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# Exploring the Determinants of Poverty Gap in Sumatra Island: A Spatial Regression Approach

**Euis Shalma[1]*, Arivina Ratih Yulihar Taher[2]**
University of Lampung, Indonesia
***E-mail Correspondence:** euishalma0103@gmail.com

**Abstract**

*The poverty gap index is an important indicator in planning more effective and targeted policies, but it has rarely been studied. This study analyzes the distribution pattern of poverty gap and the influence of non-food per capita expenditure, open unemployment rate, and Gini ratio on poverty gap in districts/municipalities in Sumatra Island in 2023. Using cross-section data from 154 districts/municipalities, the analysis was conducted through the calculation of the global Moran index and spatial autoregressive (SAR) regression. The results show that the gap of poverty in Sumatra Island has a clustered spatial pattern. Regions with moderate to high poverty gap are concentrated in the northern, southern, and western islands, especially in Aceh, Bengkulu, South Sumatra, Lampung, and Nias, Mentawai, and Meranti Islands. In contrast, the central part of Sumatra tends to have lower poverty gap. From the regression analysis, non-food per capita expenditure has a negative effect and Gini ratio has a positive effect on poverty gap. These findings emphasize the importance of considering spatial factors in the formulation of poverty alleviation policies in Sumatra.*

*Keywords* *Poverty Gap Index, Spatial, Spatial Autoregressive Model (SAR).*

## INTRODUCTION

Poverty was originally seen as an economic problem, where the income of an individual or family is insufficient to meet a decent standard of living according to social norms (Zhou & Liu, 2022). Poverty is still an unresolved problem globally, which requires urgent attention as it has the tendency to give rise to other problems, all of which are highlighted in the sustainable development goals (Ratih et al., 2023). The government continues to reduce poverty through national development programs that are a continuation of the Sustainable Development Goals (SDGs) (Tri Wandita et al., 2022). The problem of poverty is still a fundamental problem in development in various regions in Indonesia, one of which is on the island of Sumatra. Sumatra as one of the most populous islands in Indonesia also has the second largest number of poor people after Java, which is 5.67 million people and until 2023, Sumatra Island has a poverty rate of 9.27 percent.

Poverty is not only seen in terms of the number or percentage of poor people, but also in terms of its Gap. The Poverty gap Index measures how far the expenditure of the poor is from the poverty line, which is important in planning more targeted policies (de Haan et al., 2022). According to Ringga (2024), understanding the gap of poverty in small areas helps in allocating budgets more efficiently. According to Haughton & R. Khandker (2009), the minimum cost of addressing poverty can be measured through the Poverty Gap Index, which is aligned with the government's social assistance policy. Meanwhile, the Poverty Gap Index shows the amount of funds needed to lift the poor out of poverty if transfers are well targeted (Muñoz et al., 2018).

By using the Poverty Gap Index, the government can estimate the number of interventions needed to lift the poor out of poverty. Thus, this indicator is very important in planning more effective and targeted policies towards the groups that need it most. The following is the development of the Poverty Gap Index for Provinces in Sumatra Island during 2019-2023.

