Time Effect

Table 4. 7. Modeling Using FEM for Individual and Time Effects

	Estimate	Std. Error	t-value	Pr(>|t|)	
X_1	3.2986E-03	1.1335E-03	2.9100	0.0047881	**
X_2	-2.9750E-03	8.9035E-04	-3.3414	0.0013165	**
X_3	7.2956E-03	4.6180E-03	1.5798	0.1184745	
X_4	6.8497E-03	1.8171E-03	3.7695	0.0003293	***
X_5	1.9937E-06	1.4730E-06	1.3535	0.1800730	

Table 4.8. Fix Effect Model

Effects	Estimate	Effects	Estimate	Effects	Estimate
Bandung-2019	0.2951735	Karawang-2019	0.2689812	Tasikmalaya City-2019	0.3047768
Bandung-2020	0.2865855	Karawang-2020	0.2603932	Tasikmalaya City-2020	0.2961888
Bandung-2021	0.2839771	Karawang-2021	0.2577849	Tasikmalaya City-2021	0.2935804
Bandung-2022	0.2926282	Karawang-2022	0.2664359	Tasikmalaya City-2022	0.3022314

West Bandung-2019	0.2891187	Bandung City-2019	0.2724458	Kuningan-2019	0.2569667
West Bandung-2020	0.2805307	Bandung City-2020	0.2638578	Kuningan-2020	0.2483787
West Bandung-2021	0.2779224	Bandung City-2021	0.2612494	Kuningan-2021	0.2457704
West Bandung-2022	0.2865734	Bandung City-2022	0.2699005	Kuningan-2022	0.2544214
Bekasi-2019	0.2540294	Banjar City-2019	0.2721746	Majalengka-2019	0.2637287
Bekasi-2020	0.2454414	Banjar City-2020	0.2635866	Majalengka-2020	0.2551407
Bekasi-2021	0.242833	Banjar City-2021	0.2609782	Majalengka-2021	0.2525324
Bekasi-2022	0.251484	Banjar City-2022	0.2696293	Majalengka-2022	0.2611834
Bogor-2019	0.2844806	Bekasi City-2019	0.239438	Pangandaran-2019	0.2634802
Bogor-2020	0.2758926	Bekasi City-2020	0.23085	Pangandaran-2020	0.2548921
Bogor-2021	0.2732842	Bekasi City-2021	0.2282416	Pangandaran-2021	0.2522838
Bogor-2022	0.2817352	Bekasi City-2022	0.2368926	Pangandaran-2022	0.2609348
Ciamis-2019	0.2768608	Bogor City-2019	0.259821	Purwakarta-2019	0.262396
Ciamis-2020	0.2682728	Bogor City-2020	0.251233	Purwakarta-2020	0.253808
Ciamis-2021	0.2656644	Bogor City-2021	0.2486246	Purwakarta-2021	0.2511996
Ciamis-2022	0.2743154	Bogor City-2022	0.2572756	Purwakarta-2022	0.2598507
Cianjur-2019	0.2611364	Cimahi City-2019	0.278572	Subang-2019	0.2606653
Cianjur-2020	0.2525484	Cimahi City-2020	0.269984	Subang-2020	0.2520773
Cianjur-2021	0.24994	Cimahi City-2021	0.2673757	Subang-2021	0.2494689
Cianjur-2022	0.2585311	Cimahi City-2022	0.2760267	Subang-2022	0.2581199
Cirebon-2019	0.2639784	Cirebon City-2019	0.2542263	Sukabumi-2019	0.271532
Cirebon-2020	0.2553904	Cirebon City-2020	0.2456383	Sukabumi-2020	0.262944
Cirebon-2021	0.252782	Cirebon City-2021	0.2430299	Sukabumi-2021	0.2603357
Cirebon-2022	0.261433	Cirebon City-2022	0.2516809	Sukabumi-2022	0.2689867
Garut-2019	0.2804506	Depok City-2019	0.2598085	Sumedang-2019	0.3279811
Garut-2020	0.2718626	Depok City-2020	0.2512205	Sumedang-2020	0.3193931
Garut-2021	0.2692542	Depok City-2021	0.2486122	Sumedang-2021	0.3167847
Garut-2022	0.2779052	Depok City-2022	0.2572632	Sumedang-2022	0.3254357
Indramayu-2019	0.2608953	Sukabumi City-2019	0.2570578	Tasikmalaya-2019	0.2711304
Indramayu-2020	0.2523073	Sukabumi City-2020	0.2484698	Tasikmalaya-2020	0.2625424
Indramayu-2021	0.249699	Sukabumi City-2021	0.2458614	Tasikmalaya-2021	0.2599341
Indramayu-2022	0.25835	Sukabumi City-2022	0.2545124	Tasikmalaya-2022	0.2685851

