

Sectoral Public Expenditure and Income Inequality in Indonesia: A Spatial Panel Approach

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ABSTRACT

Purpose – This study evaluated the impact of sectoral local government expenditures (economic, health, education, and social protection) on regional income inequality. To address the specification bias inherent in traditional frameworks, this research explicitly accommodated spatial spillover mechanisms.

Design/methodology/approach – The empirical analysis utilized a balanced macro-level panel dataset comprising 33 Indonesian provinces, yielding 495 observations over a 15-year observation period from 2010 to 2024. A Spatial Durbin Model accommodated unobserved individual heterogeneity while simultaneously capturing endogenous spatial interactions. Marginal policy impacts were extracted via Monte Carlo parametric bootstrap simulations.

Finding/Results – A positive spatial autoregressive parameter confirmed that income inequality in one province systematically influenced contiguous territories. Decomposing the marginal impacts revealed that local educational expenditures directly compressed internal income inequality. Conversely, health allocations exhibited a positive direct effect on the Gini ratio. Furthermore, localized economic expenditures generated negative spatial spillovers that significantly reduced income disparities across neighboring provinces.

Originality/Value – Policymakers must transition from isolated fiscal planning toward coordinated interregional public investments to leverage positive agglomeration externalities. Physical infrastructure expansion requires harmonization with targeted social protection frameworks. Future research should integrate intra-regional microdata and explore the nonlinear threshold effects of fiscal decentralization to refine territorial wealth redistribution strategies.

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1. Introduction

The persistent challenge of regional income inequality continues to hinder sustainable economic development and social cohesion worldwide. In response, central governments increasingly decentralize fiscal authorities, delegating the responsibility of wealth redistribution to local administrations (Han, 2022). This shift assumes that local policymakers hold an informational advantage, allowing them to tailor interventions to regional needs (Amri et al., 2023). Consequently, local governments channel public resources into essential sectors such as economic infrastructure, health services, educational development, and social protection programs (Medeiros et al., 2022). While the primary goal is to foster human capital accumulation and build economic resilience, the mechanisms translating these localized expenditures into equitable wealth distribution remain complex (Celikay & Sengur, 2016). Ultimately, the success of targeted fiscal allocations relies on the geographical and socioeconomic landscape of each region (Li & Haynes, 2011).

Examining these sectoral allocations reveals that different types of public investment generate divergent distributive outcomes over time (da Costa & Gartner, 2017). This phenomenon is visible in archipelagic developing nations like Indonesia, where geographical fragmentation inherently breeds logistical and developmental disparities. The precise impact of educational expenditure currently stands as a prominent empirical debate. While public schooling holds the theoretical capacity to democratize human capital and compress income gaps (Sylwester, 2002), researchers hypothesize that structural barriers like digital divides and uneven facility standards across isolated islands might obstruct equal access and generate ambiguous short term effects on the Gini ratio (Celikay & Sengur, 2016; Jiang & Yin, 2026; Sujarwoto & Tampubolon, 2016). Conversely, investments in primary health infrastructure yield consistent reductions in income concentration by delivering direct welfare improvements to vulnerable populations (Jiang & Yin, 2026). Similarly, funding allocated for physical infrastructure bridges spatial income gaps, provided policymakers harmonize these efforts with robust social protection frameworks to shield marginalized communities from economic shifts (Hakim & Rosini, 2022; Ou et al., 2026).

Even with the importance of these fiscal instruments, previous scholarly investigations have produced mixed and inconclusive results regarding their effectiveness (Quito et al., 2022). A core reason for this analytical ambiguity stems from a theoretical failure to account for spatial spillover mechanisms. Localized fiscal policies do not operate in a geographical vacuum (Rahman et al., 2024). Instead, regional spending decisions reshape economic trajectories in neighboring territories through interjurisdictional policy mimicry, labor migration, and agglomeration externalities (De Siano & D'Uva, 2017; Khan et al., 2026). In the context of an interconnected archipelagic nation, it is conceptually assumed that regional income inequality and fiscal capacities are subject to strong spatial heterogeneity, where economic disparities in one province systematically influence conditions in contiguous areas. It is therefore hypothesized that evaluating sectoral expenditures without explicitly integrating these spatial interdependencies obscures the economic feedback loops governing regional income distribution (Medeiros et al., 2022).

