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Analysis of Labor Force Participation Rate in Riau Province: A Spatial Autoregressive Approach

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Abstract

The labor force participation rate (LFPR) is one of the important indicators for measuring the participation of the labor force involved in economic activities. In Riau Province, LFPR has exceeded half the population, resulting in increasingly tight job competition. This research aims to model the factors influencing LFPR in Riau Province in 2021 using the Spatial Autoregressive Model (SAR). Based on the Moran Index, there is positive spatial autocorrelation in LFPR, while based on the Lagrange Multiplier test, the SAR model is appropriate to use because of the lag dependence on the dependent variable. SAR analysis shows that the non-labor force variables ($X1$), poverty line ($X2$), productive age population (15-64 years) ($X3$), and population growth rate ($X4$) have a significant positive influence on LFPR. In contrast, the type ratio variable gender ($X5$) has a negative influence. Apart from that, a lag coefficient of 0.4935 was obtained, which means that if the value of the LFPR figure in a region increases by 1 unit, it will increase by 0.4935 times the average LFPR in neighboring areas of the region. This highlights the need for policies aimed at increasing the LFPR to account for regional coordination, as changes in one area's LFPR can influence adjacent regions. Consequently, the Riau Provincial Government should promote collaboration among districts and cities to formulate a cohesive strategy, while each district should design policies that align with their unique local characteristics and the spatial dynamics of surrounding areas.

Keywords: labor force, moran index, population, poverty line, spatial autoregressive model, LFPR

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1. Introduction

Population growth is a problem for Indonesia, including Riau Province. This is because if the population is not able to work productively, it will become a burden for the local area, so high population growth leads to fewer opportunities for the labor force (Sari, 2023). The Central Bureau of Statistics of Riau Province (2021) notes that most of the people in Riau Province have reached working age. Of the 6,494 thousand population, there are 3,295 thousand who are in the labor force. This makes the Labor Force Participation Rate (LFPR) in Riau Province relatively high, where LFPR is the percentage of the labor force to the population aged 15 years and over.

The LFPR is an important indicator in measuring the health of the labor market. The higher the LFPR, the higher the supply of labor available to produce goods and services in an economy (Badan Pusat Statistik, 2021). In addition, a higher LFPR indicates greater labor availability which can contribute to increased productivity and economic growth (Ahn & Hamilton, 2022). On the other hand, if the LFPR decreases, it can lead to a higher dependency ratio, as fewer people are contributing to the economy. This may result in slower economic growth and potentially higher tax rates (Krueger, 2017).

The LFPR in a region has different characteristics depending on its geography, potential, population density, and other factors. The LFPR in a region can be influenced by the LFPR in its neighboring regions. This influence occurs because of the spatial dimension relationship, which shows that one region influences another (Jibril et al., 2022). Therefore, in conducting modeling, it would be more appropriate to use modeling that involves spatial influence (Anselin, 1988). Budiyanto (2010) stated that spatial modeling is done to show the concept of causal relationships by using methods from spatial data sources, to predict spatial patterns or to see the relationship between a location and its surrounding locations. This is by the first law of geography proposed by Tobler that everything must have a relationship, but something close has a much greater relationship when compared to something far away. The influence of location on adjacent locations is also called spatial autocorrelation (Anselin, 1988).

Lembo (2006) stated that spatial autocorrelation is the correlation between variables and themselves based on space, or it can also be interpreted as a measure of the similarity of objects in space (distance, time, and region). If there is a systematic pattern in the distribution of a variable, then there is spatial autocorrelation. The existence of spatial autocorrelation at a location means that there is a relationship between the value of observations at that location and other locations that are located nearby.

One way to determine spatial autocorrelation is to calculate global spatial autocorrelation. A popular method used to calculate this autocorrelation is the Moran Index method. Lee and Wong (2001) revealed that the Moran Index is one of the oldest methods used to measure and compare the value of observations at a location with those at other neighboring places.