Based on the model (4) and the table above, the FEM model for individual and time effects is obtained, namely

$$y_{it} = f_i + \lambda_t + 0.0033x_{1it} - 0.0030x_{2it} + 0.0073x_{3it} + 0.0068x_{4it} + 1.99(10)^{-6}x_{5it} + \varepsilon_{it}$$

- A one-unit increase in the education index causes income distribution inequality to increase by 0.0033 holding other variables constant.
- Each one-unit increase in LFPR causes income distribution inequality to decrease by 0.0030 holding other variables constant.
- Each one-unit increase in RMW causes income distribution inequality to increase by 0.0073 holding other variables constant.
- Each one-unit increase in the percentage of poor people causes income distribution inequality to increase by 0.0068 holding other variables constant.
- Every one-unit increase in population density causes income distribution inequality to increase by $1.99(10)^{-6}$holding other variables constant.
- The F-test p-value (4.1439e-08) < 5%. This means that we can say that the model is feasible.

- The T-test p-value for the education index, LFPR, and the percentage of poor people is <5%. This means that the variables have a significant effect on the model.
- R^2 in the model is 0.43793 or 43.703%, which indicates that the independent variables can explain the dependent variable by 43.703%.

Determining The Best Model

Based on the test results using the Chow Test, the following results are obtained.

Table 4.9. Test Results using the Chow Test

F-Statistic	df1	df2	p-value
1.7862	26	76	0.0271

The Chow Test results show that the p-value < alpha (5%) which indicates that the Fixed Effect model is more feasible to use on data on the effect of education index, LFPR, DMW, percentage of poor people, and population density on income distribution inequality in 2019-2022 for each regency/city in West Java Province.

Testing The Most Significant Influence

Because the previously selected model is the Fixed Effect model, the next step is to see the components that have a fixed effect among the effects of individuals, time, or both.

Table 4.10. FEM Test Results of Individual and Time Effects

Breusch-Pagan Test	df	p-value
4.5667	2	0.0271

Table 4.11. FEM Test Results of Individual Influence

Breusch-Pagan Test	df	p-value
4.3441	1	0.0271

Table 4.12. FEM Test Results of Time Effect

Breusch-Pagan Test	df	p-value
0.22259	1	0.6371

Based on the test results of the three effects above, it is found that the most significant effect is the individual effect with a p-value (0.03714) < alpha (0.05), which indicates that the individual effect plays a significant role in income distribution inequality in 2019-2022 for each regency/city in West Java Province.

Model Formation Using Random-Effect Model (REM)

Based on the test results using REM, the following model is obtained.

Table 4.13. Modeling Using REM

	Estimate	Std. Error	z-value	Pr(>|z|)	
Intercept	2.9970E-01	9.2367E-02	3.2447	0.001176	**
X_1	3.2679E-03	9.6963E-04	3.3702	0.000751	***
X_2	-3.3310E-03	8.0031E-04	-4.1622	3.152E-05	***
X_3	5.7530E-03	3.7989E-03	1.5144	0.129927	
X_4	6.1849E-03	1.5573E-03	3.9716	7.14E-05	***
X_5	2.2182E-06	1.2915E-06	1.7176	0.085867	

