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SPATIAL PANEL MODELING OF PROVINCIAL INFLATION IN INDONESIA TO MITIGATE ECONOMIC IMPACTS OF HEALTH CRISES

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Abstract: Probabilistic statistical modeling simplifies complex issues, including economic and health challenges, by applying inductive statistics. Spatial panel modeling, using Queen Contiguity weighting, has proven to be essential for analyzing inflation expenditure patterns during health crises, such as COVID-19 in Indonesia. This study highlights the impact of inflation on national economic stability and explores the inter-provincial relationships that influence inflation dynamics across expenditure groups. The purpose of this study is to develop a spatial panel model to address this gap, offering insights for policy and recovery strategies. The results reveal significant spatial interdependence in provincial inflation data, underscoring the role of spatial factors in economic analysis. Two models are identified: Spatial Autoregressive Model with Random Effects (SAR-RE) before the crisis and Spatial Error Model with Random Effects (SEM-RE) during the crisis. Transportation facilities consistently affect inflation, demonstrating the effectiveness of spatial panel modeling in guiding policies for economic stability and recovery.

1. INTRODUCTION

Spatial panel modeling is a statistical approach that integrates both panel and spatial data, analyzing multiple entities over time while considering their geographic locations. This technique addresses spatial dependencies and interactions between entities, evolving over time (Baltagi, 2005; Schabenberger & Gotway, 2005; Anselin et al., 2008; Elhorst, 2010; 2014). Regression analysis, a key component in statistics, models the relationship between a dependent variable and independent variables, commonly using Ordinary Least Squares (OLS) which assumes uniform coefficients across observations (Fotheringham et al., 2002). However, spatial data requires consideration of local characteristics, following Tobler's First Law of Geography, which emphasizes the stronger connections between nearby entities. Spatial regression analysis often employs spatial lag and spatial error models to effectively capture these spatial dependencies (Lesage, 1999; Hsiao, 2014; Elhorst, 2010; 2014; Maulan & Suryowat, 2019). Observing a phenomenon requires examining units across multiple time periods, not just at one moment. Spatial panel modeling effectively integrates cross-sectional and time-series data with spatial factors, offering valuable insights for fields like economics, geography, and social sciences where temporal and spatial interactions are key (Elhorst, 2010; 2014; Hsiao, 2014).

Various studies have implemented spatial panel data modeling across different fields, particularly in economics. Suprayogi (2023) used spatial panel data modeling to analyze Indonesia's economic growth, employing Gross Regional Domestic Product (GRDP) as an indicator. Rizal & Lestari (2023) assessed the health crisis's impact on provincial economies in Indonesia using a spatial panel model. Marsono (2022) examined how inflation, government spending, Gross Fixed Capital Formation (GFCF), and net exports affect economic growth using spatial panel data econometrics. Halim & Junaidi (2022) analyzed inflation determinants during the health crisis, while Budiarta & Surya (2021) used a spatial panel approach to study inflation. Setiawan & Iskandar (2020) examined the health crisis's regional economic effects. Maulan & Suryowat (2019) focused on spatial panel random effects for the Human Development Index (HDI) in Yogyakarta, and Syukron & Fahri (2019) explored labor force, foreign investment, and provincial GRDP relationships using panel regression. Additionally, Widodo et al. (2019) conducted panel regression analysis on poverty in Indonesia, while Tamara et al. (2016) created a fixed-effect spatial model for poverty in Central Java using Matlab GUI, essential for understanding regional economic growth drivers.

Spatial panel data modeling provides a comprehensive approach to analyzing variable relationships while accounting for spatial dependencies, using models like spatial lag and spatial error with fixed or random effects (Baltagi, 2005; Schabenberger & Gotway, 2005; Anselin et al., 2008; Elhorst, 2010; 2014; Hsiao, 2014). This study uses a spatial panel model with Queen Contiguity weighting to analyze provincial inflation expenditure in Indonesia during the COVID-19 pandemic, offering insights for economic and health disaster mitigation. This research addresses a gap by integrating spatial interdependencies into economic analysis, offering data-driven insights for policymakers to design targeted interventions and allocate resources effectively. The findings enhance understanding of inflation dynamics and promote sustainable economic resilience in Indonesia during and after the health crisis.

