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Spatial Quantile Autoregressive Model: Case Study of Income Inequality in Indonesia

(Model Autoregresif Kuantil Reruang: Suatu Kajian Kes Ketaksamaan Pendapatan di Indonesia)

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ABSTRACT

Substantial economic development in Indonesia has dramatically increased inequality in the last decade. This issue will hinder the country's long-term economic development as well as creating socioeconomic instability and violence. This study analysed the effects of macroeconomic factors such as gross regional domestic product, investment, unemployment rate, and labour-force participation, on Indonesian provinces' inequality. Since the economic development in Indonesia is mostly concentrated on Java Island, a spatial based analysis was appropriate. In addition, we also considered a method that enabled a specific level of inequality modelling, since previous studies used a mean-based analysis. Therefore, we proposed a spatial quantile autoregressive (SQAR) technique. The results showed that the Gini index of Indonesian provinces had a significant positive spatial autocorrelation (SA). Regions with similar Gini index values tended to cluster together. In addition, local analysis of the SA showed Java Island as a region that was characterized by high inequality, while Sumatra and Kalimantan Island were not. By contrast, the SQAR model suggested that there were various effects of macroeconomic factors on inequality at different levels of quantile. As a consequence, distinct approaches to handling inequality should be taken for provinces with low, medium, and high Gini index values.

Keywords: Gini index; Moran's I; quantile regression; spatial connectivity

ABSTRAK

Pembangunan ekonomi yang besar di Indonesia telah meningkatkan ketidaksamaan secara mendadak dalam dekad yang lalu. Isu ini akan menghalang pembangunan ekonomi jangka panjang negara serta mewujudkan ketidakstabilan sosioekonomi dan keganasan. Kajian ini menganalisis kesan faktor makroekonomi seperti keluaran dalam negara serantau kasar, pelaburan, kadar pengangguran dan penyertaan tenaga buruh terhadap ketidaksamaan wilayah Indonesia. Memandangkan pembangunan ekonomi di Indonesia kebanyakannya tertumpu di Pulau Jawa, analisis berasaskan reruang adalah sesuai. Di samping itu, kami juga mempertimbangkan kaedah yang membolehkan pemodelan ketaksamaan tahap tertentu, memandangkan kajian terdahulu menggunakan analisis berasaskan min. Oleh itu, kami mencadangkan teknik autoregresif kuantil reruang (SQAR). Keputusan menunjukkan bahawa indeks Gini Wilayah Indonesia mempunyai autokorelasi reruang (SA) positif yang signifikan. Kawasan yang mempunyai nilai indeks Gini yang serupa cenderung berkumpul bersama. Di samping itu, analisis tempatan SA mendedahkan Pulau Jawa sebagai wilayah yang dicirikan oleh ketidaksamaan yang tinggi, manakala Pulau Sumatera dan Kalimantan tidak. Sebaliknya, model SQAR mencadangkan bahawa terdapat pelbagai kesan faktor makroekonomi terhadap ketidaksamaan pada tahap kuantil yang berbeza. Akibatnya, pendekatan berbeza untuk mengendalikan ketidaksamaan harus diambil untuk wilayah yang mempunyai nilai indeks Gini rendah, sederhana dan tinggi.

Kata kunci: Indeks Gini; Moran's I; perhubungan reruang; regresi kuantil

Introduction

Indonesia has achieved substantial economic growth in the last decade. Economic liberalization, export-oriented industrialization, and financial market development, as well as increases in agricultural production and employment, and pro-poor public expenditures and transfers, have all contributed to Indonesia's excellent economic success (Rodriguez & Chowdhury 2013). Indonesia has recovered rapidly from the Asian financial crisis, as seen by better gross domestic product (GDP) per capita growth after 2000. The country's strong economic situation has allowed it to address the high poverty rate that is typical of a developing country (Balisacan, Pernia & Asra 2003). Moreover, as the country has developed, another issue has emerged: Inequality has risen dramatically in the past few years. The poverty rate, which had been harmed by the crisis, gradually recovered over time. Higher growth, by contrast, appears to have had a negative impact on income distribution, as evidenced by the Gini index, which has risen dramatically over the last decade (Wicaksono, Amir & Nugroho 2017). The income difference between the poorest and richest quantiles extended in 2014, as reflected by the Gini index values, which reached 0.41. In comparison to other developing countries, the Gini index values increased by 10 percentage points in 10 years. This was the largest rise for a South Asian country (SAAPE 2019; Wicaksono, Amir & Nugroho 2017).