Based on model (5) and the table above, the REM model is obtained, namely

$$y_{it} = 0.2997 + \lambda_t + 0.0032x_{1it} - 0.0033x_{2it} + 0.0058x_{3it} + 0.0062x_{4it} + 2.22(10)^{-6}x_{5it} + f_i + \lambda_t + \varepsilon_{it}$$

- A one-unit increase in the education index causes income distribution inequality to increase by 0.0032 holding other variables constant.
- Each one-unit increase in LFPR causes income distribution inequality to decrease by 0.0033 holding other variables constant.
- Each one-unit increase in RMW causes income distribution inequality to increase by 0.0058 holding other variables constant.
- Each one-unit increase in the percentage of poor people causes income distribution inequality to increase by 0.0062 holding other variables constant.
- Every one-unit increase in population density causes income distribution inequality to increase by $2.22(10)^{-6}$holding other variables constant.
- The F-test p-value (<2.22e-16) < 5%. This means that we can say that the model is feasible.
- The T-test p-value for the education index, LFPR, and the percentage of poor people is <5%. This means that the variables have a significant effect on the model.
- R^2 in the model is 0.50144 or 50.144%, which indicates that the independent variables can explain the dependent variable by 50.144%.

Individual Effect Significant Test

The results of the Significance Test of individual influence on REM can be seen in the following table.

Table 4.14. Individual Effect Significance Test Results

Breusch-Pagan Test	df	p-value
4.3441	1	0.0371

Based on the table above, the p-value < alpha (0.05) is obtained, which means that the individual effect is significant to the model.

Table 4.15. Random Effect of Each Individual Unit

Region	Individual Random Effect
Bandung	0.012
West Bandung	0.009
Bekasi	-0.008
Bogor	0.007
Ciamis	0.003
Cianjur	-0.007
Cirebon	-0.004
Garut	0.005
Indramayu	-0.005
Karawang	0.001
Bandung City	0.001
Banjar City	0
Bekasi City	-0.018
Bogor City	-0.006
Cimahi City	0.005
Cirebon City	-0.008
Depok City	-0.004
Sukabumi City	-0.006
Tasikmalaya City	0.016
Kuningan	-0.008
Majalengka	-0.003

Pangandaran	-0.003
Purwakarta	-0.004
Subang	-0.004
Sukabumi	0.001
Sumedang	0.029
Tasikmalaya	-0.001

The table above is a value that shows how much the value of the random error component of each unit is to the general intercept value.

FEM vs REM Model Selection
Based on the Haussman Test results, the following results are obtained.

Table 4.16. Haussman Test Results

Hausman Test	df	p-value
1.111	5	0.9531

The Hausman Test results show a p-value (0.9531) > alpha (0.05) which indicates that REM is a better model.

Diagnostic Test of Residual Model
Normality Test

Table 4.17. Normality Test Results

Shapiro-Wilk Test	p-value
0.988801	0.4520

Based on the normality test above using the Shapiro Test, the p-value (0.452)> alpha (0.05) is obtained, which means that the residual model has met the normality assumption. This can also be seen in the following histogram.

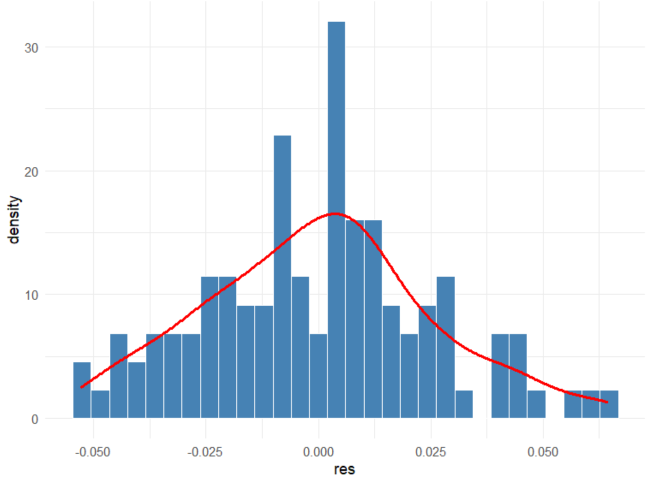

Figure 4.2. Visualization of Normality Test Using Histogram

Autocorrelation Test

Table 4.18. Autocorrelation Test Results

Breusch-Godfrey Test	df	p-value
5.3493	4	0.2533

Based on the autocorrelation test above using the Breusch-Godfrey test, the p-value (0.2533)> alpha (0.05) means that there is no autocorrelation in the residuals.