2. LITERATURE REVIEW

This section explores spatial panel modeling theories and methods, highlighting its role in analyzing provincial inflation in Indonesia. It underscores the value of spatial dependencies and panel data for understanding inflation dynamics.

2.1. Panel Spatial Regression

Panel data, or longitudinal data, combines cross-sectional and time-series information, aiding disciplines like economics, social sciences, and epidemiology. It enables analysis of individual dynamics, temporal changes, and cross-sectional patterns, helping researchers study the influence of time and individual-specific factors on outcomes (Lesage, 1999; Gujarati, 2004; Miranti & Mendez, 2021; Mendez & Kataoka, 2024). Spatial analysis involves techniques to study data with a geographic component, focusing on how location influences observed phenomena.

Research by Budiarta & Surya (2021) and Halim & Junaidi (2022) employed a spatial panel model to analyze inflation, but no study has fully integrated macroeconomic and health factors for mitigating health crisis impacts. Most existing studies, including Setiawan & Iskandar (2020), focus on the health crisis's effects in specific time frames without considering broader structural changes in provincial economies. While Rizal & Lestari (2023) highlight the significance of a spatial panel approach, their study remains limited to descriptive analysis and policy recommendations. Many studies focus on data analysis without clearly outlining practical policy implications, enabling researchers to explore how spatial relationships and geographic features affect the data. A regression model that incorporates panel data with spatial interactions between observation units is known as a panel data spatial regression model. This model is a distinctive approach designed to address the complexities of panel data, integrating both cross-sectional and time-series components. This model uniquely incorporates both spatial effects and individual- or time-specific effects in a panel dataset (Anselin et al., 2008; Putra et al., 2020; Sari & Rahmawati, 2022; Prasetyo & Firdaus, 2022). It distinguishes between pooled or common effects, fixed effects, and random effects in the Spatial Autoregressive Model (SAR) and Spatial Error Model (SEM). The model developed in this study aims to address gaps in previous research for a more comprehensive understanding. Equations (1) and (2) present a general panel data spatial regression model that accounts for various spatial and individual-specific effects (Baltagi, 2005).

$$\mathbf{y}_{it} = \boldsymbol{\lambda} \sum_{j=1}^{N} w_{ij}\mathbf{y}_{jt} + \mathbf{X}_{it}\boldsymbol{\beta} + \boldsymbol{u}_{it} \text{ with } \boldsymbol{u}_{it} = \boldsymbol{\mu} + \boldsymbol{\varepsilon}_{it} \tag{1}$$

$$\boldsymbol{\varepsilon}_{it} = \boldsymbol{\rho} \sum_{j=1}^{N} \boldsymbol{w}_{ij}\boldsymbol{\varepsilon}_{jt} + \mathbf{v}_{it}\ , t = 1,2,\dots,T; i = 1,2,\dots,N \tag{2}$$

where $\mathbf{y}_{it}$: the dependent variable (the one we want to predict) for the i-th individual at the t-th time period; λ: Autoregressive coefficient, shows how much influence the value of the dependent variable in the previous period (t-1) has on the value of the dependent variable in the current period (t); w_{ij}: weights that indicate the strength of the relationship between individual i and individual j. These weights are usually normalized so that their sum is equal to 1 for each individual i; $\mathbf{y}_{jt}$: the value of the dependent variable for the j-th individual at the t-th time period; $\mathbf{X}_{it}$: vector of independent (explanatory) variables for the i-th individual at the t-th time period; $\boldsymbol{\beta}$: vector of regression coefficients showing the influence of each independent variable on the dependent variable; $\boldsymbol{u}_{it}$: error or disturbance. Several models that can be formed from the general equation of panel data spatial regression are as follows (Millo & Piras, 2012).