This spatial blindness highlights a methodological deficiency in the existing public finance literature. Conventional panel data estimators systematically ignore horizontal dependencies among geographic units. By treating adjacent regions as independent entities, traditional frameworks inevitably produce simultaneous bias and inconsistent parameter estimates due to the omission of spatially lagged variables (J. P. LeSage & Pace, 2010; Mutl & Pfaffermayr,

2011). Modern econometric literature dictates that spatial models are necessary to capture these interregional spillovers (Anselin, 1988). Moreover, modeling a complex archipelagic landscape requires a precise spatial weight foundation, such as a nearest neighbor specification, to ensure that no island province is falsely treated as an isolated entity outside the broader economic network (J. LeSage & Pace, 2009). Specifically within the context of Indonesian fiscal decentralization, empirical literature exhibits a critical gap regarding the intersection of sectoral expenditure, provincial inequality, and spatial interdependence. Previous studies largely treat Indonesian provinces as isolated administrative units, thereby failing to capture how local fiscal policies systematically ripple across regional borders. To address these theoretical and methodological gaps, this study evaluates the multidimensional impact of realized local government expenditures on provincial income inequality in Indonesia. The primary novelty of this research extends beyond the mere application of a spatial panel model; it lies in the analytical capacity to explicitly distinguish between direct local fiscal effects and indirect neighboring spillover effects across economic, health, education, and social protection functions. By adopting a Spatial Durbin Model, the research accommodates unobserved individual heterogeneity while capturing these endogenous spatial interactions to ensure consistent estimations. Ultimately, this comprehensive approach establishes a spatially justified paradigm, offering a foundation for policymakers to design coordinated interregional fiscal interventions that effectively mitigate territorial income disparities.

2. Literature Review & Hypothesis Development

2.1. Fiscal Decentralization and Human Capital Trajectories

The theoretical mechanism linking local government intervention to income distribution fundamentally relies on the concept of fiscal decentralization. By delegating financial authority, central governments empower regional administrations to tailor public resource allocations toward specific territorial needs (Amri et al., 2023; Han, 2022). To achieve inclusive economic growth, local policymakers systematically deploy decentralized budgets across critical functions, particularly human capital development (Ullah et al., 2021; Varlitya et al., 2023). Examining the specific allocations dedicated to this sector reveals divergent distributive trajectories over time. Public health expenditure consistently generates sustained reductions in income concentration because targeted primary care investments provide direct welfare improvements to vulnerable demographics and mediate equitable access to essential medical services (Yin et al., 2026).

Conversely, the precise impact of educational spending currently stands as a prominent empirical debate driven by varying macroeconomic conditions and institutional quality (Mbewe et al., 2025). Researchers hypothesize that profound digital divides and uneven facility standards across isolated geographic units obstruct equal access, frequently exacerbating the Gini ratio in the short term before long term egalitarian benefits can materialize (Hamza & Cochrane, 2026; Jiang & Yin, 2026). Furthermore, the ultimate redistributive success of public schooling is heavily moderated by local governance thresholds and structural barriers that prevent marginalized populations from fully accumulating human capital (Trabelsi, 2019). This indicates that localized educational investments require meticulous targeting to effectively compress wage gaps without unintentionally widening interregional disparities. Based on these theoretical mechanisms, this study hypothesizes that localized human capital investments, specifically educational and health expenditures,

directly compress internal regional inequality while concurrently generating redistributive spillovers across contiguous provinces (H1).