Homogeneity Test

Table 4.19. Homogeneity Test Results

Breusch-Pagan Test	df	p-value
12.331	5	0.03053

Based on the homogeneity test above using the Breusch-Pagan test, the p-value (0.03053) < alpha (0.05) means that there is heterogeneity in the residuals. Because there is one test that does not meet the assumptions, it is necessary to transform.

Multicollinearity Test

Table 4.20. Multicollinearity Test Results

X_1	X_2	X_3	X_4	X_5
4.193896	1.184046	1.699956	2.331744	3.494667

Based on the multicollinearity test above using the VIF test, it is found that there are no variables that have a VIF value above 5, which means that there is no multicollinearity in the residuals.

Assumption Handlin

Handling unmet assumptions will be done by transforming the Gini Index data using logarithmic transformation. The results of the REM model after the data is transformed can be seen in the following table.

Table 4.21. REM Model After Transformed

	Estimate	Std. Error	z-value	Pr(>|z)	
Intercept	-1.1649	2.4543E-01	-4.7461	2.07E-06	***
dX_1	9.0005E-03	2.5872E-03	3.4789	0.0005035	***
dX_2	-9.5545E-03	2.1435E-03	-4.4575	8.294E-06	***
dX_3	1.7674E-02	1.0048E-02	1.7589	0.0785897	
dX_4	1.6352E-02	4.1377E-03	3.9520	7.75E-05	***
dX_5	5.0943E-06	3.4571E-06	1.4736	0.1405891	

Based on model (5) and the table above, the REM model is obtained, namely

$$y_{it} = -1.1649 + \lambda_t + 0.009x_{1it} - 0.0095x_{2it} + 0.0177x_{3it} + 0.0164x_{4it} + 5.09(10)^{-6}x_{5it} + f_i + \lambda_t + \varepsilon_{it}$$

- A one-unit increase in the education index causes income distribution inequality to increase by 0.009 holding other variables constant.
- Each one-unit increase in LFPR causes income distribution inequality to decrease by 0.0095 holding other variables constant.
- Each one-unit increase in RMW causes income distribution inequality to increase by 0.0177 holding other variables constant.
- Each one-unit increase in the percentage of poor people causes income distribution inequality to increase by 0.0164 holding other variables constant.
- Every one-unit increase in population density causes income distribution inequality to increase by $5.09(10)^{-6}$holding other variables constant.
- The F-test p-value (<2.22e-16) < 5%. This means that we can say that the model is feasible.
- The T-test p-value for the education index, LFPR, and the percentage of poor people is <5%. This means that the variables have a significant effect on the model.
- R^2 in the model is 0.52025 or 52.025%, which indicates that the independent variables can explain the dependent variable by 52.025%.

Diagnostic Test of the Residuals of the Transformation Model

Normality Test

Table 4.22. Normality Test Results

Shapiro-Wilk Test	p-value
0.98842	0.4830

Based on the normality test above using the Shapiro Test, the p-value (0.483)> alpha (0.05) is obtained, which means that the residual model has met the normality assumption. This can also be seen in the following histogram.

