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Does Economic Agglomeration in Rural Areas Enhance Local Economies in Indonesia?

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Citation: Setianingsih, E., & Khoirunurrofik. (2025). Does Economic Agglomeration in Rural Areas Enhance Local Economies in Indonesia? *Jurnal Bina Praja*, 17(1), 75–88. <https://doi.org/10.21787/jbp.17.2025.75-88>

Submitted: 27 February 2025

Accepted: 2 June 2025

Published: 30 April 2025

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Abstract: Integrated rural areas development is strategically bolstering the success of equitable development in Indonesia. According to Village Law, rural areas are defined as clusters of villages with geographical proximity, similar superior commodities, common purpose, and government support in overcoming various basic issues, including expanding economic scale. Complying with the policy, this study aims to analyze the economic growth of rural areas, which focus on 62 National Priority Rural Areas as stated in the 2020–2024 National Medium Term Development Plan. The spatial analysis method examines intra-regional impacts on the increase of Village Original Income (VOI) as a result of economic agglomeration utilizing panel data at the village level. According to the findings, there is a considerable spatial correlation or positive spillover impact among the nearby villages in rural areas, which may further enhance and strengthen local economies. Additionally, the PSM-DiD method is applied to investigate whether the National Priority Rural Areas Development Policy influences the growth of VOI. However, the result hasn't yielded any convincing evidence of the beneficial effects of policy implementation in a short period. Despite the interaction result being frequently positive, it is unclear whether this policy drives the increase of VOI in rural areas significantly. Progressive intervention is needed from the governments at every level, from planning and implementation to evaluation. Besides, collaboration between different stakeholders, including the private sector and off-takers, is necessary to expedite the growth of the local economies and boost regional productivity.

Keywords: Agglomeration; Rural; Village Original Income; Spatial Analysis; PSM-DiD.

1. Introduction

The achievement of equitable development in Indonesia is strategically influenced by the success of rural development. In order to create a cohesive rural area, rural development facilitates collaboration and synergy between villages rather than seeing them as separate areas for development. Cooperation among villages can generate economies of scale, which are seen as a significant economic engine that can impact an area's growth (Wang et al., 2023). This is in line with the mandate of Village Law Number 6 of 2014 as a form of government commitment to implementing village and rural development in Indonesia. Through this regulation, villages act as government administrators at the lowest administrative level that can manage the economies independently through collaboration between villages, rural area development, and Village-Owned Enterprises.

Inter-village collaboration has to perform in managing potential resources effectively with the support of local, regional, and central governments. The favorable collaboration will stimulate a positive spillover effect that creates economic agglomeration. The spillover effect may result in 1) economies of scale and improved product supply chains through resource pooling, 2) skilled and competent workers through labor pooling, and 3) increased product innovation through knowledge sharing and information exchange (Barkley & Henry, 1997; Glaeser et al., 1992; Padmore & Gibson, 1998). A beneficial spillover effect boosts a company's efficiency and reduces production and capital expenses (Ellison & Glaeser, 1999; Schmitz & Nadvi, 1999). Efficiency will lead to higher productivity (Ben Abdesslem & Chiappini, 2019; Fan & Scott, 2003), and this will contribute to regional economic growth (Cravo & Mendes Rsende, 2013; Day & Ellis, 2014; Lei Tian et al., 2010).

According to Malmberg and Maskell (1997), the idea of agglomeration in economic geography denotes the geographic concentration of a society and its economic activities. There are benefits from concentrating industry in a geographic space with homogeneous commodities, known as industrial localization (Marshall, 1920). In horizontal grouping, businesses will benefit from localization, where groups of people with similar specialties and commodities will gain from spatial effects or neighborhood variables (Deichmann et al., 2008; Wardhana et al., 2017). Spatial effects are described as spatial interactions that exist as endogenous variables throughout several interdependent (Anselin & Bera, 1998). Referring to the numerous studies above, rural area development policies can be a catalyst for economic agglomeration in creating positive spillover in local economic growth.

Referring to the Village Law, rural areas are groups of villages that have similar superior commodities, collaborate willingly, and are supported by the central and regional governments to address various economic issues. Rural areas are developed and legalized during the process based on the geographical proximity and similarity of commodities in order to increase economic size. National and local governments put considerable emphasis on rural areas as a hub of village development through infrastructure and facility provision, training, and financial support. Since the implementation of the Village Law in 2014 until 2024, 271 rural areas have been established. However, only 62 rural areas, known as National Priority Rural Areas, constitute the scope of the National Medium-Term Development Plan for 2020–2024. This policy is an effort to accelerate and improve the quality of services, village development, and empowerment of communities through a participatory approach.

