

**JEL Classification:** O 53; R 22; I 30; I 39

**DOI:** https://doi.org/10.31521/modecon.V45(2024)-14

**Hamdan Yasir**, Student at the Faculty of Economics, Sriwijaya University, Palembang, Indonesia

**ORCID ID:** 0009-0009-0166-1293

**e-mail:** hsobri25@gmail.com

**Didik Susetyo**, Doctor of Economics, Faculty of Economics, Sriwijaya University, Palembang, Indonesia

**ORCID ID:** 0000-0002-2435-3519

**e-mail:** didikusetyo60@unsri.ac.id

### **The Relationship Between Income Inequality, Poverty, And Human Development Index In North Sumatra Province**

**Abstract. Introduction.** Income inequality, poverty, and the human development index (HDI) are important indicators to measure the level of welfare and progress of a region. North Sumatra Province has significant variations in income inequality, poverty, and human development index (HDI) between districts and cities. This needs to be a concern for the government to make countermeasures in order to create equitable development and improve community welfare in all regions of North Sumatra

**Purpose.** This study aims to determine how these variables have causality between income inequality, poverty, and human development index in North Sumatra province.

**Results.** The results show that income inequality, poverty, and human development index have causality in both the long run and short run in North Sumatra province.

**Conclusions.** Of all model estimates, the long-term VECM results can be seen from the t-test value which is higher than the standard value of 1.967245. While the short-term causality model estimation results show the Chi-square probability value of significance at the significance level is at 5% alpha or p-value <0.05.

**Keywords:** income inequality (GR); poverty (P); human development index (HDI).

УДК 330.5:332.1

**Хамдан Ясір**, студент факультету економіки Університету Шривіяя, Палембанг, Індонезія

**Дідік Сусетіо**, доктор економіки, факультет економіки, Університет Шривіяя, Палембанг, Індонезія

### **Зв'язок між нерівністю доходів, бідністю та індексом людського розвитку в провінції Північна Суматра**

**Анотація.** Нерівність у доходах, бідність та індекс людського розвитку (ІЛР) є важливими показниками для вимірювання рівня добробуту та прогресу регіону. Провінція Північна Суматра має значні відмінності в нерівності доходів, бідності та індексі людського розвитку (ІЛР) між районами та містами. Це повинно викликати занепокоєння для уряду, щоб вжити контрзаходів, щоб забезпечити справедливий розвиток і покращити добробут громади в усіх регіонах Північної Суматри.

Це дослідження має на меті визначити, який ці змінні мають причинний зв'язок між нерівністю доходів, бідністю та індексом людського розвитку в провінції Північна Суматра.

Результати показують, що нерівність у доходах, бідність та індекс людського розвитку мають причинно-наслідковий зв'язок як у довгостроковій, так і в короткостроковій перспективі в провінції Північна Суматра.

З усіх оцінок моделі довгострокові результати VECM можна побачити за значенням t-критерію, яке вище стандартного значення 1,967245. У той час як результати оцінки моделі короткострокового причинного зв'язку показують значення ймовірності хі-квадрат значущості на рівні 5% альфа або р-значення <0,05.

**Ключові слова:** нерівність доходів (GR); бідність (P); індекс людського розвитку (ІЛР).

**JEL Classification:** O 53; R 22; I 30; I 39.

**Formulation of the problem.** Economic development fundamentally seeks to increase growth by reducing poverty and increasing income levels to improve individual welfare. Regional economic development is the procedure of effectively managing available resources and fostering collaborative relationships between local authorities and private entities to generate employment opportunities and stimulate economic progress within a particular area. Regional development is determined by district/city development initiatives and provincial development strategies.

The Gini coefficient serves as a statistical metric used to assess the level of income inequality within a given population. Higher values of the Gini coefficient correspond to increasing income inequality in the population. The Gini coefficient is used for cross-country, inter-regional, or intra-community comparisons to assess

the efficacy of initiatives targeting the reduction of inequality. It is important to contextualize the Gini coefficient alongside complementary metrics such as poverty prevalence and the Human Development Index (HDI) for a more comprehensive understanding of population well-being. Poverty denotes a state in which individuals or groups are unable to fulfill their basic requirements. The etiologies of poverty are diverse and varied, including disparities in the accessibility of resources such as land, financial assets, and educational opportunities that can fuel income inequality and poverty. The Human Development Index (HDI) functions as a metric that measures the level of achievement of human development in a particular area, requiring its contextualization with other indices such as poverty levels and the Gini coefficient to produce a holistic picture of population welfare.