In many aspects, as uneven income distribution poses severe obstacles to a country's long-term economic development. It may result in the deployment of redistributive policies and interventions such as tax measures and social subsidies, which are essentially distortive and lead to inefficiencies and resource misallocation (Alesina & Rodrik 1994). Similarly, inequality breeds socioeconomic instability and violence, which eventually present serious barriers to smooth growth and social cohesion in many regions of developing Asia (Keefer & Knack 2002). Furthermore, a disproportionate concentration of a country's wealth and economic resources in a few limited economic groupings results in insufficient market size and aggregate demand, which worsen an economy's competitiveness (Constantine 2017). Finally, rising inequality needs significant investments in social capital, such as human capital and infrastructure, forcing an economy to sacrifice more competent investment alternatives, thus stifling economic progress (Bénabou 1996).

Numerous investigations have been conducted to evaluate the factors that are associated with income inequality. Technological advancements, market-oriented reforms, and globalization are the primary forces driving growth, particularly in developing countries in Asia (Zhuang, Kanbur & Rhee 2014). These factors exacerbate inequality by extending the distance between capital owners and laborers, skilled and unskilled employees, and urban and rural areas. In reality, policymakers and government officials cannot limit these three factors in order to minimize inequality; this is because they are the fundamental predictors of higher productivity. Furthermore, unequal access to essential services such as education, health, and finance is also important in understanding regional inequality (Bakar, Hamdan & Sani 2020; Dabla-Norris et al. 2015; Majid & Ibrahim 2021).

The complexity and dynamics of regional inequality have generally been analysed using spatial models rather than temporal ones (Wei 2015). Initially, regional inequality was described only by its spatial pattern with causation analysis omitted (Williamson 1965). The current distribution of income inequality in Indonesia should be analysed by considering the spatial or regional dependence. This is because of the disproportionate infrastructure and trade activities, which are mostly focused on Java Island compared to other regions (Akita, Kurniawan & Miyata 2011; Khoirunurrofik 2017). This disparity can be seen from the fact that 90 percent of industrial activity in Indonesia occurs in Java (Hijrawadi & Adrian 2019). Thus, provinces on Java Island experience high economic growth as well as inequality. Spatial dependence can be defined as the similarity between observations that are collected at nearby geographical locations (Anselin 1995). Spatial dependence could play an important role in shaping the geographical distribution of regional inequality, since it implies that similar values tend to cluster together in space (Dorodjatoen 2019).

Recently, various exploratory spatial data analysis (ESDA) methods, such as spatial autocorrelation (SA) (Cliff & Ord 1973), have provided useful tools for analysing spatial agglomeration and cluster, which can show regional inequality patterns. The quantitative measurement of SA has become increasingly important in ecological, soil, landscape, and social scientific studies since its first complete evaluation in 1973 (Anselin 1995; Cliff & Ord 1973). When there is a considerable similarity or dissimilarity between the values of a variable Z at all pairs of adjacent locations *i* and *j*, then SA exists (Upton & Fingleton 1985). To detect SA and assess spatial correlations among analysis units, Moran's Index (or

Moran's I) has been utilized (Anselin 1995; Upton & Fingleton 1985).

Spatial analysis regarding regional inequality has been carried out by modelling the mean of observed variables (Skoufias 2001). Further exploration can be made by analyse the regional inequality not only at the mean level but also at the quantiles level (quantile regression). Some research relating to this has been published in which quantile regression was employed to explore the relationship between foreign direct investment (FDI) and economic growth (Chunying 2011; Girma & Görg 2003). Several economists have examined wage structure and wealth distribution using quantile regression (Angrist, Chernozhukov & Fernández-Val 2006; Buchinsky 1994; Galiani & Titiunik 2005). Specifically, research has been conducted to explore the gap in wage and wealth distribution, including the effect of gender on wage (Gardeazabal & Ugidos 2005; Kaya 2017), and wage differences between public and private entities (Tansel, Keskin & Ozdemir 2020). Therefore, the integration of spatial econometrics and quantile regression has been developed. The application of this method has been used to model local residential values (Malikov, Sun & Hite 2019), energy efficiencies (Zhang et al. 2021), and healthy life years (Trzpiot & Orwat-Acedanska 2016). While quantile-based analysis has been commonly used in economics, its application in Indonesian case studies has been limited. Moreover, the specific utilization of spatial quantile regression to inequality modelling has not been seen. Motivated by these facts, the present study analysed the pattern of inequality in Indonesia as the function of some regional economic indicators that are generally used as predictors. The outcome of this research will provide advice to decision-makers on how to handle the inequality across provinces in Indonesia.