Considering a study on agro-industrial agglomeration on increasing farmer income in China (Ding, 2023), agglomeration develops new ideas, embraces technology, and spreads it throughout the area to improve product diversity and increase income.

Aligning with the idea of Rural Areas Developing Policy, agglomeration will increase the brand of superior commodities according to rural characteristics. The utilization of village resources, facilities, and infrastructure is more efficient because they can be utilized together. Then, the supply chain can be improved so that communities can comprehend the mechanisms and delivery of suitable logistics based on local conditions, which can lower shipping costs and offer the best quality to customers. This awareness will lead the region to expand the scale of production, reduce production costs and transaction costs, as well as increase efficiency. Due to these various advantages, product prices are more competitive in the market, which leads to increased sales and income.

Recent studies on economic agglomeration in China's rural areas have led to agro-industrial agglomeration, which is examined using a spatial regression model and considerably raises farmers' income within an area, as well as in neighboring areas. In Indonesia, economic agglomeration in rural areas was examined using a spatial regression model, and the results showed a significant decrease in poverty at the district level (Wardhana et al., 2017). Meanwhile, recent studies on Indonesia's rural area agglomeration at the village level are limited to the qualitative assessment phase undertaken at a single location (Cahyo Diarto et al., 2017). There are no empirical findings that reveal whether the local economy is impacted by the agglomeration effect in rural areas. Therefore, the objective of this study is to employ a spatial regression approach to evaluate the spillover impact on local economies due to agglomeration in rural areas.

Villages are given autonomy to organize and carry out community activities and local economies independently. By doing this, local governments are granted the authority to collaborate with village communities on financial management and planning. Village Law states that village finances include any money and assets associated with the implementation of village rights and responsibilities, as well as any rights and obligations that can be valued or estimated in monetary terms. The legal foundation for village financial management refers to the Minister of Home Affairs Regulation Number 20 of 2018 concerning Village Financial Management. The basis for village financial management is the Village Revenue and Expenditure Budget, consisting of village income, village expenditure, and village financing, which takes place in one budget year from January 1 to December 31.

Village income consists of Village Original Income (VOI), transfers from state and regional budgets, as well as other legitimate income. In accordance with village rights and authorities, VOI is derived from business profit, asset utilization results, participation or cooperation, and other legitimate income. VOI describes a village's ability to manage potential resources independently. VOI can be seen as an indicator of village economic growth (Firmansyah et al., 2022) and can be determined as an indicator of rural development (Hilmawan et al., 2023). VOI comes from village businesses, and revenues come from village assets and levies. Even though not a perfect variable, VOI is considered to be able to demonstrate the village's ability to generate added value, encourage village independence, and enhance local economies. Considering the previously mentioned factors, this study utilized VOI as a proxy for the local economy at the village level.

However, under unfavorable circumstances, there is no obvious economic growth occurring in National Priorities Rural Areas. This might indicate that rural development policy has not been executed effectively. Additionally, distinct time periods yield different outcomes when estimating economic agglomeration. For instance, a study conducted in China indicated that agglomeration had significant effects on wage

dispersion both in the short and long term (Xu et al., 2023). Therefore, employing the Difference in Difference (DiD) approach, this study is interested in evaluating the implementation of the Rural Area Development Policy.

DiD approach has been widely used in evaluating village-scale policies (Hilmawan et al., 2023), district-scale policies (Deng et al., 2022) or economic agglomerations on an industrial or company scale (Ben Abdesslem & Chiappini, 2019; Zeng & Yu, 2022). This method has the ability to estimate the actual impact of policies and can effectively control the mutual impact between the dependent variable and the independent variable accurately (Xu et al., 2023). Since each village has unique characteristics, the Propensity Score Matching (PSM) method is utilized to mitigate bias in the DiD approach (Abadie, 2005). PSM method can remove endogenous issues by self-selection and determine the net impact of policies with the support of relevant indicators (Xu et al., 2023).

In summary, this study is the first empirical study to investigate the spillover effect (intra-regional impact) in 62 National Priority Rural Areas on VOI using the Spatial Panel Model. It is expected that collaboration among villages will result in economies of scale, cost reduction, and revenue improvement due to the agglomeration effect. Therefore, VOI will be increased in the area uniformly. Second, PSM-DiD will be utilized to examine whether the increase in VOI is higher in villages inside the National Priority Rural Area compared to villages outside the area to the effectiveness of rural area development policy.