2.2. Spatial Autoregressive Model (SAR Model)

The SAR panel data model is a spatial regression model designed for panel data, introducing spatial effects on the lag of the dependent variable ($\lambda \neq 0$) while not introducing spatial effects to the model error term ($\rho = 0$). In general, Panel Data SAR models encompass spatial-specific effects that can be handled as either fixed effects or random effects, as outlined in equation (3).

$$\mathbf{y}_{it} = \boldsymbol{\lambda} \sum_{j=1}^{N} w_{ij}\mathbf{y}_{jt} + \mathbf{X}_{it}\boldsymbol{\beta} + \boldsymbol{u}_{it}\ \text{, with } \boldsymbol{u}_{it} = \boldsymbol{\mu} + \mathbf{v}_{it} \tag{3}$$

The panel data SAR model can be categorized into distinct forms, encompassing the common effect SAR model, fixed effect SAR model, and random effect SAR model, as outlined below.

a. Pooled SAR Model (Common Effect)
   The common effect SAR model or pooled SAR model is a panel data SAR model without specific spatial effect ($\mu = 0$) as presented in equation (4).

$$\mathbf{y}_{it} = \boldsymbol{\lambda} \sum_{j=1}^{N} w_{ij}\mathbf{y}_{jt} + \mathbf{X}_{it}\boldsymbol{\beta} + \mathbf{v}_{it}\ , \tag{4}$$

   In the context of the pooled SAR model, it's important to note that $\mathbf{v}_{it}$ is synonymous with $\boldsymbol{u}_{it}$.

b. Fixed Effect SAR Model
   The fixed effect SAR model is a variant of the panel data SAR model, where spatial-specific effects are treated as fixed effects ($\mu = \boldsymbol{\mu}_i$), with $\boldsymbol{\mu}_i$ representing a vector of fixed effect parameters within the model, as depicted in equation (5).

$$\mathbf{y}_{it} = \boldsymbol{\lambda} \sum_{j=1}^{N} w_{ij} \mathbf{y}_{jt} + \mathbf{X}_{it}\boldsymbol{\beta} + \boldsymbol{\mu}_i + \mathbf{v}_{it} , \quad (5)$$

within the fixed effect SAR model, it's worth mentioning that $\mathbf{v}_{it}$ is identical to $\boldsymbol{\varepsilon}_{it}$.

c. Random Effect SAR Model

The panel data SAR model with spatial-specific effects considered as random effects, indicated by ($\mu = \boldsymbol{\phi}$), where $\boldsymbol{\phi}$ represents the random effect parameter in equation (6), is referred to as the random effect SAR model.

$$\mathbf{y}_{it} = \boldsymbol{\lambda} \sum_{j=1}^{N} w_{ij} \mathbf{y}_{jt} + \mathbf{X}_{it}\boldsymbol{\beta} + \boldsymbol{\phi} + \mathbf{v}_{it} , \quad (6)$$

where in the random effect SAR model $\mathbf{v}_{it}$ is equivalent to $\boldsymbol{\varepsilon}_{it}$.

2.3. Spatial Error Model (SEM Model)

This model is a spatial regression model utilized with panel data, characterized by the absence of spatial effects on the lag of the dependent variable ($\lambda = 0$), but spatial effects manifest within the model's error term ($\rho \neq 0$). The SEM panel data model, in its broader scope, incorporates spatial-specific effects that can be considered either as fixed effects or random effects, as depicted in equation (7).

$$\mathbf{y}_{it} = \mathbf{X}_{it}\boldsymbol{\beta} + \boldsymbol{\mu} + \boldsymbol{u}_{it} \text{ and } \boldsymbol{\varepsilon}_{it} = \boldsymbol{\rho} \sum_{j=1}^{N} \boldsymbol{w}_{ij} \boldsymbol{\varepsilon}_{jt} + \mathbf{v}_{it} \quad (7)$$

The SEM panel data model is amenable to different configurations, encompassing the pooled SEM model, fixed effect SEM model, and random effect SEM model, each of which can be elucidated as follows.

a. Pooled SEM Model (Common Effect)

The common effect SEM model or pooled SEM model is a panel data SEM model without specific spatial effect ($\mu = 0$) as presented in equation (8).