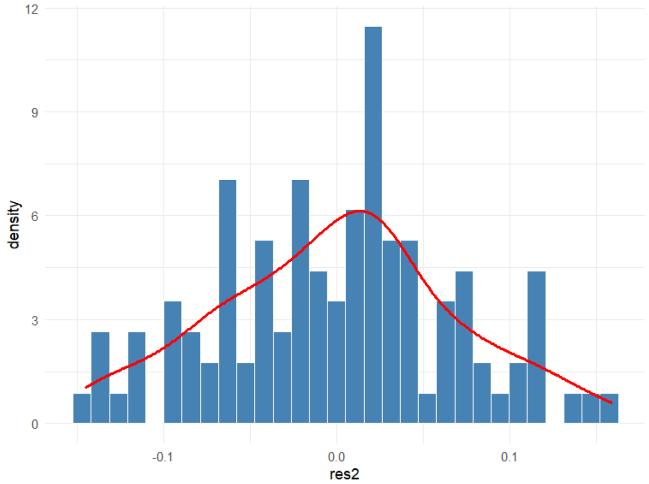

Figure 4.3. Visualization of Normality Test Using Histogram

Autocorrelation Test

Table 4.23. Autocorrelation Test Results

Breusch-Godfrey Test	df	p-value
5.5167	4	0.2383

Based on the autocorrelation test above using the Breusch-Godfrey test, the p-value (0.2383)> alpha (0.05) means that there is no autocorrelation in the residuals.

Homogeneity Test

Table 4.24. Homogeneity Test Results

Breusch-Pagan Test	df	p-value
8.4625	5	0.13250

Based on the homogeneity test above using the Breusch-Pagan test, the p-value (0.1325) < alpha (0.05) means that there is heterogeneity in the residuals.

Multicollinearity Test

Table 4.25. Multicollinearity Test Results

dX_1	dX_2	dX_3	dX_4	dX_5
4.454518	1.178401	1.682874	2.346534	3.745320

Based on the multicollinearity test above using the VIF test, it is found that there are no variables that have a VIF value above 5, which means that there is no multicollinearity in the residuals.

Outlier Test

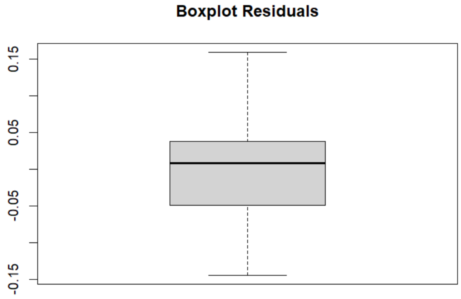

Figure 4.4. Outlier Test Using Boxplot

Based on the boxplot above, it can be seen that there are no outliers in the residuals.

Linearity Test

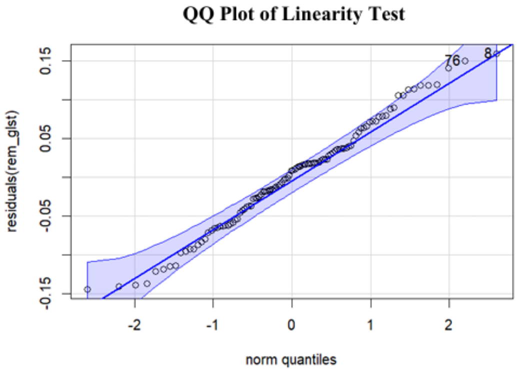

Figure 4.5. Linearity Test Using Q-Q Plot

Based on the Q-Q Plot above, it can be seen that the residual data meets the linearity assumption.

Cross-Section Unit Freedom Test:

Table 4.26. Cross-Section Unit Freedom Test Results

Breushch-Pagan LM Test		
Chisq	df	p-value
452.81	351	0.0001939

Based on the test above, it can be concluded that there are dependencies between individual units.

Discussion

Based on the regression coefficients obtained, the education index variable has a negative and significant effect on income distribution inequality in West Java Province, the Labor Force Participation Rate variable has a positive and significant effect on income distribution inequality in West Java Province, the Regency/City Minimum Wage variable has a negative but insignificant effect on income distribution inequality in West Java Province, the percentage of poor people variable has a negative and significant effect on income distribution inequality in West Java Province, and the population density variable has a negative but insignificant effect on income distribution inequality in West Java Province.