Materials and Methods

DATA AND EMPIRICAL ANALYSIS

The data set for empirical analysis was obtained from the Indonesian Central Bureau of Statistics report (published at https://www.bps.go.id) from 2016 to 2020. We included 34 provinces in Indonesia as the spatial unit. The Gini index was used as the response variable, while the rest were predictor variables. A summary of the variables used in this research is shown in Table 1.

The empirical analysis in this article was organized as follows. First, we identified the global and local autocorrelation of the Gini index. Second, we performed a heteroscedasticity test to support the used of quantile-based analysis. Third and lastly, inequality modelling was performed using spatial autoregressive (SAR) and spatial quantile autoregressive (SQAR) models.

TABLE 1. Description of research variables

No	Variable Name	Unit	Description
1.	GINI	-	Gini Index as the income inequality measure
2.	GRDP	Million Rp	Gross regional domestic product
3.	UNEMP	Percent	Unemployment
4.	INVEST	Percent	Realization of investment
5.	LABF	Percent	Labour force participation

SA TEST: GLOBAL MORAN'S I

The global SA of all data was described by the global Moran's I, which is defined as follows:

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

Here, n is the number of spatial units, x_i is the Gini index of the i-th region, w_{ij} is the element of the spatial weight matrix, which represents the adjacent relationship between the i-th and j-th region. This research used a k-nearest neighbour weighted matrix (Dudani 1976).

The global Moran's I can be used to represent geographical convergence or divergence as an indicator of spatial concentration: An increasing global Moran's I indicates that the rich continue to gain wealth while the poor become poorer, and the absolute difference between them is growing. A decreasing global Moran's I suggests that clusters are disintegrating and a more even distribution is taking place (Naim et al. 2013). The stronger the spatial correlation between regions, the closer the absolute value of Moran's I is to 1. A formal test can be performed by standardizing statistic Moran's I (Cliff & Ord 1973). Let

$$Z(I) = \frac{I - E(I)}{\sqrt{Var(I)}} \tag{2}$$

where

$$E(I) = \frac{-1}{n-1}$$

$$Var(I) = \frac{1}{w_0(n^2-1)}(n^2 w_1 - m w_2 + 3w_0^3) - E(I)^2$$

$$w_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}$$

$$w_1 = \sum_{i=1}^{n}\sum_{j=1}^{n} (w_{ij} + w_{ji})^2$$

$$w_2 = \sum_{i=1}^{n} (w_{i*} + w_{*i})^2$$

$$w_{i*} = \sum_{j=1}^{n} w_{ij}$$

$$w_{*i} = \sum_{j=1}^{n} w_{ji}$$

When the null hypothesis holds, $Z(I)$ follows a normal distribution.

Global SA analysis produced only one statistic that summed up the entire study area. To investigate the individual areas, we employed local indicators of spatial association (LISA) to assess clustering in those units by computing the Local Moran's I for the i-th area, as shown below (Anselin 1995):

$$I_i = \frac{n\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{3}$$

SQAR MODEL QUANTILE REGRESSION MODEL

Quantile regression is a regression analysis method that can describe the relationship of one or more predictor variables to one response variable at various quantile points (conditional quantiles) of the distribution of the response variables. Therefore, this method can be used in heterogeneous data conditions. The model is different from linear regression analysis, which can only describe a cause-and-effect relationship on the mean (conditional mean) of the response variables (Koenker & Hallock 2001). The general form of linear quantile regression is expressed as follows:

$$y_i = \boldsymbol{X}_i^t \boldsymbol{\beta}(\tau) + \boldsymbol{u}(\tau) \tag{4}$$

Here, y_i is the response variable; $\boldsymbol{X}_i$ is the explanatory matrix; $\boldsymbol{\beta}(\tau) = (\beta_0(\tau), \beta_1(\tau), \ldots, \beta_p(\tau))$ is the parameter vector, and $\boldsymbol{u}(\tau) = (u_1(\tau), u_2(\tau), ..u_n(\tau))$ is the error term.