$$\mathbf{y}_{it} = \mathbf{X}_{it}\boldsymbol{\beta} + \boldsymbol{\varepsilon}_{it} \text{ and } \boldsymbol{\varepsilon}_{it} = \boldsymbol{\rho} \sum_{j=1}^{N} \boldsymbol{w}_{ij} \boldsymbol{\varepsilon}_{jt} + \mathbf{v}_{it} \quad (8)$$

b. Fixed Effect SEM Model

This model represents a panel data SEM model where spatial-specific effects are taken into consideration as fixed effects ($\mu = \boldsymbol{\mu}_i$), with $\boldsymbol{\mu}_i$ denoting a vector of fixed effect parameters within the model, as outlined in equation (9).

$$\mathbf{y}_{it} = \mathbf{X}_{it}\boldsymbol{\beta} + \boldsymbol{\mu}_i + \boldsymbol{\varepsilon}_{it} \text{ and } \boldsymbol{\varepsilon}_{it} = \boldsymbol{\rho} \sum_{j=1}^{N} \boldsymbol{w}_{ij} \boldsymbol{\varepsilon}_{jt} + \mathbf{v}_{it} \quad (9)$$

c. Random Effect SEM Model

This model is a type of panel data SEM model that considers spatial-specific effects as random effects ($\mu = \boldsymbol{\phi}$), with $\boldsymbol{\phi}$ representing the random effect parameter within the model, as elucidated in equation (10).

$$\mathbf{y}_{it} = \mathbf{X}_{it}\boldsymbol{\beta} + \boldsymbol{\phi} + \boldsymbol{\varepsilon}_{it} \text{ and } \boldsymbol{\varepsilon}_{it} = \boldsymbol{\rho} \sum_{j=1}^{N} \boldsymbol{w}_{ij} \boldsymbol{\varepsilon}_{jt} + \mathbf{v}_{it} \quad (10)$$

2.4. Queen Contiguity

The choice of weighting depends on the spatial weighting matrix relevant to the area being studied. This matrix (**W**) can be based on data related to the distances between neighboring units or the spatial separation of different regions. In this study, Queen Contiguity is employed. Queen Contiguity is characterized by $w_{ij} = 1$ for regions that share borders or have corner points that intersect with the corner points of the region of interest, while $w_{ij} = 0$ is assigned to regions that don't meet these criteria.

2.5. Morans'I

The Moran's I coefficient is employed for assessing the presence of spatial dependency or autocorrelation among observations or locations. As for value Moran's I index is obtained using equation (11) (Paradis, 2017).

$$I = \frac{N}{S_0} \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(X_i-\bar{X})(X_j-\bar{X})}{\sum_{i=1}^{N}(X_i-\bar{X})^2} \text{ where } S_0 = \sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij} \quad (11)$$

2.6. Spatial Dependency Test and Hausman Test

Before estimating parameters in the panel data spatial regression model, it is essential to investigate spatial dependencies or regional interdependencies within the data. This is done using the Lagrange Multiplier (LM) test to identify the presence of spatial dependency effects (Hsiao, 2014; Irawati et al., 2016). To determine spatial dependency effects on the lag of the dependent variable or model error and to identify random effects, a thorough assessment was performed using the LM Joint test. The test statistics used are presented in equations (12) and (13) (Elhorst, 2010; 2014).

a. Spatial Lag (SAR)

$$LM_{Lag} = \frac{\left(\boldsymbol{e}'(\boldsymbol{I_T}\otimes\boldsymbol{W})\boldsymbol{y}/\hat{\boldsymbol{\sigma}}_{\boldsymbol{e}}^{\boldsymbol{2}}\right)^{\boldsymbol{2}}}{\boldsymbol{J}} \quad (12)$$

b. Spatial Error (SEM)

$$LM_{Error} = \frac{\left(e'(I_T\otimes W)e/\hat{\sigma}_e^{2}\right)^2}{T\times T_W} \quad (13)$$

To assess the appropriateness of the model, the Spatial Hausman test was employed. The objective of this examination is to make a comparison between the fixed effects and random effects in both the SAR and SEM models.

2.7. Residual Assumption of Model

When examining the residual assumptions of the panel spatial model, several assumptions must be met, namely that the residuals are identical, independent, and normally distributed.