2. Methods

This study focuses on 642 villages as a part of 62 National Priority of Rural Areas. Hence, the purposive population is applied rather than random selection. The village financial dataset is gathered from the Village Revenue and Expenditure Budget Dataset and the Village Development Index by the Ministry of Villages, Development of Disadvantaged Regions, and Transmigration from the period 2018 to 2023. Village Potential from Statistics Indonesia (BPS) also completes the data analysis. Additionally, other variables that influence village income refer to a study of China's Regional Consolidation Policy (Deng et al., 2022), which compared the income per capita of the region before and after the policy implementation. These variables consist of fiscal condition and the caliber of community services. Total transfers from the government, as well as total village expenditures for each year, are depicted as fiscal indicators for each village. Meanwhile, village community services can be observed from health infrastructures, electrification, communication infrastructures, and economic institutions, including completed administration by village administrators. All variables are adjusted to the data availability at the village level and converted into natural logarithms.

2.1. Spatial Regression Analysis

Spatial regression is a technique that allows one variable to be evaluated with another by providing spatial impacts on many sites that serve as the center of observation. Spatial regression analysis consists of spatial dependence and spatial heterogeneity (Anselin, 1988). Meanwhile, spatial heterogeneity occurs because of the non-uniformity of the effects of each region or the characteristics of each region. Spatial impacts, including spatial dependency and spatial heterogeneity, will be demonstrated by spatial econometrics. The analysis is carried out by first constructing a spatial weighted matrix to identify among regions. This matrix quantifies spatial relationships between areas using weights that are commonly identified from two ideas: the contiguity matrix and the inverse distance matrix. In an inverse distance matrix, neighbor identification

is determined based on the distance within a certain radius. This matrix must be row standardized by modifying each element so that the number of each row in the spatial weighting matrix equals one in order to remove reliance on the data scale (Lesage & Pace, 2014; Neumayer & Plümper, 2016; Rüttenauer, 2024).

Second, determine spatial dependence using Moran's Index (Cliff & Ord, 1972; Moran, 1950). This index is used to measure regional dependence in general and to represent the average condition of the entire region. A positive, negative, and null value denotes areas with similar traits, distinct characteristics, and no relationship, respectively. Third, select the appropriate model by adopting the General Nesting Spatial Model (Anselin, 1988; Elhorst, 2014) as follows:

$$Y = \alpha_n + \rho WY + X\beta + WX\theta + u, \text{ where } u = \lambda WZ + \varepsilon \quad (1)$$

Where Y is the output variable (VOI), α_n is the constant, W is the spatial weighting matrix, ρ is spatial lag auto-regression coefficient for the output variable, X is the predictor variable (fiscal condition and the caliber of community services for each village), β is vector of regression parameter coefficients for the predictor variable, θ is spatial lag auto-regression coefficient for predictor variable, u is residual with pairwise correlation, λ is spatial residual regression coefficient, and ε is residuals without autocorrelation. In simple terms, model selection will be done when interacting the weight matrix with the output variable (WY), predictor variable (WX), error variable (WZ) or a combination of these three variables.

This study uses panel data to investigate intra-regional impact relationships on VOI among villages in a single rural area. As a part of data processing, this study adopts xsmle syntax for the Spatial Panel Model by Belotti et al. (2017). This syntax is designed to handle balanced panel data where n is difficult to observe precisely in period T. Models that can be adopted in this study are the Spatial Autoregressive (SAR) Model, Spatial Durbin Model (SDM), and Spatial Error Model (SEM). Spatial Autoregressive Model is a model that combines a simple regression model with a spatial lag on a dependent variable. Spatial autoregressive is formed when θ and λ equal 0 (zero). Therefore, the autoregressive process only occurs in the response variable. This model assumes that the dependent variable influences the dependent variable in one region in another region. The basic equation for the SAR Panel Model is:

$$Y_t = \rho WY_t + X_t\beta + u + \varepsilon_t, \text{ where } t = 1, \dots, T \quad (2)$$

The spatial Durbin Model is a special case of the Spatial Autoregressive model, which is an autoregressive model that incorporates spatial lag into its analysis of both independent and dependent variables. This model is created when λ is equal to 0. The basic equation is:

$$Y_t = \rho WY_t + X_t\beta + WZ_t\theta + u + \varepsilon_t \quad (3)$$

SEM is a model where there is a spatial correlation in the error. This model assumes that the autoregressive process only occurs in the model error. The basic of SEM equation is:

$$Y_t = X_t\beta + u + v_t, \text{ where } v_t = \lambda Mv_t + \varepsilon_t \quad (4)$$