2.2. Social Protection and Redistributive Resilience

To complement human capital functions, regional administrations deploy social safety nets as direct redistributive tools. Targeted social protection initiatives, such as conditional and unconditional cash transfers, deliver direct financial relief to marginalized communities. These specific interventions systematically narrow demographic asset gaps and provide immediate redistributive resilience against unpredictable economic shocks (Kerimov & Shapoval, 2024; Light et al., 2024). Furthermore, well designed cash transfer programs hold the capacity to incentivize positive social behaviors, such as continuous school attendance and proactive health service utilization, which generate additional long term egalitarian benefits (Nazareno & de Castro Galvao, 2023; Stampini et al., 2025).

The optimal execution of these protective instruments necessitates precise demographic targeting to prevent unintended socioeconomic consequences. Empirical evidence confirms that channeling cash transfers specifically toward women effectively reduces gender asset gaps and empowers vulnerable household members (Morton, 2019). However, poorly configured conditionality parameters occasionally induce adverse fertility effects among low income groups, potentially neutralizing the intended redistributive gains (Kitaura & Miyazawa, 2021). Therefore, the overall effectiveness of localized social transfers ultimately depends on their proportional share in total household income and the administrative efficiency of local governments in targeting the most deprived demographics (Giangregorio, 2024). Consequently, this study hypothesizes that localized social protection expenditure yields a significant negative effect on the regional Gini ratio, operating both directly within the province and indirectly through spatial safety net externalities (H2).

2.3. Physical Infrastructure and Spatial Economic Externalities

Beyond direct social welfare interventions, localized economic expenditures allocated for public infrastructure projects are vital for bridging spatial income gaps and stimulating regional industrial development (Hakim & Rosini, 2022; Ou et al., 2026). Physical infrastructure expansion holds the theoretical capacity to elevate local productivity, yet uneven public facility provision inherently intensifies interregional disparities. Empirical evidence indicates that geographic segregation and exclusionary land use patterns strongly dictate the actual impact of local infrastructure investments, potentially aggravating inequality if not harmonized with inclusive policies (Cortés, 2021; Xiong et al., 2025; Yuan et al., 2024). Furthermore, unbalanced allocations between public infrastructure and private domestic investments frequently exacerbate regional wealth concentration unless complementary social frameworks are actively enforced.

Even with the strategic importance of these sectoral instruments, previous scholarly investigations have produced remarkably mixed and inconclusive results regarding their true redistributive effectiveness (Quito et al., 2022). A fundamental theoretical reason for this analytical ambiguity stems from a widespread failure to account for spatial economic spillover mechanisms. Localized fiscal policies do not operate within an isolated geographical vacuum. Instead, regional spending decisions actively reshape economic trajectories in neighboring territories through complex interjurisdictional policy mimicry, dynamic labor migration, and powerful agglomeration externalities (Khan et al., 2026; Rahman et al., 2024). Consequently, evaluating sectoral expenditures by treating contiguous regions as independent entities systematically obscures the authentic economic feedback loops governing regional wealth

distribution. Addressing this theoretical void is imperative for constructing a rigorously justified paradigm capable of guiding spatially informed fiscal redistributions across interconnected archipelagos (Kumar et al., 2025; Runge, 2023). Therefore, it is hypothesized that localized economic infrastructure expenditure generates significant negative spatial spillovers, effectively reducing income disparities across interconnected neighboring territories (H3).

3. Methodology

3.1. Data Sources

This study utilized a balanced macro-level panel dataset comprising 33 Indonesian provinces (N=33) over a 15-year observation period (T=15) from 2010 to 2024, yielding a total of 495 observations. Restricting the panel to 33 provinces ensures spatial and temporal consistency throughout the analysis. Because the Indonesian administrative structure experienced recent territorial expansions, such as the formation of new provinces in 2022, the macroeconomic data for these newly established units were systematically consolidated into their original parent provinces. This consolidation rigorously aligns the empirical dataset with the constant geographic boundaries defined in the spatial weight matrix, thereby preventing structural inconsistencies when estimating interregional spillovers. Subsequently, the Gini ratio, obtained from Statistics Indonesia (BPS), served as the dependent variable to proxy regional income inequality. To stabilize error variance and enable elasticity interpretations, all fiscal expenditure variables were transformed into natural logarithms (ln) (Wooldridge, 2016). Although total expenditure risks capturing regional scale effects rather than pure fiscal priorities, the logarithmic specification is deliberately retained to measure absolute fiscal elasticity. To explicitly neutralize the scale bias associated with larger provincial economies, the empirical model incorporates structural control variables, primarily Gross Regional Domestic Product (GRDP). Furthermore, this logarithmic transformation minimizes data skewness, mitigates potential heteroskedasticity, and linearizes exponential trends in regional panel data modeling (Cameron & Trivedi, 2005).