2.8. Inflation

In accordance with Bank Indonesia (BI) terminology, inflation is described as the persistent escalation of the general price level over an extended duration. To measure inflation, the Consumer Price Index (CPI) proves to be a valuable tool, as it monitors the shifts in the prices of consumer goods and services across time.

3. METHOD

This research uses Consumer Price Index data from five major Indonesian provinces—DKI Jakarta, DI Yogyakarta, Jawa Barat, Jawa Tengah, and Jawa Timur, covering January 2018 to December 2022. The study analyzes inflation percentage as the dependent variable (Y), with independent variables including Food, Drink, and Tobacco (X_1), Clothing (X_2), Housing (X_3), Household Equipment (X_4), Health (X_5), Transportation (X_6), Communication Information (X_7), Education (X_8), and Recreation (X_9). R Software is employed for statistical computations and syntax construction. Pre-COVID-19 data spans January 2018 to February 2020, while COVID-19 data runs from March 2020 to December 2022. The analytical process consists of several key stages: (1) Evaluating spatial autocorrelation using the Moran I index with Queen Contiguity weighting; (2) Assessing spatial dependencies through the Lagrange Multiplier (LM) test; (3) Selecting a spatial panel model using the Hausman test. The chosen model is constructed, parameters are estimated, hypotheses are tested, assumptions are checked, and results are interpreted for recommendations. Detailed steps include: (1) Data identification and collection; (2) Preprocessing, including cleaning, transformation, and spatial coding; (3) Descriptive analysis, including statistics and visualization; (4) Testing panel model assumptions for stationarity and multicollinearity; (5) Spatial panel modeling with appropriate models like Fixed or Random Effects, or Spatial Durbin Model; (6) Spatial analysis, including Moran's I and inflation distribution visualization; (7) Model evaluation; and (8) Conclusions and recommendations.

4. RESULTS AND DISCUSSION

This section analyzes spatial panel models, highlighting provincial inflation patterns in Indonesia and their implications for economic stability and disaster mitigation strategies during health crises.

Descriptive statistics for the research data are shown in Tables 1 and 2, indicating variations in averages and standard deviations across provinces. In DKI Jakarta, Food, Drink, and Tobacco have the highest average, while Information and Communication has the lowest. Transportation has the largest standard deviation, and inflation averages 0.25% with a 0.26 standard deviation. In DI Yogyakarta, Housing shows the highest average, and Recreation the lowest, with Housing having the largest standard deviation and inflation averaging 0.13% with a 0.19 standard deviation. Similar trends are observed in West Java, Central Java, and East Java, where Housing or Transportation dominate averages, and Information and Communication consistently shows the smallest standard deviation, with inflation ranging from 0.12% to 0.16%.

Table 1. Descriptive Statistics for Research Data Before Covid-19

Variable	DKI Jakarta		DI Yogyakarta		West Java		Central Java		East Java	
	Avg	SD	Avg	SD	Avg	SD	Avg	SD	Avg	SD
X_1	150.47	13.31	130.37	7.18	136.71	9.52	133.48	8.1	140.04	10.89
X_2	128.1	7.86	125.02	5.92	118.19	4.97	114.64	3.9	121.14	6.35
X_3	130.71	8.43	131.32	8.39	123.74	6.5	127.78	7.2	129	7.94
X_4	128.72	7.93	113.83	2.79	112.44	2.99	115.08	3.07	124.84	6.61
X_5	125.43	5.95	123.94	5.45	125.96	6.36	121.04	5.38	127.6	7.67
X_6	138.61	11.01	128.02	8.04	143.37	11.92	138.13	10.7	140.31	11.26
X_7	104.12	0.8	107.97	2.52	105.3	1.62	107.16	2.04	101.13	0.43
X_8	118.97	5.2	118.26	5.06	130.26	7.46	129.97	8.96	139.56	10.64
X_9	106.37	1.42	112.28	2.57	116.49	3.52	115.02	3.62	112.04	3.32
Y	0.25	0.26	0.13	0.19	0.16	0.21	0.12	0.18	0.14	0.195