Akaike's Information Criterion (AIC) model is employed, which can assess the model's suitability from estimates using maximum likelihood estimates from the same data. The model selection process is based on the minimum predicted error and

creates new observation data (error) that is evenly dispersed from the data utilized. The basic equation for AIC calculation is:

$$AIC = 2k - 2\log(\hat{L}) \quad (5)$$

Where, $\hat{L}$ is the maximum likelihood function for the model, and k is the number of estimated model parameters.

2.2. Propensity Score Matching – Difference in Difference (PSM-DID)

The Difference in Difference (DiD) approach is employed to observe the economic growth of villages inside the National Priority Rural Area (treatment group) compared with villages outside the area (control group) with the same characteristics before and after policy implementation. In order to control policy similarity, control groups are confined to the same regency. Then, to ensure pure influence among groups, villages in control groups are not adjacent to the ones in the treatment group. The basic equation for DiD regression model is:

$$Y_{i,t} = \alpha * Treat_{i,t} + \gamma\beta X_{i,t} + \vartheta_i + \epsilon_{i,t} \quad (6)$$

Where $Y_{i,t}$ describes the output (VOI) of village i in the year t . $VariableTreat_{i,t}$ describes the *policy dummy* in year t where, the value is 1 for the treatment group and 0 for the control group. The α value is the coefficient of $Treat_{i,t}$ variable. Variable $X_{i,t}$ is a composite/control variable at village level, and $\gamma\beta$ value is the coefficient of $X_{i,t}$ variable. The ϑ_i value is the village/individual fixed effect and $\epsilon_{i,t}$ is the error term grouped at the village level.

Control variables describe fiscal conditions as well as proxies for the quality of community services (Deng et al., 2022), which are adjusted to the availability of data at the village level. Fiscal conditions at the village level can be in the form of funds received by the village (transfer) as well as spending incurred by the village (expenditure). Meanwhile, the quality of services at the village level can be seen from the number of health facilities (health), users of electricity facilities (electrification), use of BTS facilities (communication), and village administration services projected with a Village-issued Certificate of Incompetence (VIC). Apart from that, this study also considers economic facilities in the village that can contribute to increasing VOI, such as cooperatives and the number of markets.

Furthermore, the Propensity Score Matching (PSM) approach is utilized to ensure comparable traits between two groups. PSM method can reduce bias in the DiD method (Abadie, 2005). Propensity scores will be estimated between two groups using the initial characteristics of each village using 1 year of data (2018) before the implementation of the National Priority Rural Area policy. The fit indicators refer to the Village Law and are projected with the data availability at the village level by considering the characteristics of 1) geographical similarity with the same superior products, 2) intervention/proximity with local government, 3) the existence of a jointly managed village economy or Village-Owned Enterprise, and 4) participatory society.

3. Results and Discussion

3.1. Analysis of Intra Regional Impact Using Spatial Regression Model

Descriptive analysis of the data was carried out using spatial analysis regression in 642 villages in the period 2018 to 2023 except 2021 due to the lack of readily available data. The aforementioned findings, shown in Table 1, demonstrate that not

every village inside the National Priorities of Rural Areas has VOI annually. Besides, T-test findings indicate that only health facilities and the number of markets have findings indicate that only health facilities and the number of markets have significant differences.

Table 1. Descriptive Analysis of Villages Inside National Priorities of Rural Areas

Variables	Obs.	Max.	Min.	Mean	Std. Dev.	Mean T-test
VOI (IDR)	1.599	976	0	43	93	0,01
Transfer (IDR)	3.210	8.870	227	1.470	575	0,107
Expenditure (IDR)	3.210	9.060	77	1.410	617	-0,38
Health (Unit)	3.105	37	1	3	1,81	2,36**
Electricity (HH)	3.075	10.645	1	668	805,94	0,02
Communication (Unit)	3.190	7	1	2	1,52	0,29
VIC (Unit)	2.867	1706	1	64	101,96	0,21
Village Cooperatives (Unit)	3.210	17	0	1	1,26	0,83
Village market (Unit)	3.210	6	0	0	0,70	-7,34***

*** p<0.01, ** p<0.05, * p<0.1

A spatial weighting matrix was prepared as an initial stage for conducting the analysis. This matrix employed an inverse distance matrix with longitude and latitude data obtained from Villages Potential Data. This matrix is utilized in order to determine the cross-section dependence of VOI using the Moran Index for each year. The results are shown in Table 2, where the Moran Index value for each year fluctuates between 0 and 1. It can be claimed that a general regional linkage is proven and represents the average condition of all villages.