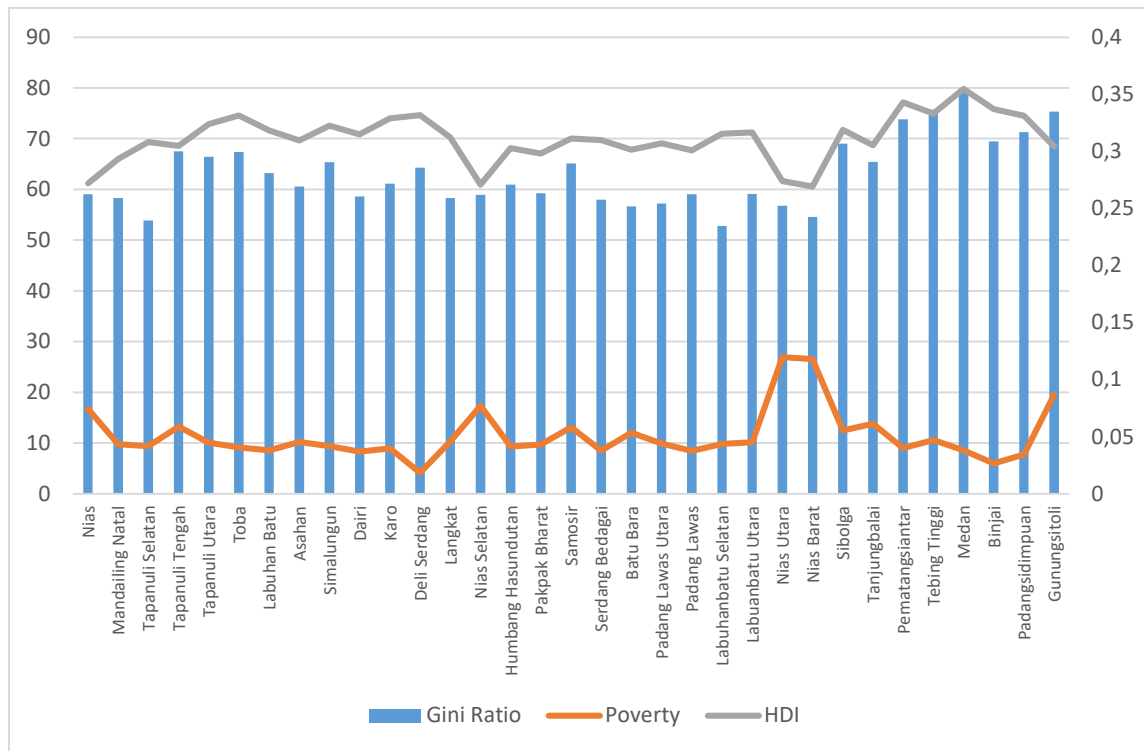


Figure 1—Average Gini Ratio, Poverty and Human Development Index for Districts and Cities in North Sumatra Province 2014-2023

Source: Badan Pusat Statistik (BPS) of North Sumatra Province 2023

Based on a report from Badan Pusat Statistik (BPS: 2023), the Gini ratio in North Sumatra, the level of inequality will decrease in March 2023, the Gini ratio in North Sumatra reached 0.309, indicating a moderate level of inequality in population expenditure. This figure is lower than in September 2022, indicating a decrease in inequality, although small. The Gini ratio shows a positive trend, inequality in North Sumatra is still a concern. BPS data shows that the richest 10% of the population in North Sumatra controls 26.18% of expenditure, while the poorest 10% of the population only controls 4.15% of

expenditure. This shows that a small portion of the population controls most of the income, while the majority of the population has a low income. Accurate and up-to-date Gini ratio data is very important for monitoring developments in inequality and evaluating the effectiveness of programs implemented. Empowering society, especially poor and marginalized groups, is also key in reducing inequality. By improving skills and access to economic opportunities, poor people can increase their income and reduce the gap with rich groups (Kawachi & Subramanian: 2014).

Meanwhile, poverty in North Sumatra, although showing a downward trend, is still an urgent issue that requires serious attention. In March 2023, 1.24 million people in this province still lived below the poverty line, with a poverty rate of 8.15%. Even though this figure is lower than the previous year, income inequality is still quite high, with the richest 10% of the population controlling 26.18% of expenditure, while the poorest 10% of the population only controls 4.15%. Efforts to overcome poverty in North Sumatra require a multidimensional and sustainable approach, including economic development increasing employment opportunities, encouraging economic growth in leading sectors, and increasing access to capital and technology for small and medium enterprises. and Social empowerment providing skills training and mentoring for poor people to increase their ability to earn a living and improve their standard of living. (Lister: 2021).

The North Sumatra Human Development Index (HDI) shows a stable upward trend over the last few years. In 2021, the HDI reached 72.00, then increased to 72.71 in 2022, and reached 75.13 in 2023. This shows that the quality of life of the people of North Sumatra continues to improve. Even though it shows improvement, North Sumatra's HDI is still lagging behind the national Human Development Index (HDI). In 2023, the national HDI will reach 71.94, indicating that there are still gaps that need to be addressed. Disparities between regions and between community groups are still a challenge in increasing HDI evenly (Lind: 2019).

**Analysis of current research and publications.** Sinaga & Zalukhu, (2022), Lakner, et al. (2022) and Halkos & Aslanidis (2023) the existence of Human Development Index (HDI) in all regions causes regions to be more developed because the quality of human resources in those regions is better, and there are regions that are left behind because the quality of human resources in those regions is still low. Poverty alleviation programs and improving the quality of life as measured by the Human Development Index (HDI) generally take time to show their effectiveness in shifting income distribution. The positive impact may only be visible in the medium or long term, so there has not been enough time to influence the Gini ratio in the short term.

Charles, et al. (2022), and Ersad, et al (2022) reducing poverty levels and increasing Human Development Index (HDI) do not directly have an impact on reducing income inequality as measured by the Gini ratio in the short term. The roots of inequality may be embedded in underlying economic and social structures, such as unequal patterns of asset ownership or unequal access to education and health. Changing this structure requires significant time and effort, so the effect on the Gini ratio is not immediately visible in the short term and can vary depending on the level of development of a region with different results.