In the previous study, the education index variable has a positive and significant relationship with income distribution inequality, while in this study, the education index variable has a negative and significant relationship with income distribution inequality. This may be because, in the previous study, the scope studied was Indonesia while in this study it is only West Java Province. The Labor Force Participation Rate variable in the previous study has a negative and significant effect on income inequality while in this study the LFPR variable has a positive and significant effect on income inequality. This may be because, in the previous study, the scope studied was the State of Indonesia and Central Java Province while in this study it is only West Java Province.

The RMW variable in the previous study has a negative and significant effect on income inequality while in this study the RMW variable has a negative but insignificant effect on income inequality. This may be because, in the previous study, the scope studied was Sumatra Island while in this study it is only West Java Province. The percentage of poor population variable in the previous study has a significant effect on income inequality as well as in this study, where the poor population variable has a negative and significant effect on income inequality. The population density variable in the previous study has a positive and significant effect on income inequality while in this study the population density variable has a negative but insignificant effect on income inequality. This may be due to the fact that in the previous study the scope studied was Indonesia while in this study it is only West Java Province.

4. Conclusions and Suggestions

Conclusions

Based on the results of the analysis and discussion in the previous chapter, the conclusions of this study are as follows:

1) The most suitable regression model used in the study of the effect of education index, labor force participation rate, regional minimum wage, percentage of poor people, and population density on income distribution inequality in each regency/city in West Java in 2019-2022 is the panel regression model with random effects (Random-Effect Model) with the model written as follows.

$$y_{it} = -1{,}1649 + \lambda_t + 0{,}009X_{1it} - 0{,}0095x_{2it} + 0{,}0177x_{3it} + 0{,}0164x_{4it} + 5{,}09(10)^{-6}x_{5it} + f_i + \lambda_t + \varepsilon_{it}$$

2) The factors that have the most significant effect on income distribution inequality in each regency/city in West Java in 2019-2022 are the education index, labor force participation rate, and percentage of poor population. The higher the education index in regencies/cities in West Java, the lower the income distribution inequality. The higher the labor force participation rate in the regencies/cities in West Java, the higher the income distribution inequality. The higher the population density in the regencies/cities in West Java, the lower the income distribution inequality.

Suggestions

Based on the results of the above research, it is hoped that the government or related parties can deal with the problem of income distribution inequality by paying attention to the variables that have been studied. In addition, the model used in this study still has limitations. Therefore, there is a need for further research that can improve the results of research that has been done before.

References

[1] Dihni, V. A. (2022). Ini provinsi Dengan Ketimpangan tertinggi Pada Maret 2022: Databoks. Pusat Data Ekonomi dan Bisnis Indonesia. https://databoks.katadata.co.id/datapublish/2022/07/19/ini-provinsi- dengan-ketimpangan-tertinggi-pada-maret-2022.

[2] Dwiningsih, N. (2020). Analisa Penggunaan Metode Penelitian Regresi Data Panel Pada Studi Kasus Skripsi Mahasiswa Bimbingan Prodi Manajemen Universitas Trilogi. Laporan Penelitian, 18-19.

[3] Gini Index - Indonesia. World Bank Open Data. (n.d.). https://data.worldbank.org/indicator/SI.POV.GINI?end=2022&locations=ID&start=2022&view= map

[4] Hernaningsih, F. (2018). Pengaruh Kestabilan Inflasi Dan Ketimpangan Pendapatan Terhadap Daya Beli Masyarkat. Jurnal Ilmiah M-Progress, 8(2).

[5] Humairo, M. (2021). Analisis Faktor Sosial Ekonomi yang Mempengaruhi Ketimpangan Pendapatan Dalam Mewujudkan Pengentasan Kemiskinan di Indonesia. http://repository.trisakti.ac.id/usaktiana/digital/00000000000000106692/2021_TA_SEP_021001701019_B ab-2-Tinjauan-Pustaka.pdf.

[6] Masruri, M. (2016). Analisis Pengaruh Pertumbuhan Ekonomi, Ipm, Tpak Dan Pengangguran Terbuka Terhadap Ketimpangan Pendapatan Antar Daerah Di Provinsi Jawa Tengah Tahun 2011-2014. Jurnal Ilmiah Mahasiswa FEB, 5(1).