Table 2. Moran Index Analysis per Year

Variables	(1) 2018	(2) 2019	(3) 2020	(4) 2022	(5) 2023
Moran's I	0,261***	0,276***	0,287***	0,281***	0,265***

*** p<0.01, ** p<0.05, * p<0.1

The spatial regression model is selected that shows differences in the spatial dependence of the data. The results are shown in Table 3. The parameters ρ (rho) and λ (lambda) illustrate the importance of spatial linkages in raising VOI in rural areas. By using the SAR Model and SDM, the spatial relationship is described by the parameter ρ (rho), which is significant at the 5% level. Meanwhile, spatial relationships using SEM are described by the parameter λ (lambda) and are significant at the 5% level. Furthermore, the best model was selected by looking at the smallest AIC value between the three models. Based on the findings, the SAR Model has the lowest AIC value and is considered the best model. This model explains that the increase in VOI in National Priorities Rural Areas is interdependent on each other. However, the growth in VOI is not influenced by any other variables that are spatially indicated at the village level.

Table 3. Spatial Regression Result

Variables	(1) SAR	(2) SEM	(3) SDM
Original Variables			
Transfer (log)	1,008 (0,840)	0,969 (0,839)	1,040 (0,845)

Expenditure (log)	1,048 (0,744)	1,064 (0,745)	1,083 (0,747)
Health (log)	-0,486 (0,444)	-0,474 (0,444)	-0,444 (0,444)
Electricity (log)	0,203 (0,190)	0,204 (0,190)	0,194 (0,190)
Communication (log)	0,0435 (0,450)	0,0288 (0,451)	0,0494 (0,450)
VIC (log)	0,0828 (0,0869)	0,0829 (0,0868)	0,0835 (0,0871)
Village Cooperatives (log)	0,646*** (0,233)	0,639*** (0,233)	0,637*** (0,234)
Village market (log)	0,818*** (0,277)	0,820*** (0,277)	0,802*** (0,277)
Spatial Lagged Variables			
Transfer (log)			-1,729 (2,313)
Expenditure (log)			1,086 (2,447)
Health (log)			1,868 (1,388)
Electricity (log)			-0,120 (0,660)
Communication (log)			-1,841 (1,498)
VIC (log)			-0,121 (0,284)
Village Cooperatives (log)			-0,728 (0,724)
Village market (log)			0,458 (0,816)
Others			
ρ / rho (SAR dan SDM)	-0,0882** (0,0414)		-0,0949** (0,0419)
λ / lamda (SEM)		-0,0847** (0,0417)	
Variance			
sigma2_e	20,087*** (0,502)	20,091*** (0,502)	20,018*** (0,500)
Observations	3.210	3.210	3.210
R-squared	0,093	0,095	0,032
Likelihood	-9.371,117	-9.371,320	-9.365,749
Akaike information criterion	18.762,234	18.762,641	18767,499

Note: Spatial Autoregressive (SAR) Model, Spatial Durbin Model (SDM) and Spatial Error Model (SEM) Standard errors in parentheses
 * p<0.10, ** p<0.05, *** p<0.01

3.2. Analysis of Rural Areas Development Policy Using PSM-DID Approach

In order to evaluate the Rural Areas Development Policy, treatment and control groups are focused on villages that have generated VOI. To prevent any potential spillover

effects, the control group is located outside the same sub-district as the treatment group. After taking these factors into account, it was discovered that 436 villages were included in the treatment group, and 5.181 villages were included in the control group. Descriptive analysis for both groups can be seen in Table 4 as follows:

Table 4. Descriptive Analysis of Treatment Group and Control Group

Variable	Treatment Group			Control Group			Mean
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	T-test
VOI (IDR)	1.546	43	94	19.976	50	99	2,575**
Transfer (IDR)	2.180	1.520	534	25.905	1.590	565	5,066***
Expenditure (IDR)	2.180	1.460	604	25.905	1.490	646	2,055**
Health (Unit)	2.135	3	2	25.795	3	2	1,083
Electricity (Household)	2.180	795	878	25.570	864	917	3,321***
Communication (Unit)	2.180	3	2	25.825	3	2	1,908*
VIC (Unit)	2.040	72	113	24.934	77	121	1,724*
Village Cooperatives (Unit)	2.180	1	1	25.905	1	1	-0,659
Village market (Unit)	2.180	0	1	25.905	0	1	1,863*