Hutagaol, et al. (2019) and Sihombing, et al. (2023), income inequality and the human development index are

significant to poverty. There is a significant negative relationship between income inequality and the Human Development Index (HDI) and poverty. Nasir & Mridha, (2017), Charles et al., (2022) and Lakner et al., (2022) Income inequality and low HDI can create a cycle of poverty that is difficult to break. Poor people with limited access to education and health have a smaller chance of getting out of poverty. High income inequality can trigger social tensions and hinder efforts to eradicate poverty (Hasan; 2021, Lestari, et al. ;2022, and Handayani; 2023).

Dizaji & Badri (2020), income inequality and poverty are significant to the human development index. Income inequality can cause inequality of access can cause inequality of access to basic services such as education, health and infrastructure. This can hinder the progress of poor groups and slow down the increase in HDI. basic services such as education, health and infrastructure. This can hinder the progress of poor groups and slow down the increase in HDI. High income inequality can trigger social tension and political instability, which can hinder economic and social development (Castells-Quintana, et al; 2019. Shah; 2016. and Ramadhan; 2024). Poverty has a significant negative influence on the Human Development Index (HDI), as poor people generally have limited access to basic services such as education and health. This can hinder their cognitive development, physical and mental health, as well as limit their opportunities to reach their full potential and Lack of access to low-quality education can lead to limited skills and knowledge, making it difficult to get a decent, high-income job (Nainggolan, et al; 2022. Bangun; 2020. and Regina, et al; 2020).

**Formulation of research objectives.** This research aims to analyze the relationship between income inequality, poverty and the human development index (HDI) in North Sumatra Province.

**Presentation of main research material.** The type of data used in this study is secondary data in the form of panel data for the period 2014-2023. The panel data consists of 10 provinces on the island of Sumatra. All data is taken from the Badan Pusat Statistik (BPS) and related government agencies. The research data in this study consisted of 3 (three) variables, namely: 1) inequality income variable is measured using the Gini Ratio (GR), 2) Poverty variable (POV) is measured by the percentage of poor population that represents the poverty level (unit: percent), 3) Human Development Index (HDI).

The analysis technique in this research is causality test using Vector Error Correction Model (VECM). The causality test can show whether the variables have a two-way or one- way relationship (Granger, 1969). If it turns out that the variables have a two-way relationship, it means that the variables affect each other (Granger & Engle, 1987). In other words, there is a causal relationship between past variables and current conditions. In the causality test, the data used is panel data because we need to see the influence of the past on

current conditions (Ekananda, 2016 and Widarjono, 2013). Furthermore, in the causality test there are no independent variables, all variables are dependent

variables. In other words, all variables are endogenous. The equation model used in the study is as follows:

$$GR = \alpha + \sum_{j=1}^m a_j GR_{t-j} + \sum_{j=1}^m a_j POV_{t-j} + \sum_{j=1}^m a_j HDI_{t-j} + ECT_{i,t-1} + \mu_{it} \dots \dots (1)$$

$$POV = \alpha + \sum_{j=1}^m a_j POV_{t-j} + \sum_{j=1}^m a_j GR_{t-j} + \sum_{j=1}^m a_j HDI_{t-j} + ECT_{i,t-1} + \mu_{it} \dots \dots (2)$$

$$HDI = \alpha + \sum_{j=1}^m a_j HDI_{t-j} + \sum_{j=1}^m a_j GR_{t-j} + \sum_{j=1}^m a_j POV_{t-j} + ECT_{i,t-1} + \mu_{it} \dots \dots (3)$$

Where  $GR_{i,t}$  is Gini Ratio,  $POV_{i,t}$  is poverty,  $HDI_{i,t}$  is Human Development Index,  $\alpha$  is a coefficient,  $m$  is the number of lags,  $ECT$  is long-term cointegration equation and the coefficient of each variable is a short-term coefficient and  $\mu_t$  is the standard error. In simple terms, models *Vector Error Correction Model* (VECM) used to determine cause and effect relationships between variables. The results of the linear model variable regression will produce regression coefficient values and hypotheses with critical values at an alpha level of 5%.

*Vector Error Correction Model* (VECM) analysis must go through the following stages/procedures: First, the unit root test (stationarity). Used to test whether the panel data is stationary or not. If the absolute value of the statistic is greater than the critical value, then the observation data shows stationary or rejects the null hypothesis. In this study, the panel data unit root test method is the Augmented Dickey-Fuller (ADF) test, Levin Lin Chu (LLC), Im Pesaran Shin (IPS, as well as Fisher-ADF and Fisher-PP testing. The unit root test equation considers the following specifications:

$$\Delta y_{it} = \alpha y_{it-1} + \sum_{j=1}^{pi} \beta_{ij} \Delta y_{it-j} + X'_{it} \delta + \varepsilon_{it} \dots \dots (4)$$

Hypothesis testing procedure if  $pi = 0$  ( $i = N_1, \dots, N$ ) on the alternative hypothesis  $pi < 0$ . Then the hypothesis on the individual series of possible equations can be integrated.