3.2. Spatial Weight Matrix Construction

Geographic proximities and spatial interactions among provinces were quantified using a non-stochastic spatial weight matrix, W . The geospatial polygon data for the Indonesian provincial boundaries were extracted from the Database of Global Administrative Areas (GADM) framework. This study applied a K-Nearest Neighbors (KNN) functional proximity criterion, setting $k=3$. Unlike distance-based or contiguity matrices, such as Queen or Rook specifications, the KNN matrix guarantees a uniform number of neighbors for each region regardless of geographical boundaries. This specification is appropriate for the archipelagic structure of Indonesia, ensuring that no island province remains isolated from the spatial network (J. LeSage & Pace, 2009). The constructed matrix W was row-standardized, allowing spatially lagged variables to be interpreted as weighted averages of neighboring regions while maintaining the stability of spatial autocorrelation parameters (Elhorst, 2014).

3.3. Exploratory Spatial Data Analysis (ESDA)

To detect spatial agglomeration and localized spillover effects, an Exploratory Spatial Data Analysis (ESDA) was conducted as an initial step. Local cluster testing was visualized through spatial hotspot maps using the local Getis-Ord statistic (Ord & Getis, 1995). The Getis-Ord statistic calculates standardized Z-scores to identify specific geographical areas where extremely high values (hotspots) or extremely low values (coldspots) cluster spatially (Getis

& Aldstadt, 2004). The evaluation of spatial significance relied on the standard normal distribution. A cluster was deemed statistically significant if it exceeded the critical thresholds at the 90% ($|Z| \geq 1.645$), 95% ($|Z| \geq 1.960$), or 99% ($|Z| \geq 2.576$) confidence levels.

3.4. Econometric Specifications

The empirical framework begins with a baseline conceptual function linking local fiscal decentralization instruments to regional income inequality. This relationship is formulated as follows:

$$Gini_{it} = f(\ln Economy_{it}, \ln Health_{it}, \ln Education_{it}, \ln Social_{it}, \ln GRDP_{it}) \quad (1)$$

In traditional econometrics that neglects spatial effects, this functional relationship is estimated using a standard panel data model to accommodate unobserved individual heterogeneity. The baseline non-spatial panel equation is expressed as:

$$Gini_{it} = \beta_0 + \beta_1 \ln Economy_{it} + \beta_2 \ln Health_{it} + \beta_3 \ln Education_{it} + \beta_4 \ln Social_{it} + \beta_5 \ln GRDP_{it} + \mu_i + \epsilon_{it} \quad (2)$$

where $Gini_{it}$ represents the income inequality level in province i at time t . The parameter β_0 represents the global intercept, while β_1 through β_4 denote the elasticity coefficients for each respective local fiscal expenditure function, and β_5 captures the effect of the structural control variable, Gross Regional Domestic Product. The term μ_i captures region-specific unobserved individual effects, and ϵ_{it} denotes the independently and identically distributed idiosyncratic error term. Whether these individual-specific effects are treated as fixed or random is subject to empirical validation using the Spatial Hausman test executed during the diagnostic phase (Mutl & Pfaffermayr, 2011)..