Table 2. Descriptive Statistics for Research Data During Covid-19

Variable	DKI Jakarta		DI Yogyakarta		West Java		Central Java		East Java	
	Avg	SD	Avg	SD	Avg	SD	Avg	SD	Avg	SD
X_1	112.67	3.03	111.02	4.65	111.39	4.72	109.11	2.13	108.32	4.37
X_2	106.47	1.04	110.53	1.25	107.54	1.4	105.51	2.03	105.46	2.13
X_3	103.94	1.2	105.69	2.34	104.45	1.93	105.51	1.31	103.76	1.13
X_4	107.98	2.53	109.25	3.02	110.25	3.04	110.11	3.55	106.54	2.9
X_5	110.21	1.75	110.64	2.16	110.67	2.01	107.79	2.21	106.7	2.84
X_6	103.87	4.91	105.41	5.6	106.95	4.51	106.57	5.84	107.42	6.33
X_7	101.4	0.21	99.6	0.25	99.26	0.33	98.98	0.86	100.32	0.13
X_8	106.51	1.77	111.34	2.17	113.54	3.06	101.73	0.89	111.64	2.97
X_9	103	1.57	107.65	2.82	106.69	0.89	105.67	2.21	102.17	1.26
Y	0.27	0.27	0.12	0.22	0.11	0.21	0.12	0.11	0.11	0.21

Table 2 shows differences in inflation and expenditure patterns across provinces. In DKI Jakarta, Food, Drink, and Tobacco have the highest average, while Information and Communication is the lowest, with inflation averaging 0.27% and a standard deviation of 0.27. In DI Yogyakarta, Education has the highest average and Information and Communication the lowest, with inflation averaging 0.12% and a 0.22 standard deviation. West Java also reports Education as the highest average, with Information and Communication the lowest, and inflation averaging 0.11%. Central Java's highest average is Housing, with Transportation showing the most variability, and inflation averaging 0.12%. In East Java, Education has the highest average, while Recreation is the lowest, with inflation averaging 0.11%.

Spatial autocorrelation is analyzed using Moran's I index. A positive value indicates clustered regions with similar dependent variable values, while a negative value shows dispersion. Table 3 presents Moran's I values for before and during-COVID-19 periods.

Table 3. Moran's I Index

Status	Month	Moran's I-Value	P-Value
Before Covid-19	Jan-18	-0.643	0.521
	Feb-18	0.209	0.834
	…	…	…
	Feb-20	1.023	0.306
During Covid-19	Mar-20	1.981	0.048
	Apr-20	1.498	0.134
	…	…	…
	Dec-22	-1.528	0.127

As presented in Table 3, The computation of Moran's I index with Queen Contiguity weighting revealed both positive and negative values for the data before and during Covid-19, indicating varying spatial autocorrelation among five provinces. Significant spatial autocorrelation was only detected in March 2020, while other instances of autocorrelation likely resulted from the residual values of the spatial model, not the dependent variable itself.

Spatial dependency effects on the dependent variable lag or model error were assessed using the Lagrange Multiplier (LM) test, shown in Table 4.

Table 4. LM Test and P-Value

Model	Before Covid-19		During Covid-19	
	LM-Test	P	LM-Test	P
Robust LM *Lag*	3.996	0.046	0.047	0.829
Robust LM *Error*	0.953	0.329	5.839	0.016

As shown in Table 4, for the before Covid-19, the Robust LM Lag test showed significant results at $\alpha = 5\%$, indicating a spatial lag effect and supporting the use of the Spatial Autoregressive (SAR) model. In contrast, during Covid-19, the Robust LM Error test was significant at $\alpha = 5\%$, suggesting a spatial error effect and the suitability of the Spatial Error Model (SEM).

An extension of the Hausman test was conducted to identify the selected model, with results available in Table 5.

Table 5. Hausman's Test

Model	Hausman's-Value	P-Value
Before Covid-19 (SAR-RE)	0.572	0.999
During Covid-19 (SEM-RE)	14.078	0.120

The spatial Hausman test results in Table 5 indicate that the SAR-RE model is suitable for before Covid-19 data, while the SEM-RE model is optimal for during-Covid-19 data.