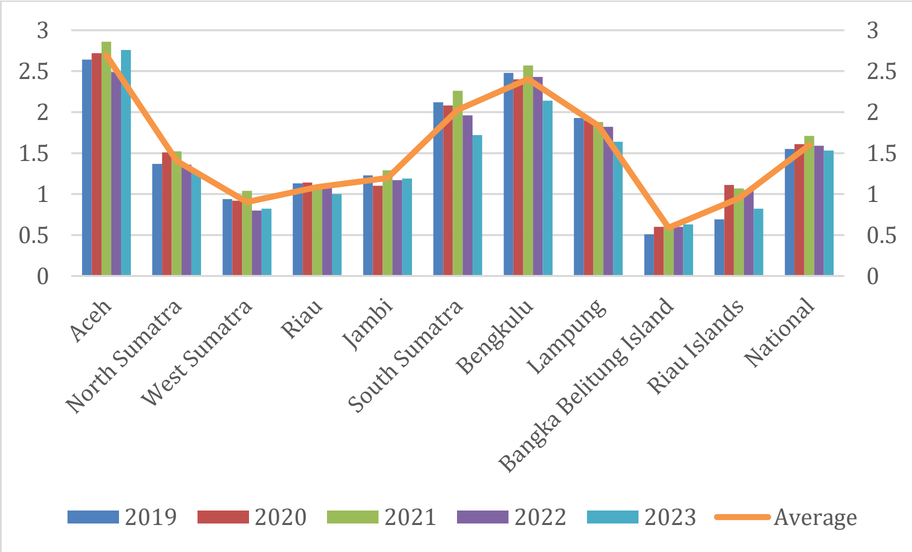


**Figure 1.** Poverty Gap Index ($P_1$) of Provinces in Sumatera Island 2019-2023
Source: Statistics Indonesia, 2023

Based on Figure 1. In Sumatra Island, the development of the Poverty Gap Index shows that Aceh Province has the highest rate, while Bangka Belitung Islands has the lowest rate. Of the 154 regencies/municipalities in Sumatra Island, 59 regencies/municipalities still have rates above the national level in 2023, highlighting regional inequality that requires more focused intervention. The Poverty Gap Index between regions in Sumatra Island has generally decreased, but there is a widening gap between regions, especially in 2023.

In 2019-2023, the provinces of Aceh, South Sumatra, Bengkulu, and Lampung consistently had a Poverty Gap Index above the national average, in line with the percentage of poor people ($P_0$) (BPS, 2023). Geographically, poverty is concentrated in the north (Aceh) and south (South Sumatra, Bengkulu, Lampung), supporting Henninger & Snel's (2002) finding that the poor tend to cluster in certain areas. This suggests that the gap of poverty on the island of Sumatra is spatially dependent as evidenced by the often concentrated and contiguous distribution of poverty, where high poverty areas tend to be surrounded by similar areas (Liu et al., 2023).

According to Emalia & Budiarty (2022), poverty analysis needs to take into account spatial aspects because poverty between regions is interrelated, where poverty conditions in a region can affect or be affected by its surrounding regions. Harmes et al. (2017), also emphasized that location factors play a role in poverty, where areas with high poverty rates tend to influence surrounding areas, resulting in the formation of clusters of areas with similar poverty conditions.

Poverty is a problem that covers many aspects. One aspect that influences poverty alleviation efforts is the economic aspect. One of the economic factors that influence poverty is the level of expenditure per capita, which reflects the income of households in fulfilling their needs (Sugianti, 2009 dalam BPS, 2023). According to BPS (2023), household consumption is divided into food and non-food consumption, where per capita expenditure on non-food needs, such as housing, services, and clothing, increases with income. Massaid et al. (2019), proved that non-food per capita expenditure has the effect of reducing poverty. (Pratama et al., 2021), also proved that non-food per capita expenditure significantly reduces poverty.

In addition to economic factors, the labor aspect also has a close relationship with poverty. A study by Apriliani et al. (2023), which analyzed the Poverty Gap Index and the open unemployment rate, found that there is a positive relationship between the open unemployment rate and the Poverty Gap Index, which means that the higher the unemployment rate, the greater the gap of poverty in a region.

Another factor that affects poverty is Income Inequality. Inequality in income distribution triggers economic disparity, which in turn becomes the main cause of poverty (Barber, 2008). Wardani et al. (2021) examined the relationship between the Gini Ratio, which reflects income inequality, and poverty through the Poverty Gap Index, finding that the Gini Ratio has a significant positive effect on the Poverty Gap Index.

Based on the explanation above, poverty alleviation requires appropriate and strategic policies, one of which is by considering geographical factors so that the effectiveness and efficiency of policies can be improved. This study aims to: (1) identify the distribution pattern of poverty gap in regencies/municipalities in Sumatra Island; (2) analyze the factors that influence the Poverty Gap Index by incorporating spatial factors between regencies/municipalities in Sumatra Island in 2023.

## METHOD

This research uses a quantitative descriptive approach and utilizes a geographic information system (GIS) with the Geoda application for spatial analysis. This study uses secondary data published by the Central Bureau of Statistics (BPS) and analyzes cross-section data from all districts/municipalities on the island of Sumatra in 2023.