[7] Nadya, A., & Syafri. (2019). (PDF) Analisis Pengaruh Faktor Pertumbuhan Ekonomi, Pendidikan, ResearchGate. https://www.researchgate.net/publication/335269556. Analisis Pengaruh Faktor Pertumbuhan Ekonomi_Pendidikan Dan Pengangguran Terhadap Ketimpangan Distribusi Pendapatan di Indonesia.

[8] Nilasari, A., & Amelia, R. (2022). Pengaruh PDRB Per Kapita, Indeks Pembangunan Manusia, dan Tingkat Partisipasi Angkatan Kerja Terhadap Ketimpangan Distribusi Pendapatan di Indonesia. Nomicpedia: Journal of Economics and Business Innovation, 2(2), 169-182.

[9] Oktaviani, N., Rengganis, S. P., & Desmawan, D. (2022). Pengaruh Ketimpangan Distribusi Pendapatan Dan Pertumbuhan Ekonomi Terhadap Tingkat Kemiskinan Di Provinsi Jawa Tengah Periode 2017-2021. Jurnal Ekonomi, Bisnis dan Manajemen, 1(3), 176-189.

[10] Rahman, R., & Putri, D. Z. (2021). Analisis Pengaruh Upah Minimum, Pertumbuhan Ekonomi, Jumlah Penduduk dan Inflasi Terhadap Ketimpangan Pendapatan Provinsi di Pulau Sumatera. Jurnal Kajian Ekonomi dan Pembangunan, 3(3), 37-48.

[11] Riadi, M. (2020, April 17). Ketimpangan Pendapatan (Pengertian, Penyebab Dan Pengukuran). KajianPustaka. https://www.kajianpustaka.com/2020/04/ketimpangan-pendapatan-pengertian-penyebab- dan-pengukuran.html.

[12] Riani, W. (2016). Keterbatasan indeks gini sebagai ukuran ketimpangan pendapatan dan solusi metoda alternatif. Prosiding SNaPP: Sosial, Ekonomi dan Humaniora, 6(1), 708-715.

[13] Subekti, P., & Islamiyah, M. (2017). Penentuan Model Hubungan Kepadatan Penduduk dan Faktornya Menggunakan Metode Forward Selection. JMPM: Jurnal Matematika dan Pendidikan Matematika, 2(1), 48-57.

[14] Sukirno, S. (2010). Teori pengantar makro ekonomi Edisi Ketiga. Raja Grafindo. Jakarta

[15] Sutama, I. N., Asmini, A., & Astika, S. (2019). Analisis Faktor-Faktor Yang Mempengaruhi Penetapan Upah Minimum Kabupaten Sumbawa Tahun 2013-2017. Jurnal Ekonomi & Bisnis, 7(3), 281-291.

[16] Sari, Y., Soleh, A., & Wafiaziza, W. (2021). Analisis Pengaruh Pendidikan Dan Penduduk Miskin Terhadap Ketimpangan Pendapatan Di Provinsi Jambi. Journal Development, 9(2), 169-180.

[17] Wahyuni, R. N. T., & Monika, A. K. (2017). Pengaruh pendidikan terhadap ketimpangan pendapatan tenaga kerja di Indonesia. Jurnal Kependudukan Indonesia, 11(1), 15-28.

AuthorProfile

Anggie Alnurin Prasetya is currently an undergraduate student of Statistics Department at Padjadjaran University. Her research interests include Regression Modeling, particularly in cross-section and panel data.

Anindya Nitisari is currently an undergraduate student of statistics department at Padjadjaran University. Her research interests include Time Series Analysis and Forecasting, Multivariate, and Regression Modeling.

Restu Arisanti received a bachelor's degree in mathematics. My thesis investigated non-full-column rank matrices in non-singular data. She received my master's degree in statistics, with a thesis on spatial modeling for poverty instances. Her doctoral program was in statistics, and my dissertation focused on the development of regression model, generalized linear mixed models (GLMM), and spatial regression. Currently, She is interested in investigating GLMM integration with neural networks in a variety of case studies.