Schwarz Information Criterion (SC) equation. The third test from Kao (1999), namely Kao Cointegration uses Dicky-Fuller and Augmented Dicky-Fuller to test for cointegration in panel data as well as in testing using the standard approach adopted in the Granger & Engle (1987) step procedure. The equation is formulated as follows:

Second, the Optimum Lag Length in determining the optimum lag length can use one of the information criteria from the Akaike Information Criterion (AIC),

$$Y_{it} = X_{it} \beta_{it} + Z_{it} \gamma_0 + \varepsilon_{i,t} \dots \dots \dots (5)$$

With residuals

$$\hat{\varepsilon}_{it} = \rho \hat{\varepsilon}_{it} + v_{it} \dots \dots \dots (6)$$

With residuals  $Y$  and  $X$  which are suspected to be non-stationary, the residual equation form can be generated as:

$$\hat{\varepsilon}_{it} = Y_{it} - X_{it} \beta_{it} - Z_{it} \hat{\gamma} \dots \dots \dots (7)$$

From equation (7) is the residual form of the equation value. To test the null hypothesis of no amount of cointegration  $H_0: p = 1$  in equality to that alternative  $Y$  and  $X$  cointegrated. To test cointegration in panel data,

Kao developed a statistical test *Dicky-Fuller* and *Augmented Dicky-Fuller* so that  $Y$  and  $X$  become cointegrated as shown by the following equation:

$$ADF = \frac{t_{ADF} + \sqrt{\frac{6N \hat{\sigma}_v}{2N \hat{\sigma}_{0u}}}}{\sqrt{\frac{\hat{\sigma}_{0u}^2}{2 \hat{\sigma}_{0u}} + \frac{3 \hat{\sigma}_{0u}^2}{10 \hat{\sigma}_{0u}}}} \dots \dots \dots (8)$$

Where  $\hat{\sigma}$  is the variance estimate. From the statistical value of panel data cointegration testing to compare with the value in *probability value* with a critical value at an alpha level of 5%.

**Result** For each of the variables under consideration, income inequality is quantified using the Gini index for Regencies and Cities in North Sumatra Province, registering at 0.28 percent, with a range from 0.19 percent to 0.40 percent. Additionally, the data in Table 1

highlights a noticeable escalation in poverty levels, as indicated by the percentage of impoverished individuals. The poverty rates for Regencies and Cities in North Sumatra Province between 2014 and 2023 exhibit an annual average of 11.44 percent, fluctuating between 3.44 percent and 32.62 percent. Throughout the 2014-2023 timeframe, the mean Human Development Index achievement for districts and cities in North Sumatra Province stands at 70.06 percent, with the highest and

lowest values recorded at 82.19 percent and 57.54 percent, respectively.

Table 1 provides an explanation that data that follows a normal distribution and has the Jarque-Bera statistical significance indicator has statistical significance at an alpha of 5% or a p-value <0.05. The dataset consists of 33 regencies and cities in North Sumatra Province, with time series ranging from 2014 to 2023, resulting in a total of 10 years of observations and 330 panel data units.

**Table 1 Description of Data**

| Statistics   | GR       | P        | HDI      |
|--------------|----------|----------|----------|
| Mean         | 0.280401 | 11.44555 | 70.06633 |
| Median       | 0.27435  | 9.83     | 70.315   |
| Maximum      | 0.402    | 32.62    | 82.19    |
| Minimum      | 0.1935   | 3.44     | 57.54    |
| Std. Dev.    | 0.039035 | 5.100174 | 4.865735 |
| Skewness     | 0.543043 | 1.923703 | -0.31685 |
| Kurtosis     | 2.914922 | 6.868996 | 3.184977 |
| Jarque-Bera  | 16.31876 | 409.3603 | 5.992018 |
| Probability  | 0.000286 | 0.0000   | 0.049986 |
| Sum          | 92.5322  | 3777.03  | 23121.89 |
| Sum Sq. Dev. | 0.501309 | 8557.874 | 7789.2   |
| Observations | 330      | 330      | 330      |

Source: Data processed 2024

The analysis aimed at establishing a causal link among income inequality, poverty, and the Human Development Index for districts and cities in North Sumatra Province, whether in the short or long term, engages in causality

examination. A crucial prerequisite for conducting causality analysis is ensuring the stationarity and integration of the dataset. Consequently, the initial phase involves an evaluation of data stationarity.