When spatial dependence is present in the data, such as cross-regional income inequality spillovers or policy interactions, standard Ordinary Least Squares (OLS) and classic panel estimators violate the assumption of independent observations. This violation leads to simultaneous bias and inconsistency. The omitted variable bias in the non-spatial estimator is demonstrated through its probability limit, which deviates from the true parameter as follows (Neier, 2023):

$$plim(\hat{\beta}_{OLS}) = \beta + \rho \cdot plim(X'X/NT)^{-1}(X'WY/NT) \neq \beta \quad (3)$$

where $plim(\hat{\beta}_{OLS})$ denotes the biased and inconsistent OLS estimator, and β represents the true parameter vector. The parameter ρ signifies the spatial dependence factor, X is the matrix of explanatory variables, and WY embodies the spatial lag of the dependent variable, which acts as the omitted variable causing simultaneity bias (J. P. LeSage & Pace, 2010). To mitigate this bias and accurately evaluate spatial policy spillovers, this study transitioned to spatial panel econometric specifications.

As the primary comprehensive framework, this study employed the Spatial Durbin Model (SDM) specification (Anselin, 1988). The SDM is highly recommended as a general nesting approach because it simultaneously accommodates two types of spatial dependence: endogenous interaction from the dependent variable (spatial lag of Y) and exogenous interaction from the independent variables in neighboring regions (spatial lag of X). Mathematically, the general SDM equation for panel data is formulated as follows:

$$Y_{it} = \rho \sum_{j=1}^N W_{ij} Y_{jt} + X_{it}\beta + \sum_{j=1}^N W_{ij} X_{jt}\theta + \mu_i + \epsilon_{it} \quad (4)$$

where Y_{it} is the dependent variable $Gini_{it}$ for province i at time t , and ρ stands as the endogenous spatial autocorrelation parameter capturing global spillovers. The term W_{ij} refers to the elements of the spatial weight matrix, while X_{it} is the matrix of explanatory fiscal and control variables. The parameter β denotes the local direct effect coefficients, and θ captures the exogenous spatial spillover coefficients originating from neighboring provinces. Additionally, μ_i represents unobserved individual-specific effects, and ϵ_{it} signifies the random error term. The SDM ensures that a shock to an independent variable in one province creates spatial feedback loops that propagate through the entire regional network, effectively eliminating omitted variable bias (Elhorst, 2014; J. LeSage & Pace, 2009).

As an alternative specification to evaluate local spillovers, this study also estimated the Spatial Durbin Error Model (SDEM). Unlike the SDM, which models global spillovers, the SDEM restricts spatial interactions exclusively to local spillovers affecting immediately adjacent neighbors (Halleck Vega & Elhorst, 2015). The SDEM accommodates exogenous spatial spillovers from explanatory variables (spatial lag of X) and spatially autocorrelated errors but omits the spatially lagged dependent variable. The mathematical equation for the SDEM is written as:

$$Y_{it} = \alpha + X_{it}\beta + \sum_{j=1}^N W_{ij} X_{jt}\theta + \mu_i + u_{it}, \quad u_{it} = \lambda \sum_{j=1}^N W_{ij} u_{jt} + \epsilon_{it} \quad (5)$$

In the SDEM framework, α serves as the global intercept, β represents the local effects of the explanatory variables, and θ measures the exogenous spatial spillovers from neighboring regions weighted by the spatial matrix W . The distinguishing feature of this model is the composite error term u_{it} , which follows a spatial autoregressive process. Within this error structure, λ is the spatial error dependence coefficient capturing local spillovers in unobserved shocks, and ϵ_{it} represents the random idiosyncratic error. The SDEM specification is crucial if the spillover effects of fiscal decentralization policies are assumed to have no interregional feedback loops but only a unidirectional impact on inequality formation in adjacent provinces through cross-border trade or commuter labor absorption (J. P. LeSage & Pace, 2010).

3.5. Model Diagnostics and Selection Strategy

The model selection process strictly followed a statistical diagnostic sequence. First, a Spatial Hausman Test was conducted to determine whether the unobserved individual-specific effects component μ_i was more appropriately treated as Fixed Effects (FE) or Random Effects (RE) (Muhl & Pfaffermayr, 2011). Subsequently, nested Likelihood Ratio (LR) tests and the Akaike Information Criterion (AIC) were calculated to empirically verify whether the comprehensive SDM could be simplified into more restrictive specifications, such as the Spatial Autoregressive (SAR) or the Spatial Error Model (SEM). Finally, the selected optimal model was estimated using the Maximum Likelihood (ML) method to obtain consistent and unbiased parameters (Lee, 2004).