*** p<0.01, ** p<0.05, * p<0.1

Refer to Table 4, the treatment group and control group differ significantly, as indicated by the mean T-Test value. PSM analysis was carried out to compare the two groups before the policy implementation. This approach is thought to be able to balance the traits of two groups by minimizing bias, testing the net impact of policies, and eliminating endogenous issues that result from self-selection by matching pertinent indicators (Xu et al., 2023). Determination of suitability indicators refers to Village Law, which is projected based on the data availability at the village level. First, geographical similarities are described by topography, coastline, forest line, and sea level. Second is the proximity of the regional government described by the distance to the sub-district and the number of transfers to the village. Third is the existence of a jointly managed village economy, which is illustrated by the number of businesses that are managed by Village Owned Enterprises (VOE). Fourth is a participatory society, described by the number of technical assistants in villages.

The Nearest Neighbor PSM method is employed to determine the control group, which was analyzed in 2018 before the implementation of the National Medium-Term Development Plan for 2020–2024 policy. From the results, we found that 1.699 villages in the control group have similar characteristics to 436 villages in the treatment group. The differences between the two groups can be seen in Table 5. Based on the findings, the matching ratio for the two groups is 0,83 or between 0,5 and 2, then Rubin's B value is 10,1% or less than 25%. It may be claimed that the traits of the two groups are comparable and have similar characteristics.

The following stage is to assess the significance of the interaction value using basic DiD and PSM-DiD regression models. The dependent variable was then subjected to a regression analysis in order to determine the significance of the interaction value (DiD) using the OLS model and Fixed Effect robust clustered standard error at the region level. The outputs are in Table 6, where basic DiD regression results are represented by models (1), (2), (3), and (4), and PSM-DiD regression results are represented by models (5), (6), (7), and (8). The impact can be seen from the DiD interaction variable, with no significance in increasing VOI for basic DiD and PSM-DiD after the implementation of the policy. The constant of the interaction variable is consistently positive, which indicates an increase in VOI. Nevertheless, it remains uncertain whether this growth is

a direct consequence of the rural development policy, which is a priority of the National Medium-Term Development Plan for 2020–2024.

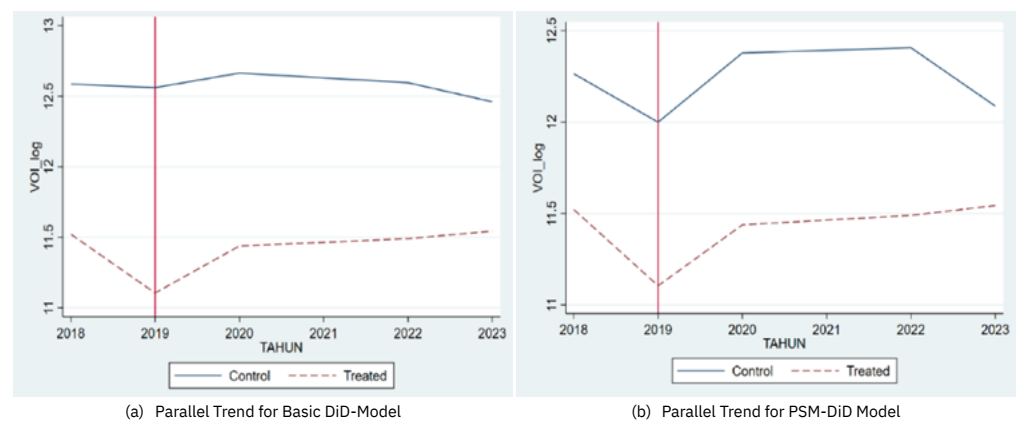
Table 5. Balancing Test

Variable				Mean		%bias	t-test		V(T) / V(C)
				Treated	Control		Obs	Mean	
Topography				0,58	0,60	-5,6	-0,84	0,40	,
Coastal_line				0,27	0,27	0,0	-0,00	1,00	,
Forest_line				0,32	0,32	0,8	0,12	0,91	,
Sea_level				3,56	3,55	0,4	0,06	0,95	1,11
Subdistric_distance				2,02	2,00	-3,5	-0,51	0,61	0,91
Transfer				21,09	21,08	2,4	0,35	0,72	1,31*
VOE_business				0,69	0,70	-3,7	-0,55	0,58	1,05
Technical_assistance				1,39	1,37	5,5	0,82	0,41	0,69*
* if variance ratio outside [0.90; 1.20]									
Ps	R2	LR	chi2	p>chi2	MeanBias	MedBias	B	R	%Var
	0,002		2,21	1,974	2,7	2,9	10,1	0,83	40