Utilizing the Spatial Autoregressive Random Effect Model, denoted as the SAR-RE model, on the before Covid-19 dataset leads to the formulation of the following statistical model.

$$\hat{y}_{it} = 0.494 \sum_{j=1}^{N} w_{ij} y_{jt} + 1.026 - 0.014x_{1it} + 0.021x_{2it} - 0.009x_{3it}$$
$$+0.004x_{4it} - 0.021x_{5it} + 0.020x_{6it} - 0.004x_{7it} - 0.003x_{8it} - 0.002x_{9it}$$

$\hat{y}_{it}$: estimator of the percentage of inflation of the i-th province in the t-th month before and during Covid-19

$w_{ij}y_{jt}$: average percentage of inflation in the t-th month before covid of the neighboring provinces of the i-th province

x_{1it} : food, beverage and tobacco ratio variable of province i-th in the t-th month before and during Covid-19

x_{2it} : clothing ratio variable of province i-th in the t-th month before and during Covid-19

x_{3it} : housing ratio variable of province i-th in the t-th month before and during Covid-19

x_{4it} : household equipment ratio variable of province i-th in the t-th month before and during Covid-19

x_{5it} : the health ratio variable of the i-th province in the t-th month before and during Covid-19

x_{6it} : the variable ratio of transportation of the province i-th in the t-th month before and during Covid-19

x_{7it} : information and communication ratio variable of province i-th in the t-th month before and during Covid-19

x_{8it} : the variable ratio of education of province i-th in the t-th month before and during Covid-19

x_{9it} : recreation ratio variable of province i-th in the t-th month before and during Covid-19

where $\sum_{j=1}^{N} W_{ij} y_{jt}$ in SAR-RE model is the average percentage of inflation in the t^{th} month before Covid in provinces neighboring the i^{th} province. The spatial lag coefficient of 0.494 indicates a positive association, where high or low inflation rates in one province tend to reflect similarly in adjacent provinces. In both SAR-RE and SEM-RE models, the signs of model parameters determine the relationship between predictor and response variables. A positive sign signifies that a one-unit increase in the predictor variable leads to a corresponding increase in the response variable, while a negative sign indicates the response variable decreases as the predictor increases. This relationship highlights how predictor variables influence inflation dynamics across regions, providing insights for targeted and effective policy interventions.

In the SAR-RE model that is formed, it shows that the predictor variables x_{1it}, x_{3it}, x_{5it}, x_{7it}, x_{8it}, and x_{9it} have a negative sign and the predictor variables x_{2it}, x_{4it}, and x_{6it} have a positive sign. For example, an increase in the housing ratio by 1 decreases inflation by 0.009, assuming other variables remain constant. Spatially, provinces closer to those with higher housing ratios experience reductions in inflation. Conversely, a 1 unit rise in the clothing ratio raises inflation by 0.021, with nearby provinces also experiencing similar increases. Other variables follow this concept, with their influence interpreted based on the direction, sign, and magnitude of the model parameters. This approach emphasizes the importance of spatial proximity and its effect on inflation trends across provinces in a dynamic economic framework.

The inflation expenditure group variables significantly influencing inflation movement in Indonesia before Covid-19 were, in order, as follows: (1) Transportation, (2) Clothing, (3) Food, Drink, and Tobacco, (4) Health, (5) Housing, (6) Education, (7) Household Equipment, (8) Information and Communication, and finally (9) Recreation.

The SEM-RE model, short for Spatial Error Random Effect Model is employed to model the data during the Covid-19 period, yielding the following results.

$$\hat{y}_{it} = -5.245 + 0.004x_{1it} - 0.009x_{2it} + 0.037x_{3it} + 0.004x_{4it} + 0.007x_{5it}$$
$$+0.019x_{6it} - 0.008x_{7it} + 0.005x_{8it} - 0.007x_{9it} + 0.312\sum_{j=1}^{N} w_{ij}\phi_{jt}$$

$w_{ij}\phi_{jt}$: average percentage of inflation in the t-th month during Covid-19 of the neighboring provinces of the i-th province

where $\sum_{j=1}^{N} w_{ij}\phi_{jt}$ in SEM-RE model is the average percentage of inflation in the t^{th} month during Covid in provinces neighboring the i^{th} province. The spatial error coefficient of 0.312 indicates a positive correlation, meaning high inflation in one province during Covid likely corresponds to higher inflation in neighboring provinces, and vice versa.