There have been many studies using spatial analysis in Indonesia. Juniar & Ulinnuha (2020) conducted a study using the Moran Index method and the Spatial Autoregressive Model (SAR) to examine the autocorrelation and factors that influence the percentage of poor people in West

Java in 2018. This study indicates that there is spatial autocorrelation in the percentage of poor people in West Java and the best model to model the data is SAR. Further research conducted by Rahmawati & Bimanto (2021) compared SAR and SEM in modeling Human Development Index in East Java Province and found that SEM is the best model. Research on SAR modeling was also conducted by Suryowati et al., (2021) to analyze the influence of regional characteristics and their relationship between locations in air pollution.

Given that the labor force participation rate (LFPR) is thought to have a spatial relationship, it is important to conduct research with spatial models. Some studies related to LFPR focus more on female LFPR, such as the study conducted by Aaronson et al., (2014); Bawazir et al., (2022); Hakimzai, (2022); Nazah et al., (2021). These studies also tend to do general modeling without considering the element of spatial dependence. Therefore, this study aims to implement SAR modeling to determine the factors affecting LFPR in Riau Province in 2021. The year 2021 is the focus of this study because it is still heavily influenced by the COVID-19 pandemic that has brought significant changes to the economy and labor market, including the impact on the labor force participation rate (LFPR) in Riau. In addition, the use of data in 2021 was adjusted to the availability of the latest and updated data when the research was conducted. Examining the LFPR in 2021 is expected to provide the best modeling that can explain the factors that affect the LFPR in Riau Province based on spatial influences.

2. Research Method

2.1. Data Collection Technique

The data used in this study are secondary data obtained from the publication of the Riau Province Central Statistics Agency (BPS) in 2021. The variables used in this study consist of dependent and independent variables. The dependent variable (Y) is the dependent variable in the form of the labor force participation rate (LFPR). Because the LFPR is the ratio of the working labor force to the total labor force, the approach used is to use factors that influence people to enter the world of work (work) and unemployment. Therefore, this research uses independent variables consisting of several variables that are considered to affect LFPR, namely non-labor force ($X1$), poverty line ($X2$), productive age population (15-64 years) ($X3$), population growth rate ($X4$), and sex ratio ($X5$).

2.2. Data Analysis

The data analysis in this study is conducted using R-Studio software, with the following steps outlined in detail:

a. Collecting data through BPS publications
b. Exploring the data through descriptive statistical analysis to describe the distribution of labor force participation rates by district/city in Riau Province.
c. Construct a contiguity matrix and standardize it into a spatial weighting matrix with queen contiguity type.

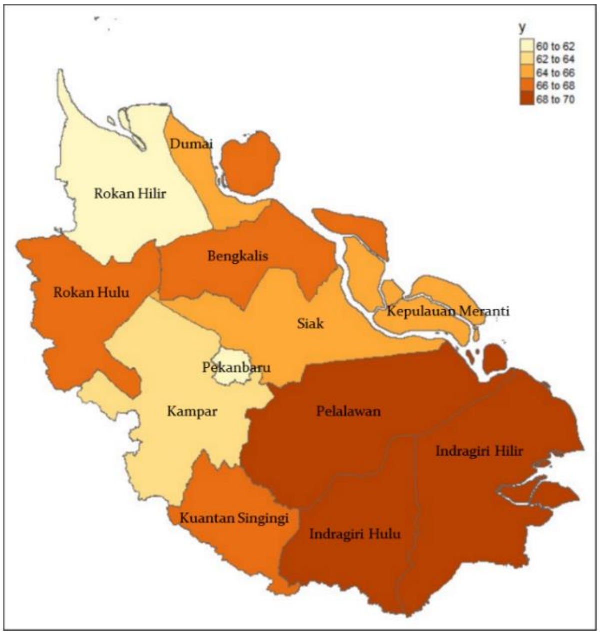
d. Conduct a spatial autocorrelation test using the Moran Index to test the spatial dependence of the data.
e. Perform the Lagrange-Multiplier (LM) test to test whether there is dependence on lags and errors and to ensure Spatial Autoregressive Model (SAR) modeling is appropriate to identify factors affecting LFPR in Riau Province.
f. Conduct the SAR (Spatial Autoregressive) modeling
g. Interpret the results of the model

3. Results and Discussion

3.1. Descriptive Analysis

The average LFPR in Riau Province in 2021 was 65.03. This value is lower than the national LFPR value of 67.80. In general, the LFPR in the province, which has 10 regencies and 2 cities, is in the range of 60% to 70%. The lowest LFPR value is in Rokan Hilir Regency, which is 60.74, while the highest LFPR is in Pelalawan Regency, which is 69.18.