### Spatial Weight Matrix

Before examining the spatial aspects, it is necessary to do weighting to determine the neighborliness of the region. The spatial weight matrix plays a role in measuring the relationship between regions based on spatial proximity or linkage (Chen, 2021). thus becoming the basis for a more detailed and systematic analysis of spatial phenomena (Safitri et al., 2022). The elements in this matrix are organized as follows (Fischer & Wang, 2011) :

$$W = \begin{bmatrix} W_{11} & W_{12} & \cdots & W_{1N} \\ W_{21} & W_{i2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ W_{N1} & W_{N2} & \cdots & W_{NN} \end{bmatrix}$$

The rows and columns of the weight matrix represent the regions that are the units of analysis. $W_{ij}$ is the weight of the i-th and j-th region linkages, where $W_{ij} \geq 0$, $W_{ij} = W_{ji}$ and $W_{ii} = 0$ for i = 1,2,3, … , N.

Sumatra Island has several regencies/cities that are separated from the mainland, such as Sabang City, Simeulue, Karimun, Anambas Islands, Batam City, Lingga, Natuna, Meranti Islands, and Mentawai Islands, so they are not detected as neighboring areas in the Queen Contiguity method. To overcome this, this study uses a manually modified Queen Contiguity matrix. According to Arbia (2014), separate areas can be adjusted by the Queen's Move method which allows connectivity in all directions. With this modification, areas that are not physically adjacent are still considered to be connected based on the closest distance between area centers.

## Spatial Autocorrelation

The Global Moran Index is used to measure spatial autocorrelation, which indicates the relationship between regions in general (Anselin, 1995). The Moran index ranges from -1 to 1 (Gedamu et al., 2024), where $-1 < I < 0$ indicates negative autocorrelation, $0 < I \leq 1$ indicates positive autocorrelation, and I = 0 means no clustering. Spatial autocorrelation is a measurement of the relationship between observed values based on the geographic location of the same variable (Pratama et al., 2022). In this analysis, the variable used is the Poverty Gap Index by district/city in Sumatra Island in 2023. The Moran Index formulation is (Fischer & Wang, 2011):

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j\neq i}^{n} W_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \qquad (1)$$

The global Moran index ($I$) measures the spatial relatedness of the Poverty Gap Index between districts/municipalities on the island of Sumatra. This analysis involves the number of observed locations ($n$), the Poverty Gap Index value in each district/city (i and j), and the average Poverty Gap Index ($\bar{x}$). In addition, a spatial weighting matrix ($W_{ij}$) is used to see the relationship between regions, so that poverty distribution patterns can be analyzed more clearly.

## Spatial Regression Analysis

The analysis of factors affecting the gap of poverty is done with classical regression or spatial regression. Spatial regression, developed by Anselin (1988), integrates spatial aspects in the model and is formulated as follows:

$$y = \rho W y + X\beta + u \qquad (2)$$

$$u = \lambda W u + \varepsilon;\ \varepsilon \sim N(0, \sigma^2 I) \qquad (3)$$

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where:

| | | |
|---|---|---|
| $y$ | : | Vector of dependent variables |
| X | : | Independent variable matrix |
| β | : | Vector of regression coefficient parameters |
| $\boldsymbol{\rho}$ | : | Coefficient parameter for spatial lag effect on the dependent variable |
| λ | : | Coefficient parameter for spatial error effect |
| $\varepsilon$ | : | Random error vector of size $n \times 1$ |
| $u$ | : | Spatial error vector of size $n \times 1$ |
| W | : | Spatial weight matrix |
| $n$ | : | Total number of observations or locations |
| $k$ | : | Number of independent variables |

From the general equation (2), it can be written that :

1. if $\rho = 0$ and $\lambda = 0$, the model is formed:
   $$y = X\beta + \varepsilon \tag{4}$$
   This model is Ordinary Least Square (OLS) without spatial influence.
2. If $\rho \neq 0$ and $\lambda = 0$, the model is formed:
   $$y = \rho Wy + X\beta + \varepsilon \tag{5}$$
   This model is called the Spatial Autoregressive Model (SAR), which shows the spatial dependence of the dependent variable, where the value of the dependent variable of an area is influenced by the surrounding area.
3. If $\rho = 0$ and $\lambda \neq 0$, the model is formed:
   $$y = X\beta + \lambda Wu + \varepsilon \tag{6}$$
   This model is called the Spatial Error Model (SEM), which shows spatial dependence on errors, where the estimation error of a region is influenced by errors in neighboring regions.