Parameter estimation of the quantile regression model began by stating the cumulative probability function of random variable Y, as shown in equation **(5)**, so that the quantile of this variable could be written as equation **(6)**.

$$F(y) = P(Y \le y) \tag{5}$$

$$Q_Y(\tau) = inf\{y: F(y) \ge \tau\} \tag{6}$$

If there were n observations $\{y_i : i = 1, \ldots, n\}$ as a random sample from Y with distribution function F, then the τ-th quantile could be defined as the solution of the following minimization problem:

$$\min_{\boldsymbol{\beta}\in\mathbb{R}^p}\left[\sum_{i=1} \rho_\tau(y_i - max(\boldsymbol{x}_i^t\boldsymbol{\beta}(\tau), \boldsymbol{\tau}))\right] \tag{7}$$

Here $\rho_\tau(u) = (\tau - 1_{\{u<0\}})u$ was called the check function. Furthermore, a linear programming method, such as the simplex technique, along with numerical analysis were utilised to solve equation **(7)** (Fitzenberger 1997).

SAR MODEL

The SAR model took the following form (Anselin 1988):

$$\boldsymbol{Y} = \lambda \boldsymbol{WY} + \boldsymbol{X\beta} + \boldsymbol{u} \tag{8}$$

Here **Y** is the vector of response variables; **W** is the spatial weight matrix; λ is the autoregression parameter; **X** is the matrix of predictors; **β** is the vector of parameters; and **u** is the error terms vector.

Model (8) was a linear regression model with a spatial autoregression factor added. The correlation between the value of a variable in one localization and its value in the other localization was measured by SA (region, for example). The spatial lag term λWY represented spatial autoregression of the response variable. The error term vector had a multivariate normal distribution: $u \sim N(0, \sigma I)$

The parameters of model **(8)** had an inconsistent least squares estimator (Lee 2002). As a result, several consistent alternatives, notably maximum likelihood and instrumental variables, have been suggested (Anselin 1988), as well as a generalized method of moments or two-stage least squares (Liu & Saraiva 2015). For large-scale spatial models, Bayesian estimation has also been employed (Lesage 1997).

The SQAR model is combination of the two techniques discussed previously. It can be written as follows:

$$\begin{gathered} y_i = \lambda(\tau)d_i + \boldsymbol{X}_i^t\boldsymbol{\beta}(\tau) + \boldsymbol{u}(\tau) \\ \boldsymbol{Y} = \lambda(\tau)\boldsymbol{WY} + \boldsymbol{X\beta}(\tau) + \boldsymbol{u}(\tau) \end{gathered} \tag{9}$$

where **Y** is the vector of response variables; **W** is the spatial weight matrix; λ (τ) is the autoregression parameter of the -th quantile; **X** is the matrix of predictors; **β**(τ) is the vector of parameters of the τ-th quantile; and u(τ) is the error terms vector of the τ-th quantile. Here, $d_i = \sum_{j=1}^{n} w_{ij}y_j$.

In economic modelling, endogenous variables are essential because they are determined by their relationships with other variables in the model. They also demonstrate whether a variable is responsible for a certain impact. The spatial lagged factor d_i in the SAR **(8)** and SQAR **(9)** models could be regarded as an endogenous variable. Thus, we applied the instrumental variables technique to preserve the accuracy of the parameter estimate (Chernozhukov & Hansen 2006; Kim & Muller 2004) with the following steps:

Estimate the ordinary -th quantile regression model for $\boldsymbol{WY}$

$$\boldsymbol{WY} = \boldsymbol{X\beta}^*(\tau) + \boldsymbol{WX\gamma}^*(\tau) + \boldsymbol{u}^* \tag{10}$$

where $\boldsymbol{\beta}^*(\tau)$ is the vector of parameters of predictors for the τ-th quantile, and $\gamma^*(\tau)$ is the vector of parameters spatially dependence predictors for the τ-th quantile.

Calculate the predicted values from **(10)**

$$\widehat{\boldsymbol{WY}} = \boldsymbol{X}\widehat{\boldsymbol{\beta}}^*(\tau) + \boldsymbol{WX}\widehat{\boldsymbol{\gamma}}^*(\tau) \tag{11}$$

Use the predicted values as predictor variables in the original model, so that

$$\boldsymbol{Y} = \lambda(\tau)\widehat{\boldsymbol{WY}} + \boldsymbol{X\beta}(\tau) + \boldsymbol{u}(\tau) \tag{12}$$

Finally, estimate the parameter by solving the minimizing problem stated in (7).

RESULTS

Figure 1 demonstrates that the distribution of inequality in Indonesia in 2016 varied from 0.281 to 0.422. The highest Gini index value was found for Java Island, while the lowest were for Maluku and Kalimantan. Meanwhile, medium Gini index values were mostly found for Sulawesi and Sumatra Island. Further investigation on the SA of the Gini index is exhibited in Table 2.