* if B>25%, R outside [0.5; 2]

In addition, to guarantee the DiD results and the indicators chosen in the PSM method, a parallel trend analysis was conducted to ensure a similar pattern before the policy implementation. The findings in Figure 1 illustrate trends prior to the implementation, where both groups have similar trends with a significant decrease in VOI. In other words, the PSM approach can lessen the bias to improve the overall effect of policy review. Besides, the findings also illustrate that the average VOI in the treatment group is lower compared to the control group. This aligns with the missions of the policy, which targeted underdeveloped and undeveloped villages with similar potential to accelerate the development of the village's services and economies.

Figure 1. Parallel Trend



Spatial regression results align with the value of the Moran Index, which characterizes the correlation between increasing the output of villages in the National Priority of Rural Areas. This result is aligned with Ding's (2023) study, which verified China's agricultural agglomeration at the micro level using the spatial panel method. The study proved that there was an increase in farmers' income due to agglomeration. However, the growth of agricultural organizations had a greater impact on the increase in income than the rise in agricultural production. This finding also confirms

hypothesis 1 and emphasizes the beneficial spillover impact among villages, which has the chance to be further developed and accelerate the local economies. Village cooperation needs to be fostered in order to stimulate the sharing of knowledge that lowers production costs and enhances productivity. Then, by generating economies of scale, this encourages each village in the rural areas to raise their VOI. In addition, these findings also strengthen the basis of village selection for the rural areas since it aligns with the Rural Area Development Plan for each region, which is not a random selection.

Table 6. Basic DiD and PSM-DiD Regression Results

Variables	(1) OLS	(2) FULL-OLS	(3) FE	(4) FULL-FE	(5) OLS	(6) FULL-OLS	(7) FE	(8) FULL-FE
DiD	0,177 (0,322)	0,181 (0,311)	0,177 (0,257)	0,187 (0,256)	0,0182 (0,354)	0,0277 (0,342)	0,0182 (0,258)	0,0334 (0,261)
Transfer (log)		1,511*** (0,199)		-0,0314 -1,104		1,735*** (0,346)		0,0635 -1,238
Expenditure (log)		0,788*** (0,148)		1,747** (0,811)		1,051*** (0,259)		2,187* -1,159
Health (log)		0,648*** (0,132)		0,0456 (0,129)		0,923*** (0,216)		0,323 (0,242)
Electricity (log)		0,293*** (0,0455)		0,165 (0,121)		-0,0434 (0,0726)		0,0938 (0,162)
Communication (log)		1,916*** (0,116)		0,468** (0,217)		2,128*** (0,191)		0,591** (0,265)
VIC (log)		0,0399 (0,0351)		0,00718 (0,0521)		0,0992* (0,0580)		0,0505 (0,0820)
Village Cooperatives (log)		0,989*** (0,0872)		0,487*** (0,0897)		0,919*** (0,146)		0,328** (0,127)
Village market (log)		0,335*** (0,108)		0,435*** (0,0875)		0,284 (0,181)		0,412** (0,179)
2019	-0,0552 (0,133)	-0,0677 (0,129)	-0,0552 (0,0968)	-0,0574 (0,0951)	0,0182 (0,354)	0,0277 (0,342)	0,0182 (0,258)	0,0334 (0,261)
2020	0,0518 (0,136)	0,0556 (0,131)	0,0518 (0,111)	0,0574 (0,112)	-0,296 (0,221)	-0,335 (0,214)	-0,296* (0,170)	-0,308* (0,170)
2022	-0,00695 (0,136)	-0,00831 (0,131)	-0,00695 (0,105)	-0,00690 (0,105)	0,0696 (0,232)	0,0651 (0,225)	0,0696 (0,148)	0,0705 (0,150)
2023	-0,128 (0,136)	-0,128 (0,131)	-0,128 (0,0832)	-0,123 (0,0815)	0,103 (0,232)	0,0819 (0,225)	0,103 (0,141)	0,0988 (0,143)
Constant	12,60*** (0,0963)	-41,48*** -3,082	12,50*** (0,0655)	-25,53 (17,32)	12,28*** (0,166)	-50,57*** -5,332	12,11*** (0,0998)	-37,25** (14,09)
Observations	28.085	28.085	28.085	28.085	10.675	10.675	10.675	10.675
R-squared	0,002	0,071	0,000	0,009	0,002	0,065	0,001	0,011
N of villages	5.617	5.617	5.617	5.617	2.135	2.135	2.135	2.135