**Testing for Spatial Effects**

According to Anselin (1995), an area has two types of spatial effects, namely spatial heterogeneity and spatial dependence. Testing for spatial effects in this study includes:

**Spatial Heterogeneity**

Spatial heterogeneity measures the variation in the effect of independent variables on the dependent variable across regions. In spatial regression, it remains global like classical regression, so each region is assumed to have the same characteristics (BPS, 2013). Testing is done with the Breusch-Pagan test, with the hypothesis:

**$H_0$**: There is no spatial heterogeneity

**$H_a$**: There is spatial heterogeneity

$H_0$ is rejected if the value of Breusch-Pagan statistic > chi-squared value or p-value < 0.05, which means there is a spatial heterogeneity problem.

## Spatial Dependence

Spatial dependence measures the interconnectedness between regions through spatial autocorrelation. Testing is done with Moran's Index using a modified Queen Contiguity matrix, as well as the Lagrange Multiplier (LM) test to determine the appropriate model.

LM-Error hypothesis:

**$H_0$**: $\lambda = 0$ (no spatial dependence between errors)

**$H_a$**: $\lambda \neq 0$ (there is spatial dependence between errors)

LM-Lag hypothesis:

**$H_0$**: $\rho = 0$ (no spatial dependence among dependent variables)

**$H_a$**: $\rho \neq 0$ (there is spatial dependence among dependent variables)

$H_0$ is rejected if the value of LM statistic > chi-squared value or p-value < 0.05, which means there is spatial dependence. According to Anselin (2005), if LM-Lag is significant, the Spatial Autoregressive (SAR) model is used, while if LM-Error is significant, the Spatial Error (SEM) model is used. If both are significant, model selection is based on the Robust LM test, where if Robust LM-Lag is significant, SAR is chosen, and if Robust LM-Error is significant, SEM is chosen.

## RESULTS AND DISCUSSION

### Overview of the Distribution of the Poverty Gap Index in Districts/Municipalities on the Island of Sumatra in 2023

The distribution of the gap of poverty of districts/municipalities in Sumatra Island in 2023 is visualized through thematic maps with three categories using the Equal Interval method, which is easy to interpret because it has the same range of values, making it easier for lay audiences to understand (Shafira et al., 2023).

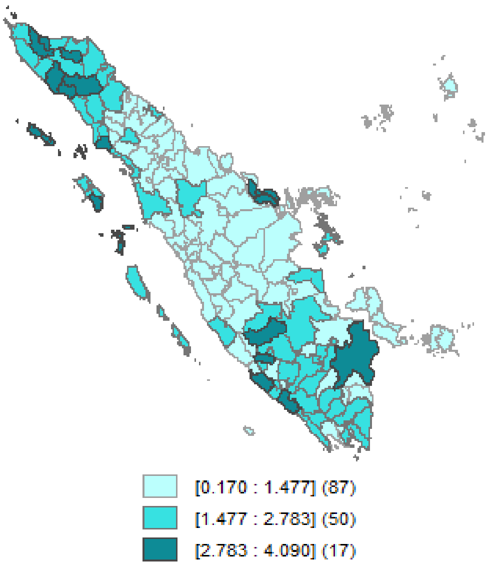


**Figure 2.** Thematic Map of Poverty Gap Index of Districts/Cities in Sumatera Island in 2023

Based on Figure 2. shows that regions with moderate to high poverty gap are mostly spread in the north, south and west of the islands. Then the central part of the island of Sumatra has a poverty gap condition that tends to be low. The regions with moderate to high poverty gap are concentrated in Aceh, and scattered in Bengkulu, South Sumatra, Lampung, Nias Islands, Mentawai Islands, and Meranti Islands. Kabupaten Pidie in Aceh recorded the highest poverty gap in Sumatra at 4.09 percent. Meanwhile, regions with low poverty gap are generally located in central Sumatra, with Sawah Lunto City in West Sumatra as the region with the lowest poverty rate at 0.17 percent in 2023.