Table 2 shows that the Moran's I values of the Gini index in Indonesia were positive. All of the Moran's I values were statistically significant at the provided significance level of 1%, implying that the null hypothesis that there was no SA in Indonesia's Gini index values was rejected. Moran's I values fluctuated from 2016 to 2020, with little change year to year, implying a favourable association. Overall, the Gini index Moran's I has a small increasing tendency, and the SA of the Gini Index was progressively growing, however the future direction remains uncertain.

The LISA clustering graphs (Figure 2) showed that the geographic agglomeration of the Gini index in Indonesia's provinces was relatively consistent. The Gini index values of locations with comparable characteristics tended to congregate (with high values adjacent to high values, and low values adjacent to low values). The map was divided into four quadrants, which were as follows: a space unit with a high Gini index was represented by the first quadrant (High-High) and its bordering provinces had high Gini index values as well; the second quadrant (Low–High) depicted the region with a low Gini index, and the values of its adjacent regions were high; the third quadrant (Low–Low) denoted a low Gini index value, as were those of its nearby provinces; and the fourth quadrant (High–Low) depicted a territory with a high Gini index value, but a low index value in its adjacent region.

Figure 2 demonstrates that the regions in the first quadrant (High-High) are mostly the provinces and cities on Java Island with the highest economic development, such as Jakarta, West Java, Central Java, Yogyakarta, and East Java. These provinces' economies are rapidly developing, and they have a favourable impact on one another's growth. Provinces in the third quadrant (Low–

Low) were mostly found in the Indonesian islands of Sumatra and Kalimantan, where income disparity was low or income distribution was relatively even. The provinces of Sulawesi, by contrast, were located in the second quadrant (Low–High). Meanwhile, there were no provinces in the fourth quadrant (High–Low).

Based on the findings, there was clear geographic autocorrelation and geographical clustering in Indonesia's Gini index values. Because the Gini index of each province was influenced by nearby regions, it was appropriate to characterize the data using an SAR model. In addition, a Breusch-Pagan (BP) test was also performed to check homoscedasticity as an important assumption of classical linear regression. The result of this test indicated the existence of heteroscedasticity (BP test statistics=15.927, p-value=0.0031). Thus, the SQAR model was used to investigate the impact of factors on Gini index values at quantiles of τ=0.10,0.20,0.30,0.40, 0.50,0.60,0.70,0.80,0.90.

Interpretation of SQAR results is quite similar to SAR. For example, at τ = 0.10, it indicated the model for low Gini index. In this model, the SAR coefficient was positive and significant. Meanwhile, the predictors were positive with Pr > 0.05. It implies that in quite equal provinces, macroeconomic factors such as GRDP, unemployment, labour force, and investment may increase the Gini index but the effects were not significant. Both Tables 3 and 4 show that the SAR coefficient (λ) ranged from 0.9295 to 1.6294 and was statistically positive for all quantiles at the 1% significance level. This demonstrated that a region's Gini index value had a positive effect on neighbouring provinces. At the same time, this was in alignment with Moran's I > 0 conclusion. By contrast, in the SAR model (Table 3), the spatial effect coefficient of 0.7566 was notably positive and much lower than that in the SQAR model at quantile 0.9. The spatial effect estimate in SAR was rougher less realistic. Data heteroscedasticity may explain why this occurred.

Considering the influence factors, we obtained the following results: 1) The GRDP influence on the Gini index varied, with a positive relationship observed at the lower and upper quantiles (τ = 0.10,0.20,0.70,0.80) as well as the SAR model, and a negative association identified at the mid (τ = 0.30,0.40,0.50) and upper extreme quantile (τ = 0.90). As a result, the SAR model's regression findings were not ideal. In general, this conclusion suggested that economic growth may exacerbate the inequality between provinces with low and high Gini indices. On the other hand, this factor will reduce inequality in provinces with a medium Gini index. 2) The estimates of the parameter of the variable UNEMP (unemployment rate) were positive for all quantiles (except for τ = 0.80) and the SAR model. This implied that a high unemployment rate clearly fostered inequality. As the Gini index fell, the positive influence of promotion became more pronounced. 3) The parameter estimates of the variable LABF (percentage of labour force participation) were shown to be positive in most of the quantiles and the SAR model, with the exception of τ = 0.70, 0.80. Meanwhile, the effect of INVEST (realization of investment) was diverse. A positive effect was found at quantile τ = 0.10, 0.20, 0.50, while the rest were negative. Hence, these results support the finding that an increased number of investments in a province will lead to lower inequality.