**Table 2 Unit Root Test**

| Level                              | GR        |         | P         |         | HDI       |         |
|------------------------------------|-----------|---------|-----------|---------|-----------|---------|
|                                    | Statistic | Prob.** | Statistic | Prob.** | Statistic | Prob.** |
| <i>Levin, Lin &amp; Chu t*</i>     | -4.5279   | 0.0000  | -0.1313   | 0.4478  | 5.1563    | 1.0000  |
| <i>Im, Pesaran and Shin W-stat</i> | -1.1891   | 0.1172  | 2.9647    | 0.9985  | 6.9887    | 1.0000  |
| <i>ADF - Fisher Chi-square</i>     | 88.5901   | 0.0333  | 23.7374   | 1.0000  | 9.3828    | 1.0000  |
| <i>PP - Fisher Chi-square</i>      | 145.6930  | 0.0000  | 30.8913   | 0.9999  | 102.7260  | 0.0026  |
| 1st Difference                     | D(GR)     |         | D(P)      |         | D(HDI)    |         |
| Method                             | Statistic | Prob.** | Statistic | Prob.** | Statistic | Prob.** |
| <i>Levin, Lin &amp; Chu t*</i>     | -17.5957  | 0.0000  | -2.9434   | 0.0016  | 4.2076    | 1.0000  |
| <i>Im, Pesaran and Shin W-stat</i> | -8.5888   | 0.0000  | -2.0041   | 0.0225  | -4.4839   | 0.0000  |
| <i>ADF - Fisher Chi-square</i>     | 208.1580  | 0.0000  | 88.1780   | 0.0355  | 136.3510  | 0.0000  |
| <i>PP - Fisher Chi-square</i>      | 411.5520  | 0.0000  | 356.8810  | 0.0000  | 267.2480  | 0.0000  |
| 2st Difference                     | D(GR,2)   |         | D(P,2)    |         | D(HDI,2)  |         |
| Method                             | Statistic | Prob.** | Statistic | Prob.** | Statistic | Prob.** |
| <i>Levin, Lin &amp; Chu t*</i>     | -35.6191  | 0.0000  | -3.4880   | 0.0002  | -1.7980   | 0.0361  |
| <i>Im, Pesaran and Shin W-stat</i> | -12.5643  | 0.0000  | -1.2364   | 0.1082  | -4.5342   | 0.0000  |
| <i>ADF - Fisher Chi-square</i>     | 250.2830  | 0.0000  | 78.2337   | 0.1440  | 140.1910  | 0.0000  |
| <i>PP - Fisher Chi-square</i>      | 531.9970  | 0.0000  | 375.6540  | 0.0000  | 349.8180  | 0.0000  |

Note: LLC=Levin, Lin & Chu. ADF-Fisher= Augmented Dickey-Fuller-Fisher PP-Fisher=Philips-Perron-Fisher.  
 Value in parentheses () is p-value. \* = Significant at alpha 1 %, 5 %, 10 %.

Source: Data processed 2024

The presentation of Table 2 encompasses pivotal details concerning unit root tests for appraising the stationarity of panel data through diverse methodologies. Upon completion of level-based tests, it was evident that all scrutinized variables displayed non-stationarity or failed to dismiss the null hypothesis, thus indicating the existence of unit roots. Consequently, the adoption of differentiation processes emerges as a viable approach to attain data stationarity. Subsequent scrutiny of the first difference data reveals the significance of all variables at a 5% alpha significance level or a p-value of < 0.05. This signifies the rejection of the null hypothesis and suggests that all first difference variables exhibit stationarity or lack unit roots of the same order (i.e., integrated, I(2)).

The determination of an optimal lag length is crucial for understanding the interrelations among variables and impacts the capacity to refute hypotheses, potentially leading to biased estimation outcomes. The ensuing outcomes from this endeavor are encapsulated below. The selection of the optimal lag length is contingent on employing information criteria such as the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SC) equations. The meticulous selection of an optimum lag length, devoid of correlation and other regression complications, is a vital aspect of research that favors a parsimonious number of lags. Based on the outcomes, the Akaike Information Criterion (AIC) line 2 reveals the number of lags employed, culminating in the selection of an optimal lag length of 2, in alignment with the findings delineated in table 3.

**Table 3 Optimum Lag Length Results**

| Lag | LogL     | LR        | FPE       | AIC        | SC         | HQ         |
|-----|----------|-----------|-----------|------------|------------|------------|
| 0   | -210.151 | NA        | 0.128156  | 6.459118   | 6.558648   | 6.498447   |
| 1   | 164.4231 | 703.7451  | 1.98E-06  | -4.61888   | -4.220763* | -4.461566* |
| 2   | 175.4046 | 19.63356* | 1.87e-06* | -4.678927* | -3.98222   | -4.40362   |
| 3   | 178.6379 | 5.486766  | 2.24E-06  | -4.50418   | -3.50888   | -4.11089   |
| 4   | 186.9961 | 13.42388  | 2.30E-06  | -4.48473   | -3.19084   | -3.97346   |
| 5   | 193.0438 | 9.163127  | 2.55E-06  | -4.39527   | -2.80279   | -3.766     |
| 6   | 197.2864 | 6.042503  | 3.01E-06  | -4.2511    | -2.36004   | -3.50385   |
| 7   | 203.9617 | 8.900437  | 3.32E-06  | -4.18066   | -1.991     | -3.31542   |
| 8   | 213.029  | 11.26539  | 3.45E-06  | -4.1827    | -1.69445   | -3.19947   |

Source: Data processed 2024

The subsequent step involves executing a cointegration examination to verify the existence of a prolonged relationship amid the variables within the

framework. To achieve this objective, the Kao residual cointegration test technique is employed, as delineated in Table 4.

**Table 4 Kao Residual Cointegration Test**

| Cointegration Test | t-Statistic | Prob.  |
|--------------------|-------------|--------|
| ADF                | -2.298479   | 0.0108 |
| Residual variance  | 0.000964    |        |
| HAC variance       | 0.000604    |        |

Source: Data processed 2024

The data furnished by the cointegration assessment in Table 4 discloses that the statistical importance of the Kao ADF residual cointegration test is at a significance level of 5% or p-value < 0.05, signifying a lasting correlation among the variables. The existence of a cointegration association signifies a causal relationship, albeit the causal direction between variables remains undetermined. All variables have effectively surpassed the unit root test and cointegration phase, which are

validity prerequisites established via causality scrutiny. The subsequent phase entails the execution of Vector Error Correction Model (VECM) estimation to procure crucial insights into the dynamic trends of causal connections among educational inequality, poverty, and economic advancement in the near and distant horizons. Hypothesis testing will be conducted utilizing a critical value of 5% significance level or p-value < 0.05, considering a total of 330 data points and 327 degrees of

freedom (derived by deducting the variables under examination from the total data points), yielding a figure of 1.967245. The outcomes of the Vector Error Correction Model (VECM) estimation can be located in Table 5.