**Poverty Gap Analysis without Spatial Concepts**

To analyze the effect of non-food Per Capita Expenditure, Open Unemployment Rate, and Gini Ratio on Poverty Gap Index in Sumatera Island without spatial concept, multiple linear regression or ordinary least square (OLS) method was used. The OLS model is transformed using natural logarithms to make the variable relationship more linear, reduce skewness, and overcome heteroscedasticity (Benoit, 2011; D.N. Gujarati & Porter, 2009). The following are the results of the OLS Regression estimation in Table 1.

**Table 1. OLS Regression Estimation Results**

| Variable | *Coefficient* | *Std.Error* | *t-Statistic* | *Probability* |
|---|---|---|---|---|
| **C** | 15.4775 | 2.40514 | 6.43518 | 0.00000* |
| **LnEXP** | -3.48622 | 0.549128 | -6.34863 | 0.00000* |
| **LnTPT** | 0.0349607 | 0.0916235 | 0.38157 | 0.70332 |
| **LnGR** | 1.58788 | 0.393517 | 4.03509 | 0.00009* |

***Significance at $\alpha$ = 5 percent**

There are several classic assumption tests carried out, including normality, homoscedasticity and multicollinearity tests. The following is a summary of the Normality and Homoscedasticity tests in Table 2.

**Table 2. Normality and Homoscedasticity Test**

| Test | DF | Value | Probability |
|---|---|---|---|
| ***Jarque-Bera*** | 2 | 2.8517 | 0.24031 |
| ***Breusch-Pagan*** | 3 | 2.4518 | 0.48406 |

The Jarque-Bera test in Table 2. shows a p-value of 0.24031 (> 0.05), so $H_0$ is accepted and the residuals are normally distributed. The Breusch-Pagan test with a statistic of 2.4518 (< 7.814728) and a p-value of 0.48406 (> 0.05) also accepts $H_0$, which means the assumption of homoscedasticity is met.

Multicollinearity is identified by examining the Variance Inflation Factor (VIF) value, as presented in Table 3 below.

**Table 3. Multicollinearity Test**

| Independent Variables | VIF |
|---|---|
| LnEXP | 1.797733 |
| LnTPT | 1.121786 |
| LnGR | 1.658863 |

Multicollinearity occurs if VIF> 10 (Widarjono, 2018). In Table 3. VIF < 10, so the model is free from high multicollinearity.

**Poverty Gap Analysis with Spatial Concepts**

According to Anselin (1995), a region has two spatial effects, namely spatial heterogeneity and spatial autocorrelation. Testing for spatial effects in this study was conducted as follows: The Breusch-Pagan test shows a statistical value of 3.0808 (< 7.814728) and a p-value of 0.37934 (> 0.05), so $H_0$ is accepted, indicating that there is no spatial heterogeneity that causes variation in the effect of the independent variable on the dependent variable in each region.

Spatial autocorrelation is known that the Moran Index value is 0.457. The value is in the range $0 < I \leq 1$, which indicates a positive spatial autocorrelation. This autocorrelation reflects the tendency of neighboring locations to have similar values and form clustered patterns.

Spatial model selection is done by Lagrange Multiplier (LM) test on lag and error and Robust LM test to detect spatial effects. If the LM lag and LM error are not significant, then there is no spatial linkage. This test was conducted using modified Queen Contiguity weights, with summary results presented in Table 4.

**Table 4. Spatial Regression Model Selection**

| Spatial Dependence Test | Value | Chi-Square | p-*value* | Description |
|---|---|---|---|---|
| *LM* (*lag*) | 34.8086 | 3.841459 | 0.00000* | Ho rejected |
| *Robust* LM (*lag*) | 7.2624 | 3.841459 | 0.00704* | Ho rejected |
| *LM* (*error*) | 27.6616 | 3.841459 | 0.00000* | Ho rejected |
| *Robust* LM (*error*) | 0.1155 | 3.841459 | 0.73399 | Ho accepted |

*Significance at α= 5 percent

The results of the spatial dependency test in Table 4. show that the LM test is significant on both lag and error (p-value = 0.00000), so $H_0$ is rejected at 5 percent significance. Further Robust LM test shows that only lag is significant (p-value =0.00704), while error is not significant. Therefore, the best model is the Spatial Autoregressive Model (SAR), with the SAR regression estimates presented in Table 5.