The factors economic growth, unemployment, and labour force participation had significant effects on the Gini index values in the SQAR model (τ = 0.20, 0.50, 0.60) at the 10% significance level. Meanwhile, economic growth and realization of investment had significant influences in the SAR model at the 5% significance level.

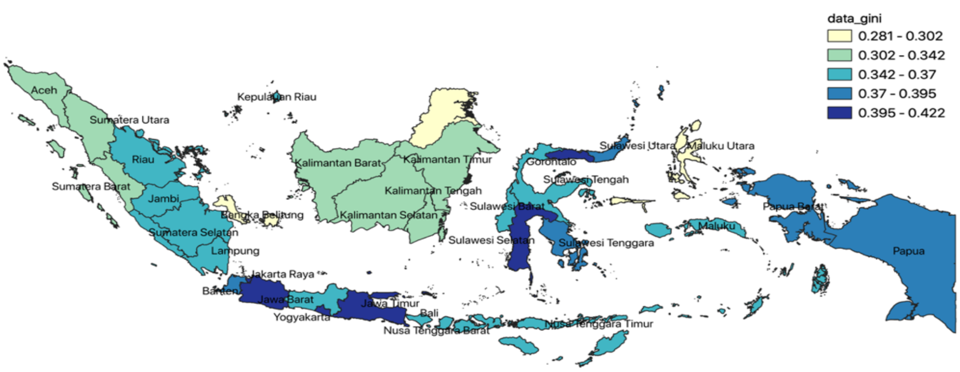

FIGURE 1. Gini Index of Indonesia, 2016

TABLE 2. Moran's I test of provincial Gini Index in Indonesia

Year	Moran's I	Prob.
2016	0.318	0.0020
2017	0.382	0.0010
2018	0.378	0.0020
2019	0.384	0.0010
2020	0.377	0.0020