**Table 5 Summary of Vector Error Correction Model (VECM) Estimation Results**

| Long-Run  |                 |                |                  |             |                |          |
|---|-----------------|----------------|------------------|-------------|----------------|----------|
| Dependent Variable                                | $\Delta(GR, 2)$ | $\Delta(P, 2)$ | $\Delta(HDI, 2)$ | ECT         | Summary        |          |
|   |                 |                |                  |             | R-squared      | 0.704367 |
| $\Delta(GR, 2)$                                   |                 | -13.53047      | 4.006087         | -0.64907    | Adj. R-squared | 0.693476 |
|   |                 | (-2.11974)     | (-0.81211)       | (-0.09404)  | F-statistic    | 64.66996 |
|   |                 | [-6.38307]*    | [ 4.93293]*      | [-6.90192]* | Akaike AIC     | -4.27181 |
|   |                 |                |                  |             | Schwarz SC     | -4.13895 |
|   |                 |                |                  |             | R-squared      | 0.482715 |
| $\Delta(P, 2)$                                    | -0.01644        |                | -0.14271         | 20.33423    | Adj. R-squared | 0.463657 |
|   | (-0.00334)      |                | (-0.0296)        | (-2.17551)  | F-statistic    | 25.32892 |
|   | [-4.92248]*     |                | [-4.82113]*      | [ 9.34689]* | Akaike AIC     | 0.800404 |
|   |                 |                |                  |             | Schwarz SC     | 2.143594 |
|   |                 |                |                  |             | R-squared      | 0.42324  |
| $\Delta(HDI, 2)$                                  | 0.016892        | -0.818748      |                  | -6.54775    | Adj. R-squared | 0.401991 |
|   | (-0.00704)      | (-0.1628)      |                  | (-0.83347)  | F-statistic    | 19.91807 |
|   | [ 2.40042]*     |                | [-5.02930]*      | [-7.85596]* | Akaike AIC     | -0.70624 |
|   |                 |                |                  |             | Schwarz SC     | 0.224766 |
| VEC Granger Causality/Block Exogeneity Wald Tests |                 |                |                  |             |                |          |
| Chi-square & Probability                          |                 |                |                  |             |                |          |
| $\Delta(GR, 2)$                                   |                 | 25.78103       | 8.676807         |             |                |          |
|   |                 | 0.0000*        | 0.0131*          |             |                |          |
| $\Delta(P, 2)$                                    | 55.32297        |                | 34.09375         |             |                |          |
|   | 0.0000*         |                | 0.0000*          |             |                |          |
| $\Delta(HDI, 2)$                                  | 30.41623        | 45.98554       |                  |             |                |          |
|   | 0.0000*         | 0.0000*        |                  |             |                |          |

Included observations: 150 after adjustments

t-statistics in signifikan [ ]\*

Significant Chi-square probability level at \*\*\*1%, \*\*5%, and \*10%

Source: Data processed 2024

The outcomes of the estimation of the Vector Error Correction Model (VECM) indicate that all three models under consideration exhibit a long-term causal effect. The initial model's estimation reveals that the Gini ratio variable, as the dependent variable, demonstrates a noteworthy impact on the Gini ratio from both the poverty variable and the human development index. These findings are evident from the t-test value, surpassing the standard value of 1.967245. Statistically, a 1% rise in the proportion of impoverished individuals from the previous year corresponds to a -13.53% reduction in the Gini ratio. Similarly, a 1% increase in the human development index from the previous year results in a 4% rise in the Gini ratio.

The estimation of the second model highlights the poverty variable as the dependent variable, indicating a

significant influence on poverty from both the Gini ratio and human development index variables. This conclusion is drawn from the t-test value falling below the standard value of 1.967245. Statistically, a 1% decrease in poverty rates from the previous year with a low Gini ratio will lead to a 0.01% reduction in the proportion of impoverished individuals. Similarly, a 1% decrease in the human development index from the previous year corresponds to a -0.14% decrease in the poverty rate.

Moreover, the third model identifies the human development index variable as the dependent variable, showcasing a significant impact from the Gini and poverty ratios of the preceding year on the human development index. This observation is supported by the t-test value exceeding the standard value of 1.967245. Statistically, a 1% increase in income inequality from the

previous year will elevate the current human development index by 0.01%. Conversely, a 1% rise in the proportion of impoverished individuals from the previous year will reduce the Gini ratio. Meanwhile, a 1% increase in the human development index from the previous year will lead to a -0.81% decline compared to the human development index.

In light of these results, it is conjectured that the significant Error Correction Parameters (ECT) substantiate the presence of a variable adjustment mechanism impacting the long term. The impact of poverty and the human development index on the Gini ratio is estimated at -0.64% in the long run. Furthermore, the impact of the Gini ratio and human development index on poverty stands at 20.33% in the long term. Additionally, the impact of the Gini and poverty ratios on the human development index is calculated at -6.54%. The shock imbalances from the previous period reintegrate into the long-run equilibrium of the current period. Essentially, it can be inferred that a long-term causal relationship exists among the Gini ratio, poverty, and the human development index of districts and cities in the North Sumatra Province.