Figure 1 shows the distribution of LFPR in Riau Province in 2021 which is categorized into 5 categories, namely the very low category (LFPR with a value of 60-62%), low category (LFPR with a value of 62-64%), medium category (LFPR with a value of 64-66%), high category (LFPR with a value of 66-68%), and very high category (LFPR with a value of 68-70%). It can be seen that 9 out of 12 districts/cities in Riau province are in the moderate to very high category. Only Rokan Hilir Regency and Pekanbaru City are in the very low category and Kampar Regency is in the low category. This figure also shows that districts/cities that have a high LFPR are usually surrounded by districts/cities that also have a high LFPR. This indicates a tendency for spatial dependency between locations.



Picture 1. Distribution of LFPR distribution in Riau Province in 2021

3.2. The weight matrix in Spatial Dependency

The weight matrix used in spatial dependency analysis is based on the area-based aspect of neighborliness. This weight states that the entire area at a particular location is the observed area. The weight matrix formed based on the queen contiguity type where the neighboring area refers to the location j that intersects the side and angle to location i is shown in Table 1.

Table 1. Neighborhood relationship in Riau Province spatial data

No	Spatial Data	Neighborhood
1	Bengkalis	Kampar, Kepulauan Meranti, Rokan Hilir, Rokan Hulu, Siak, Dumai.
2	Indragiri Hilir	Indragiri Hulu, Pelalawan.
3	Indragiri Hulu	Indragiri Hilir, Kuantan Singingi, Pelalawan.
4	Kampar	Bengkalis, Kuantan Singingi, Pelalawan, Rokan Hulu, Siak, Pekanbaru.
5	Kepulauan Meranti	Bengkalis.
6	Kuantan Singingi	Indragiri Hulu, Kampar, Pelalawan.
7	Pelalawan	Indragiri Hilir, Indragiri Hulu, Kampar, Kuantan Singingi, Siak.
8	Rokan Hilir	Bengkalis, Rokan Hulu, Dumai.
9	Rokan Hulu	Bengkalis, Kampar, Rokan Hilir.
10	Siak	Bengkalis, Kampar, Pelalawan, Pekanbaru.
11	Dumai	Bengkalis, Rokan Hilir.
12	Pekanbaru	Kampar, Siak.

3.3. Moran Index and LM Testing

The next step is to test for spatial effects using the Moran Index and the Lagrange-Multiplier Test (LM test). The Moran Index is used to test spatial autocorrelation between observation locations. The results of the Moran Index test with queen contiguity type for each variable used in the study are presented in Table 2.

Table 2. Moran's Index Autocorrelation Test

Variable	Moran Index	p-value
Y	0,2913	0,0238***
$X1$	0,0831	0,1837
$X2$	-0,3591	0,9176
$X3$	0,0098	0,3010
$X4$	-0,189	0,6944
$X5$	-0,1859	0,6886

Notes: ***significant at α=5%

Based on Table 1, the variable Y or LFPR has a positive Moran Index value of 0.2913 and a p-value smaller than α = 5%. This indicates that LFPR as the dependent variable has a positive and significant spatial dependence. This means that areas that are close together tend to have similar LFPR. The variables X1 and X3 also have positive Moran Index values, indicating positive spatial dependence, but the Moran Index values for both variables are very small and statistically insignificant (p-value>0.05). Other variables, namely X1, X4, and X5 have negative Moran Index values with p-values greater than 0.05, indicating that adjacent areas tend to have different characteristics.

Furthermore, the Lagrange-Multiplier test (LM test) was carried out to determine the best spatial regression model for modeling LFPR data in Riau Province in 2021. The LM test results for the SAR and SEM models are presented in Table 3.