Note: Spatial Autoregressive (SAR) Model, Spatial Durbin Model (SDM) and Spatial Error Model (SEM)

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.01

Furthermore, the DiD Method impact study results consistently demonstrated that the policy had no discernible impact on the rise in VOI in 62 National Priority Rural Areas. This study has not discovered any solid proof of the efficacy of policy implementation in a short period of time. Even though the interaction value is favorable in the overall

assessment, it is still unclear if the policy is responsible for the areas' rising VOI. This can occur as a result of a number of factors, including the COVID-19 epidemic, which restricts people's mobility, and the failure of the government to strengthen its roles in implementing the development.

As an illustration, Bali Aga, one of the 62 National Priority Rural Areas located in Buleleng Regency, has superior cultural tourism products such as waterfalls and is supported by agricultural derivative products managed by the Joint Village Owned Enterprise (BUMDesma). The COVID pandemic significantly impacted superior regional product tourism, so creativity is required to identify opportunities to aid in economic recovery. A proper development strategy is also required when the potential of villages and regions has not been fully utilized. One way to expedite regional development is through the use of IT and online product marketing for small businesses.

In addition, the time period yields varying findings when estimating economic agglomeration. For instance, agglomeration has a major impact on wage distribution both in the medium and long term, according to a Chinese study. However, the study also discovered that regional size has a large impact on inequality over the long run but not in the short term (Xu et al., 2023). Consequently, longer data periods and ongoing policy improvements can yield better results.

According to a qualitative review by the Ministry of Villages, Disadvantaged Regions, and Transmigration, there are a number of things that need to be strengthened in order to develop rural areas economically. These include: 1) the need to increase the role of central, regional, and village governments in raising the capacity of cooperation, management, and standardization/certification of superior products, as well as the ability to access funding, promotion, and marketing; 2) the need for an agreement between villages and area managers not to commercialize land to communities outside the area; and 3) the necessity of regional and village governments playing an active role in promoting economic institutions in villages, such as Joint Village Owned Enterprise and cooperatives.

4. Conclusion

A favorable intraregional impact within a particular rural area is indicated by the spatially linked increase in VOI among villages in 62 National Priority Rural Areas. The ideal model for this study is the Spatial Autoregressive (SAR) Model, which explains that no other variables spatially indicated at the village level have an impact on the growth of VOI in rural areas. These results support hypothesis 1 and highlight the positive spillover effect among villages, which has the potential to advance and boost local economies. Besides, the growth of VOI has not been substantially impacted by the Rural Areas Development Policy, which is enforced under the National Medium-Term Development Plan 2020–2024. Despite a typically positive interaction variable, it is uncertain if the policy is accountable for the increase in village income. The lack of government support, poor cooperation, and the pandemic are some of the factors why this policy has not been running optimally. Longer data periods and ongoing policy improvements can yield better results for policy analysis.

Furthermore, this study can be taken into account when assessing how Indonesia's Rural Area Development Policy is being implemented. Some considerations: First, progressive intervention is needed from central, regional, and village governments in planning, implementation, and rural area evaluation. Second, re-map the village's potential and determine whether the product can boost the local economy. Third, collaboration between different stakeholders, including the private sector and off-

takers, is necessary to boost regional productivity and expedite the growth of the village economies.

There are some restrictions on this research, including the fact that the data was unavailable in 2021, and the study period before and after the policy's implementation was very brief. In order to more precisely quantify the impact of policy, further research periods must be considered, and village-level data must be enhanced as a control variable for impact assessments. Secondly, Village Potential data and Village Development Index (IDM) data cannot provide data related to village area and population, so this research could not consider village community density, which can be an influential variable in agglomeration. As an alternate strategy for further research, data interpolation or the use of proxy variables from Village Potential Data-Statistic Indonesia (BPS) should be explored.

Acknowledgment

We would like to convey our gratitude to the Ministry of Villages and Development of Disadvantaged Regions, which has provided data support and participation in this research. The entire academic community of Universitas Indonesia for their sincere sharing of their time, materials, and expertise.

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