After looking at the *Vector Error Correction Model* (VECM) estimation results above, the implications of this research model show that there is a two-way relationship between the Gini ratio, poverty and the human development index, where these three variables influence each other.

The outcomes of the short-term causality model estimation reveal that the Gini ratio, poverty, and human development index collectively impact each other in the initial model by examining the null hypothesis (H0) on short-term causality. The statistical significance is demonstrated by the Chi-square probability value at a 5% significance level or a p-value <0.05, leading to the acceptance of the hypothesis, indicating a short-term correlation between independent and dependent variables. The same procedure is replicated in the second model to examine short-run causality among previous lags of the Gini ratio, poverty, and the human development index as illustrated in Table 5.

The estimation results indicate a joint influence among the Gini ratio, poverty, and human development index. The model estimation outcomes in Table 5 suggest that, in the short term, the poverty variable and human development index significantly impact the Gini ratio, while the Gini ratio and human development index

significantly influence poverty. Additionally, the previous year's Gini and poverty ratio significantly affect the human development index, consistent with the Vector Error Correction Model (VECM) long-term estimation, implying mutual causality among these variables.

In a broader context, the policy implications of examining the Gini ratio, poverty, and human development index for districts and cities in North Sumatra province reveal that the varying Gini ratio values across regions signify differing income inequalities. Regions with low Gini ratios should prioritize equity maintenance and emphasize enhancing economic opportunities through initiatives such as the development of Micro, Small, and Medium Enterprises (MSMEs), vocational training, and infrastructure enhancement. Areas with persistent high poverty rates necessitate precisely targeted and comprehensive policies, including community empowerment schemes, expanded educational and healthcare access, and local economic enhancement, while regions with low Human Development Index (HDI) require strategies focusing on improved basic service access like education, healthcare, and infrastructure. Effective policy formulation and implementation demand cooperation among stakeholders at national, regional, and local levels, with active community involvement crucial for monitoring and supporting policy execution.

**Conclusion.** The results of these findings suggest that the three models demonstrate the presence of significant error correction parameters, thus indicating the existence of a variable adjustment mechanism over the long term. Put differently, there is a long-term causality observed from the Gini ratio, poverty, and human development index concerning districts and cities within the North Sumatra province. Similarly, in the short term, the evidence points to the same conclusion. Alternatively, a cause-and-effect relationship is established over the long term between the Gini ratio, poverty, and human development index within the districts and cities of North Sumatra province. These findings serve as a valuable instrument to aid governments and various stakeholders in crafting effective policies geared towards achieving an inclusive and sustainable development agenda. By comprehending the broader policy implications derived from this analysis and through the formulation and implementation of suitable policies, there lies the potential to foster fairer, more prosperous, and resilient societies.

#### References:

1. Bangun, R.H. (2020). Menentukan Peningkatan Pembangunan Manusia Di Sumatera Utara. *Publikauma: Jurnal Administrasi Publik Universitas Medan Area*, 8(1), 32-39. DOI: 10.31289/Publika.V8i1.3066.
2. Castells-Quintana, D., Royuela, V., & Thiel, F. (2019). Inequality And Sustainable Development: Insights From An Analysis Of The Human Development Index. *Sustainable Development*, 27(3), 448-460. DOI: 10.1002/Sd.1917.
3. Charles, V., Gherman, T., & Paliza, J. C. (2022). The Gini Index: A Modern Measure Of Inequality. In *Modern Indices For International Economic Diplomacy* (Pp. 55–84). Springer International Publishing. [https://doi.org/10.1007/978-3-030-84535-3\\_3](https://doi.org/10.1007/978-3-030-84535-3_3).
4. Charles, V., Gherman, T., & Paliza, J. C. (2022). The Gini Index: A Modern Measure Of Inequality. In *Modern Indices For International Economic Diplomacy* (Pp. 55-84). Cham: Springer International Publishing. [https://doi.org/10.1007/978-3-030-84535-3\\_3](https://doi.org/10.1007/978-3-030-84535-3_3)