**Table 5. SAR Model Estimation Results**

| Variable | *Coefficient* | *Std.Error* | *z-value* | *Probability* |
|---|---|---|---|---|
| W_lnP1 | 0.45248 | 0.0748959 | 6.04146 | 0.00000* |

| | | | | |
|---|---|---|---|---|
| C | 10.4184 | 2.17002 | 4.80107 | 0.00000* |
| LnEXP | -2.39692 | 0.493974 | -4.85232 | 0.00000* |
| LnTPT | 0.0381866 | 0.0791806 | 0.482272 | 0.62961 |
| LnGR | 0.956309 | 0.34643 | 2.76047 | 0.00577* |

*Significance at $\boldsymbol{\alpha} = 5$ percent

Model Equation:

$$LnP1_i = 10.4184 + 0.45248 \sum_{j=1,i\neq j}^{n} W_{ij}\, LnP1_i - 2.39692 LnEXP_i + 0.956309\, LnGR_i + e_i \quad (7)$$

The lag coefficient (ρ) in equation (7) of 0.45248 shows that the gap of poverty in a district/city has a significant effect on its neighbors. This positive coefficient means that an increase in poverty gap in one region will increase poverty gap in its neighboring regions.

In the SAR model, the interpretation of regression coefficients is hampered by simultaneity due to the lag of the dependent variable (Kopczewska, 2020), so it is necessary to calculate the direct and indirect effects (spillover effect), as shown in Table 6.

**Table 6. SAR Model Effect**

| | Direct Effect | Indirect Effect | Total Effect |
|---|---|---|---|
| LnEXP | -2.5539725 | -1.82380595 | -4.37777849 |
| LnTPT | 0.0406887 | 0.02905603 | 0.06974472 |
| LnGR | 1.0189694 | 0.72765168 | 1.74662106 |

Table 6. shows that the direct effect of each variable is almost equal to the parameter estimates in the SAR model and larger than the indirect effect. Non-food per capita expenditure has a negative effect, where a 1 percent increase will decrease poverty gap by 2.55 percent in the region and 1.82 percent in its neighboring regions. Meanwhile, the Gini Ratio has a positive effect, where a 1 percent increase will increase the gap of poverty by 1.02 percent in the region and 0.73 percent in its neighboring regions, assuming other variables remain constant.

**Table 7. Comparison of OLS Model and SAR Model**

| Koefisien | OLS | SAR |
|---|---|---|
| *Intercept* | 15.4775 | 10.4184 |
| LnEXP | −3.48622* | −2.39692* |
| LnGR | 1.58788* | 0.956309* |
| LnTPT | 0.0349607 | 0.0381866 |
| $R^2$ | 0.220485 | 0.402705 |
| AIC | 261.112 | 231.253 |
| *Log Likelihood* | -126.556 | -110.626 |
| W_lnP1 | | 0.45248 * |

| Koefisien | OLS | SAR |
|---|---|---|

*Significance at $\alpha = 5$ percent

The model is considered good if it has the lowest AIC value and the highest Log-Likelihood and $R^2$ (Widarjono, 2019). Table 7. shows that the Spatial Autoregressive Model (SAR) is the best model because it has the lowest AIC and Log-Likelihood and $R^2$ higher than the OLS model.

## CONCLUSION

The spatial distribution of poverty gap in Sumatra in 2023 shows that Aceh has many areas with high poverty gap, in line with its position as the province with the highest poverty gap, while West Sumatra is dominated by areas with low poverty gap. The SAR model shows that Non-Food Per Capita Expenditure has a negative effect, income inequality (Gini Ratio) has a positive effect, while the Open Unemployment Rate has no significant effect on poverty gap in Sumatra in 2023.

Poverty reduction policies should consider the spatial dimension collectively by involving neighboring regions. Policy priorities need to be focused on poverty pockets by taking into account regional characteristics to increase program effectiveness. Increasing non-food expenditure, such as education and health, is proven to reduce the gof poverty. Therefore, investments in these sectors, including education and health subsidies, should be encouraged so that the benefits extend to surrounding areas. In addition, high income inequality exacerbates the gap of poverty. Inequality reduction strategies should be designed with regional linkages in mind to prevent widespread negative impacts.

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