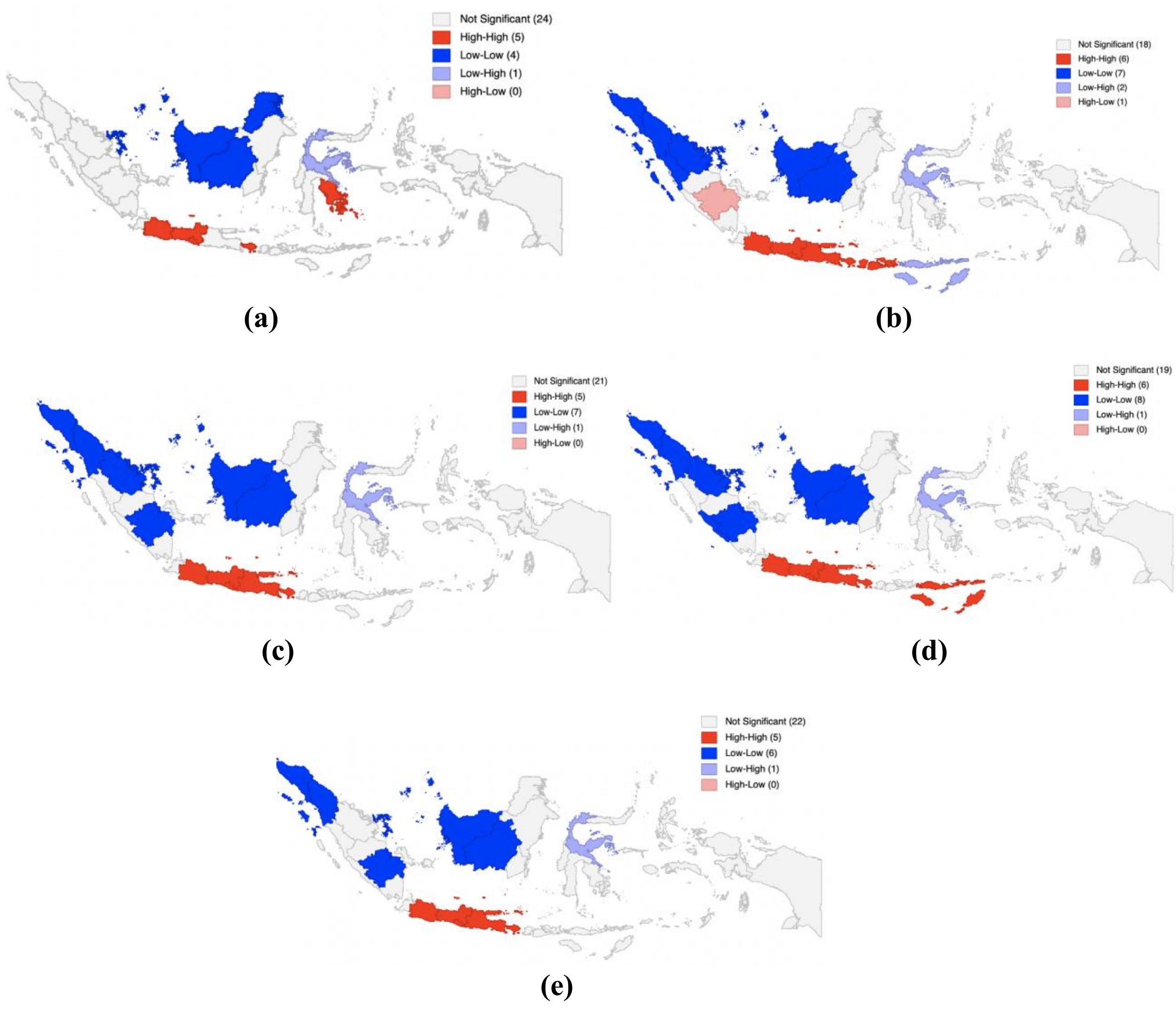

FIGURE 2. LISA of Indonesia's Gini index, (a) 2016; (b) 2017; (c) 2018; (d) 2019; (e) 2020

TABLE 3. Estimation results of the standard spatial autoregression (SAR) model

Parameter	Estimate	Std. Error	z-value	Pr(>|z|)
λ	0.7566	0.0346	21.8376	0.0000
Intercept	-1.0962	0.5889	-1.8613	0.0627
GRDP	0.0204	0.0068	3.0120	0.0026
UNEMP	0.0061	0.0178	0.3418	0.7325
LABF	0.1579	0.1369	1.1534	0.2488
INVEST	-0.0109	0.0044	-2.5002	0.0124

TABLE 4. Estimation results of SQAR model

Parameter	Estimate	Std. Error	z-value	Pr(>|z|)
		$\tau = 0.10$		
	1.3236	0.2434	5.4385	0.0000
Intercept	-1.1839	1.0972	-1.0790	0.2806
GRDP	0.0277	0.0180	1.5429	0.1229
UNEMP	0.0324	0.0438	0.7407	0.4589
LABF	0.2616	0.2906	0.9002	0.3680
INVEST	0.0005	0.0139	0.0387	0.9692
		$\tau = 0.20$		
	1.0352	0.2080	4.9772	0.0000
Intercept	-1.5327	1.2724	-1.2046	0.2284
GRDP	0.0253	0.0127	1.9849	0.0472
UNEMP	0.0203	0.0370	0.5483	0.5835
LABF	0.2857	0.3080	0.9276	0.3536
INVEST	0.0001	0.0099	0.0059	0.9953
		$\tau = 0.30$		
	1.0764	0.2063	5.2182	0.0000
Intercept	-0.5765	1.3664	-0.4219	0.6731
GRDP	0.0152	0.0154	0.9892	0.3226
UNEMP	0.0254	0.0463	0.5492	0.5828
LABF	0.1090	0.3203	0.3404	0.7336
INVEST	-0.0051	0.0106	-0.4846	0.6280

		$\tau = 0.40$		
	0.9622	0.2156	4.4635	0.0000
Intercept	-1.5042	1.3538	-1.1110	0.2666
GRDP	-0.0056	0.0179	-0.3135	0.7539
UNEMP	0.0596	0.0502	1.1883	0.2347
LABF	0.3465	0.3162	1.0959	0.2731
INVEST	-0.0060	0.0095	-0.6342	0.5260
		$\tau = 0.50$		
	1.2378	0.1898	6.5205	0.0000
Intercept	-2.2682	1.5494	-1.4639	0.1432
GRDP	-0.0067	0.0180	-0.3730	0.7091
UNEMP	0.0790	0.0455	1.7355	0.0827
LABF	0.5882	0.3608	1.6304	0.1030
INVEST	-0.0035	0.0086	-0.4131	0.6795
		$\tau = 0.60$		
	1.2428	0.1927	6.4497	0.0000
Intercept	-2.8778	1.5588	-1.8462	0.0649
GRDP	-0.0104	0.0180	-0.5766	0.5642
UNEMP	0.0882	0.0506	1.7441	0.0811
LABF	0.7370	0.3806	1.9366	0.0528
INVEST	-0.0008	0.0091	-0.0838	0.9332
		$\tau = 0.70$		
	0.9295	0.1989	4.6724	0.0000
Intercept	-0.7481	1.6608	-0.4505	0.6524
GRDP	0.0025	0.0146	0.1741	0.8618
UNEMP	0.0359	0.0430	0.8356	0.4034
LABF	0.1500	0.3793	0.3955	0.6925
INVEST	-0.0046	0.0092	-0.5058	0.6130
		$\tau = 0.80$		
	1.6294	0.4057	4.0159	0.0001
Intercept	1.2977	2.0334	0.6382	0.5233
GRDP	0.0072	0.0161	0.4443	0.6569
UNEMP	0.0036	0.0485	0.0740	0.9410
LABF	-0.1578	0.4118	-0.3832	0.7016
INVEST	-0.0156	0.0104	-1.5087	0.1314
		$\tau = 0.90$		
	0.9535	0.4771	1.9985	0.0457
Intercept	0.5200	2.2700	0.2291	0.8188
GRDP	0.0081	0.0159	0.5115	0.6090
UNEMP	-0.0250	0.0710	-0.3518	0.7250
LABF	-0.1152	0.4984	-0.2311	0.8172
INVEST	-0.0136	0.0149	-0.9132	0.3611