5. Dizaji, M., & Badri, A. K. (2020). Human Development, Social Security Costs And Poverty With A VAR Approach. *Asian Journal Of Sociological Research*, 5-18. <https://globalpresshub.com/index.php/ajs/article/view/912>.
6. Ekananda, Mahyus. (2016). *Analisis Ekonometrika Time Series*. Edisi Kedua. Mitra Wacana Media: Jakarta.
7. Ersad, M. E., Amir, A., & Zulhani, Z. (2022). Dampak IPM, Tingkat Pengangguran Dan Tingkat Kemiskinan Terhadap Ketimpangan Pendapatan Di Sumatera Bagian Selatan. *Jurnal Paradigma Ekonomika*, 17(2), 425-438. <https://doi.org/10.22437/jpe.v17i2.15614>.
8. Granger, C. W. (1969). Investigating Causal Relations By Econometric Models And Cross-Spectral Methods. *Econometrica. Journal Of The Econometric Society*, 424-438. DOI: <https://doi.org/10.2307/1912791>.
9. Granger, C. W. J., & Engle, R. F. (1987). Econometric Forecasting: A Brief Survey Of Current And Future Techniques. *Climatic Change*, 11(1-2), 117-139. DOI: <https://doi.org/10.1007/bf00138798>.
10. Halkos, G. E., & Aslanidis, P. S. C. (2023). Causes And Measures Of Poverty, Inequality, And Social Exclusion: A Review. *Economies*, 11(4), 110. <https://doi.org/10.3390/economies11040110>.
11. Handayani, L. (2023). Analysis Of The Influence Of The Unemployment Rate And HDI On Poverty Levels In Province Of Central Java. *Journal Of Economic Education*, 12(1), 125-132. DOI: 10.15294/JEEC.V12I1.74065.
12. Hasan, Z. (2021). The Effect Of Economic Growth And Human Development Index On Poverty In Indonesia. *Journal Of Economics And Sustainability*, 3(1), 12-12. DOI: <https://doi.org/10.32890/jes2021.3.1.5>
13. Hutagaol, D. T., Tarmizi, H. B., & Daulay, M. (2019). An Analysis On The Influence Of Population Growth Rate, Economic Growth, Human Development Index, Income Distribution, And Unemployment Rate Toward Poverty In All Provinces In Indonesia. *International Journal Of Research & Review*, 6(1), 101-108. [https://www.ijrrjournal.com/ijrr\\_vol.6\\_issue.1\\_jan2019/abstract\\_ijrr0016.html](https://www.ijrrjournal.com/ijrr_vol.6_issue.1_jan2019/abstract_ijrr0016.html).
14. Kao, C. (1999). Spurious Regression And Residual-Based Tests For Cointegration In Panel Data. *Journal Of Econometrics*, 90(1), 1-44. DOI: [https://doi.org/10.1016/s0304-4076\(98\)00023-2](https://doi.org/10.1016/s0304-4076(98)00023-2).
15. Kawachi, I., & Subramanian, S. V. (2014). Income inequality. *Social epidemiology*, 126, 126-152.
16. Lakner, C., Mahler, D. G., Negre, M., & Prydz, E. B. (2022). How Much Does Reducing Inequality Matter For Global Poverty? *The Journal Of Economic Inequality*, 20(3), 559-585. <https://doi.org/10.1007/s10888-021-09510-w>.
17. Lakner, C., Mahler, D. G., Negre, M., & Prydz, E. B. (2022). How Much Does Reducing Inequality Matter For Global Poverty?. *The Journal Of Economic Inequality*, 20(3), 559-585. <https://doi.org/10.1007/s10888-021-09510-w>.
18. Lestari, E. P., Rahayu, H. C., Retnaningsih, T. K., & Suhartono, S. (2022). Significant Role Of The Human Development Index In Alleviating Poverty. *Journal Of Social Economics Research*, 9(3), 147-160. DOI: 10.18488/35.V9i3.3170.
19. Lind, N. (2019). A Development Of The Human Development Index. *Social Indicators Research*, 146(3), 409-423. <https://doi.org/10.1007/s11205-019-02133-9>.
20. Lister, R. (2021). *Poverty*. John Wiley & Sons.
21. Nainggolan, L. E., Lie, D., Nainggolan, N. T., & Siregar, R. T. (2022). How Determinants Of The Human Development Index Impact Indonesia. *Indonesian Interdisciplinary Journal Of Sharia Economics (IIJSE)*, 5(2), 687-700. DOI: <https://doi.org/10.31538/ijse.v5i2.2477>.
22. Nasir, A., & Mridha, H. A. (2017). Does Income Inequality Dampen Growth Effect On Poverty? Evidence From The US County Data. *The Journal Of Developing Areas*, 51(4), 167-177. <https://doi.org/10.1353/jda.2017.0095>.
23. Ramadhani, R. (2024). Pengaruh Tingkat Ketimpangan (Gini Ratio) Terhadap Indeks Pembangunan Manusia Di Provinsi Jawa Barat Pada Tahun 2022. *Jurnal Bisnis Dan Manajemen West Science*, 3(01), 108-118. <https://doi.org/10.58812/jbmws.v3i01.1020>.
24. Regina, R., Siring, B., & Arifin, A. (2020). Analysis The Effects Of Poverty, General Allocation Fund And Economic Growth To Human Development Index (HDI) In Indonesia. *Jurnal Economic Resource*, 3(1), 1-12. <https://doi.org/10.57178/jer.v3i2.300>.
25. Shah, S. (2016). Determinants Of Human Development Index: A Cross-Country Empirical Analysis. *Munich Personal Repec Archive*, 1-5. <https://mpra.ub.uni-muenchen.de/73759/>
26. Sihombing, P. R., Sinarwati, N. K. S., & Astawa, I. G. P. B. (2023). Korelasi Antar Variabel Makro Penentu Kemiskinan Di Indonesia. *Jurnal Ilmiah Dinamika Sosial*, 7(1), 29-44. DOI: <https://doi.org/10.38043/jids.v6i1.3772>.
27. Sinaga, M., & Zalukhu, R. S. (2022). The Impact Of Poverty And Human Development Index On Inequality Of Income Distribution Of Regency/City In North Sumatra. *International Journal Of Economics And Management Research*, 1(2), 219-228. DOI: <https://doi.org/10.55606/ijemr.v1i2.89>.
28. Widarjono, A. (2013). *Ekonometrika: Pengantar dan Aplikasinya disertai Panduan Eviews*. Yogyakarta: UPP STIM YKPN.