Table 3. LM statistical test results

Model	LM Test Statistics	*p*-value
SAR	5,8566	***0,0155
SEM	0,7581	0,3839

Notes: ***significant at α=5%

Based on the results of the LM test presented in Table 2, it can be seen that the SAR model has a p-value <0.05, which means that there is a lag dependence on the dependent variable, while for the SEM model, the p-value> 0.05, which means that there is no error dependence effect. This shows that at a significance level of 5%, it is sufficient to reject *H*o in SAR modeling and fails to reject *H*o in SEM modeling. Furthermore, modeling can be continued with the SAR method.

SAR modeling is a spatial regression modeling that adds an autoregressive component to the dependent variable into the model. The estimated coefficient results in the SAR model along with their p-values are presented in Table 4.

Table 4. SAR modeling estimation results

Variable	Coefficient	*p*-value
Constant	0,8774	**0,0000
X1	-0,8990	**0,0003
X2	0,2120	**0,0081
X3	0,2343	**0,0001
X4	0,6934	**0,0059
X5	-0,8202	**0,0000
ρ	0,4935	**0,0147

Notes: ***significant at α=5%

Table 3 shows the estimated parameters of the SAR model. Based on the estimated values of these parameters, information is obtained that non-labor force ($X1$), poverty line ($X2$), productive age population (15-64 years) ($X3$), population growth rate ($X4$), sex ratio ($X5$) significantly affect the independent variables at the 5% significance level. Non-labor force variable ($X1$) and sex ratio ($X5$) have a negative influence on LFPR while other variables have a positive influence.

The non-labor force variable ($X1$) hurts LFPR. This indicates that the more individuals who are classified as not in the labor force, the smaller the amount of labor force available for work. This is because LFPR is measured as a percentage of the total working-age population that is active in the labor force (both working and looking for work). If more people are outside the labor force, then automatically, the proportion of the population that is active in the labor force will decrease. Therefore, the local government of Riau Province needs to develop programs that can attract non-labor force groups, such as housewives and unemployed school graduates, to enter the labor market. Some activities that could be undertaken include skills training, certification programs, or incentives for participation in formal and informal employment.

Similar to non-labor force participation, the sex ratio also has a negative influence on the LFPR. This indicates a potential gender inequality in labor force participation. A higher sex ratio may reduce female labor force participation, especially among women with low education. Moreover, if this ratio is unbalanced, i.e. more men than women, then the overall LFPR may be affected especially if women experience barriers to labor market entry (Rahmani, 2021). To overcome these problems, the government is expected to establish programs to empower women, eliminate gender discrimination in the workplace, and create policies that support gender equality to ensure that more women can participate in the labor market.

On the other hand, the rate of population growth has a positive impact on the LFPR. Rapid population growth can increase the number of individuals entering the working age, thus enlarging the potential labor force, which in turn can increase the LFPR (Rozmar et al., 2017). In addition, as the population increases, so does the availability of labor that can be utilized to increase the productivity and production capacity of a region, which contributes to an increase in the LFPR. Therefore, the government needs to manage population growth sustainably, starting with better urban planning, infrastructure development, and policies that support economic growth in order to absorb the increasing population in the labor market.

Productive age, which covers the age range of 15-64 years, also has a significant positive impact on LFPR. The productive age group is the group most likely to participate in the labor force. This means that when the number of people of productive age increases, the potential number of people who can work or look for work also increases. This in turn can increase the LFPR (Ikhsan, 2016). In addition, the productive-age population also tends to have more energy and better health so that they can work more effectively and efficiently. This can increase productivity and competitiveness, which in turn can increase the LFPR. Therefore, for more optimal utilization of productive labor, the government needs to work with the private sector to create relevant and quality jobs so that it can absorb more productive-age labor.