DISCUSSIONS

SA and clustering of inequality in terms of the Gini index in Indonesia's provinces clearly existed based on yearly data from 2016 to 2020. Regions located in Java Island evidently had high Gini index values and tended to cluster together with positive correlation. Java island has been the centre of trade and government since Indonesia's independence (Sulistiyono & Rochwulaningsih 2013). As a result, infrastructure development and industrial activities are intense in this region. Until 2020, the economic contribution in Java remained the largest, reaching 58.75% of Indonesia's economic growth (Santoso 2021). The high economic growth in Java has resulted in high economic inequality in this region, especially between urban and rural areas (Nugraha & Prayitno 2020).

In recent times, the government has begun to shift development to areas outside Java, such as Sumatra, Kalimantan, Sulawesi, and Papua, in the form of toll roads, power plants, airports, and ports (Sukwika 2018). This is a manifestation of economic equality in accordance with the National Medium-Term Development Plan (Nazara 2010). This condition was supported by the realization of investment outside of Java Island (50.5%) which overtook Java (49.5%) (BKPM 2021). This effort to equalize the economy cannot be completed in the short term; this is because infrastructure development outside Java is still in process, and so it has not yet been effective in creating new economic centres elsewhere. As a result, the economic contribution outside Java is still limited - namely Sumatra Island 21.36%, Kalimantan Island 7.94%, Sulawesi 6.66%, Maluku and Papua 2.35%, and Bali and Nusa Tenggara 2.94% (BKPM 2021).

In addition to focusing on regional analysis of the factors that influence economic inequality in Indonesia, we also proposed the use of a quantile-based analysis method. This method can provide a more comprehensive picture of the factors that influence inequality at various quantile levels, while the standard method describes them only at the mean level. The results of the analysis showed that macroeconomic factors such as economic growth, unemployment rate, and labour force participation had a significant effect on the Gini index values at the medium level. This means that efforts to reduce economic inequality by taking into account economic growth and employment will have a more effective impact on provinces that currently have moderate inequality. As for the provinces with high and low Gini index values, controlling these economic factors will not have a significant impact. Equitable efforts for such areas can be carried out by formulating policies targeting the household level (micro) such as improving basic public services, increasing skills and certification (Suryahadi et al. 2010), micro, small and medium enterprise (MSME) credit, and strengthening people-based industries (Adrian 2019).

Model in this research was developed by taking into account spatial dependency of Gini index in Indonesia's provinces into quantile regression equation. However, we did not incorporate the spatial connectivity which might occurred in error terms. This kind of model is probably more accurate to capture relationship between macroeconomics factors and Gini Index in regional level.

CONCLUSION

Inequality is one of the major problems faced by many developing countries, including Indonesia. This study demonstrated that inequality in Indonesia's provinces, which was represented by the Gini index, had a significant positive SA. Therefore, regions with similar Gini index values tended to cluster together. Local analysis of the SA showed that Java Island was a region that was characterized by high inequality, while Sumatra and Kalimantan Island were not. Furthermore, SQAR modelling of the macroeconomic effect on the Gini index showed that the coefficient regressions of each factor were not constant across quantiles, thereby making the SAR model approach inappropriate for this case. The quantile model suggested that economic growth, unemployment rate, and labour force participation had a significant effect on provinces with moderate inequality. Meanwhile, these factors did not significantly affect provinces with high and low inequality. Hence, other approaches should be taken to control the inequality rate.

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