In the SEM-RE model that is formed, it shows that the predictor variables x_{2it}, x_{8it}, and x_{9it} have a negative sign and the predictor variables x_{1it}, x_{3it}, x_{4it}, x_{5it}, x_{6it}, and x_{7it} have a positive sign. For instance, a 1-unit increase in the ratio of food, beverages, and tobacco results in a 0.004 increase in inflation during COVID-19, suggesting that provinces near one with a high ratio will experience higher inflation. Conversely, a 1-unit increase in the clothing ratio leads to a 0.009 decrease in inflation, indicating that provinces near those with a high clothing ratio experience lower inflation. This interpretation applies similarly to other variables based on their signs and values. The inflation expenditure group variables significantly affecting inflation movements in Indonesia during the COVID-19 pandemic included: (1) Transportation, (2) Housing, (3) Education, (4) Clothing, (5) Recreation, (6) Food, Drinks, and Tobacco, (7) Health, (8) Information and Communication, and (9) Household Equipment. The analysis indicated that transportation facilities and infrastructure were the most influential variables in the inflation expenditure category, impacting inflation trends both before and during the pandemic. Other variables also significantly affected inflation but had varying management priorities.

The assessment of model residual assumptions confirms that all requirements are met for both the SAR-RE and SEM-RE models. Residuals are homogeneous, independent, and normally distributed. For the SAR-RE model, homogeneity was tested using the F test (p = 0.102), showing homogeneous residuals. Autocorrelation was assessed with the Durbin-Watson test (p = 0.1), confirming no residual autocorrelation. Normality was tested using the Kolmogorov-Smirnov test (p = 0.058), indicating normal residual distribution. Similarly, for the SEM-RE model, homogeneity was confirmed with the F test (p = 0.6365), residual independence with the Durbin-Watson test (p = 0.18), and normality with the Kolmogorov-Smirnov test (p = 0.1465). These results validate the robustness of the models, ensuring that their assumptions are satisfied, thus supporting reliable and unbiased statistical inference in analyzing spatial panel data.

Previous research, such as that by Budiarta & Surya (2021), has identified spatial dependence in inflation data among Indonesian provinces. This study builds on those findings by investigating spatial dependence both before and during health crises. Research by Setiawan & Iskandar (2020), Halim & Junaidi (2022), and Rizal & Lestari (2023) emphasizes the health crisis's impact on inflation, although not directly through statistical model performance. This study highlights the health crisis's effects by comparing the performance of spatial panel models for inflation data across different periods. Furthermore, Rizal & Lestari (2023) suggest the implementation of effective disaster mitigation policies and enhanced collaboration among provinces to improve inflation management and support economic recovery strategies. This study highlights the need for adaptive policies to tackle economic challenges during health crises. It recommends using accurate, timely data and advanced statistical tools like spatial panel modeling to analyze regional inflation dynamics. Coordination between Central and Regional Governments is crucial for data sharing, and a joint task force should address inflation and health crises. Prioritizing transportation and infrastructure investments is essential to mitigate inflation, and an economic emergency response framework is needed to support vulnerable populations while ensuring ongoing policy evaluation and adjustments.

4. CONCLUSION

This study examines spatial dependence and regional inflation variations in Indonesia using a spatial panel regression model with provincial data. It aims to inform economic disaster mitigation during health crises. Significant spatial relationships were identified among DKI Jakarta, DI Yogyakarta, West Java, Central Java, and East Java, requiring different models: SAR-RE before and SEM-RE during the Covid-19 pandemic. Transportation and infrastructure consistently influenced inflation, though other variables varied in priority. Findings stress the need for central and regional governments to monitor inflation closely and adapt policies based on crisis presence. Recommendations include timely data collection, advanced spatial modeling, and enhanced intergovernmental coordination for data sharing and inflation management. Establishing joint task forces, investing in infrastructure, and developing an economic emergency framework are crucial for mitigating inflation and protecting vulnerable populations.

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