The poverty line is also one of the factors that has a significant effect on the LFPR. When the poverty line increases, more individuals will be encouraged to look for work to fulfill their basic needs. This means that more people will enter the labor market to avoid poverty, which has an impact on increasing the LFPR. For this reason, there is a need for policy interventions that ensure that the jobs available to people below the poverty line are decent and can improve the quality of life. Roziq (2023) mentions that steps that can be taken to alleviate poverty are (1) expansion of employment and business opportunities, (2) training, vocational education, and productivity, and (3) as well as labor protection and social security. In addition, the spatial lag autoregressive coefficient (ρ) also has a real effect at the 0.05 significance level with a spatial lag autoregressive coefficient value of 0.4935. In general, the Spatial Lag Model equation formed is as follows:

$$y_i = 0{,}8774 + 0{,}49357 \sum_{j=1, i\neq 1}^{n} W_{ij} y_i - 0{,}8990X_1 + 0{,}2120X_2 + 0{,}2343X_3 + 0{,}6934X_4 - 0{,}8202X_5 + s_i$$

Based on the shape of the SAR model, some information is obtained, namely:

a. The lag coefficient value is 0.4935. This means that if the value of the LFPR in a district/city increases by 1 unit and other variables are constant, then the value of the LFPR in the neighboring district/city will also increase by 0.4935 units multiplied by the LFPR of the surrounding district/city.

b. The coefficient value of the number of non-labor force ($X1$) is -0.8990. This indicates that if the number of non-labor force ($X1$) in Riau Province increases by 1 unit and other variables are constant, it will reduce the LFPR in Riau Province by 0.8990 units.

c. The coefficient value of the poverty line ($X2$) is 0.2120. This means that when the poverty line ($X2$) in Riau Province increases by 1 unit and other variables are constant, the LFPR in Riau Province will increase by 0.2120 units.

d. The coefficient value of productive age ($X3$) is 0.234. If the productive age population ($X3$) in Riau Province increases by 1 unit and other variables are constant, it will increase the LFPR in Riau Province by 0.2343 units.

e. The coefficient value of the population growth rate ($X4$) is 0.6934. If the population growth rate ($X4$) in Riau Province increases by 1 unit and other variables are constant, the LFPR in Riau Province will increase by 0.6934 units.

f. The coefficient value of the sex ratio ($X5$) is -0.8202. This means that if the sex ratio ($X5$) in Riau Province increases by 1 unit and other variables are constant, it will reduce the LFPR in Riau Province by 0.8202 units.

Each district/city will have a different SAR model, depending on the nearest district/city. This is because the SAR model depends on the weighting matrix (W) of the district/city adjacent to the observed district/city. For example, for Kuantan Singingi Regency, because the district is adjacent to Kampar, Pelalawan, and Indragiri Hulu, the SAR model formed is:

$$y_{\text{Kuantan Singingi}} = 0{,}8774 + 0{,}49357\text{Kampar} + 0{,}49357\text{Pelalawan} + 0{,}49357\text{Indragiri Hulu} - 0{,}8990X_1 + 0{,}2120X_2 + 0{,}2343X_3 + 0{,}6934X_4 - 0{,}8202X_5 + s_i$$

The interpretation of the model formed in Kuantan Singingi Regency is that if the value of the LFPR rate in Kuantan Singingi Regency increases by 1 unit, the LFPR value in Kampar Regency, Pelalawan Regency, and Indragiri Hulu Regency, which are neighbors of Kuantan Singingi Regency, will increase by 0.49357 units.

4. Conclusion and Recommendations

Based on the analysis conducted, there is an interesting pattern of dependency between regions. With a Moran Index value of 0.2913, it is evident that neighboring districts/cities tend to have similar LFPR characteristics. This finding is reinforced by the results of Spatial Autoregressive (SAR) modeling, which shows a spatial coefficient of 0.4935, indicating that an increase in LFPR in a region has a positive impact on LFPR in its neighboring regions. Five main factors influence LFPR in Riau Province. The non-labor force population and sex ratio have a negative effect, indicating that an increase in these two factors tends to reduce LFPR. In contrast, the poverty line, the number of productive-age people, and the population growth rate have a positive effect on LFPR.

This indicates that policies related to increasing LFPR must consider coordination between regions because an increase or decrease in LFPR in one region may have an impact on other adjacent regions. Therefore, the Riau Provincial government needs to encourage cooperation between districts/cities to develop an integrated strategy and each district/city needs to develop policies that are tailored to the local characteristics and spatial effects of neighboring areas. For example, Kuantan Singingi Regency could undertake regional initiatives with Kampar, Pelalawan, and Indragiri Hulu to improve LFPR together.

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