3.6. Extraction of Marginal Impacts

A critical methodological feature of spatial econometrics, particularly for the SDM, is that point estimates (β and θ) cannot be directly interpreted as marginal partial derivatives. This limitation arises due to spatial feedback loops generated by the spatially lagged dependent variable, which reverberate back to the region of origin (J. LeSage & Pace, 2009). Therefore, the SDM equation must be rewritten into its reduced form for each cross-section at time t to obtain the spatial multiplier matrix:

$$Y_t = (I_N - \rho W)^{-1}(X_t\beta + WX_t\theta + \mu + \epsilon_t) \quad (6)$$

From this reduced form, the $N \times N$ partial derivative multiplier matrix for the k -th explanatory variable at time t can be analytically derived as follows (Arbia et al., 2020):

$$S_{kt}(W) = \frac{\partial Y_t}{\partial X_{kt}} = (I_N - \rho W)^{-1}(\beta_k I_N + \theta_k W) \quad (7)$$

where Y_t represents the $N \times 1$ vector of the dependent variable at time t , I_N denotes an $N \times N$ identity matrix, and $(I_N - \rho W)^{-1}$ acts as the global spatial multiplier matrix translating feedback loops across the regional system. Furthermore, β_k and θ_k respectively denote the direct and spillover scalar parameters for the k -th explanatory variable, while $S_{kt}(W)$ symbolizes the $N \times N$ partial derivative multiplier matrix used to extract marginal impacts.

Based on the elements within this partial derivative matrix, the spatial impacts of fiscal policy were summarized into three scalar measures. The Average Direct Impact is computed as the average of the diagonal elements of the partial derivative multiplier matrix, measuring the effect of a change in a province's fiscal allocation on its own inequality while natively incorporating spatial feedback effects (Elhorst, 2014). The Average Indirect (Spillover) Impact is derived from the average of the non-diagonal elements, measuring the spatial spillover impact resulting from fiscal policy changes in neighboring provinces. The Average Total Impact represents the sum of both direct and indirect impacts, reflecting the overall effect of a change in an explanatory variable across the entire spatial system (Arbia et al., 2020).

To generate robust standard errors and evaluate the statistical significance of these three impact metrics, statistical inference was executed using a Monte Carlo Parametric Bootstrap Simulation (Piras, 2013). This computational procedure was carried out by drawing 1,000 random iterations from the asymptotic variance-covariance matrix of the estimated parameters (Arbia et al., 2020).

4. Result and Discussion

4.1. Descriptive Statistics and Exploratory Spatial Data Analysis

The empirical investigation commenced by examining the descriptive statistics of the core variables, which are summarized in Table 1. Throughout the 15-year observational timeframe, the Gini ratio across the 33 Indonesian provinces recorded a mean value of 0.3607, indicating a moderate yet persistent level of regional income inequality.

Table 1. Descriptive statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Gini ratio	0.3607	0.0406	0.2360	0.4590
ln_Economy	26.9845	0.8883	24.2934	30.3128
ln_Health	26.7443	1.0475	23.8368	30.0220
ln_Education	27.6150	1.3448	22.0858	30.7119
ln_Social	24.8690	0.9048	21.8245	28.9913
ln_GRDP	11.8781	1.1696	9.6147	14.5815

Prior to estimating the global spatial econometric models, an Exploratory Spatial Data Analysis (ESDA) was executed to verify the presence of spatial agglomeration. Utilizing the Getis-Ord local statistic, spatial hotspot maps were generated for the Gini ratio (Figure 1) and for each of the sectoral fiscal expenditure allocations, namely economic, health, education, and social protection spending (Figures 2–5).

Figure 1 maps the spatial distribution of the Gini ratio across the 33 Indonesian provinces. The Getis-Ord G_i^* statistic is used to identify statistically significant clusters of high and low

inequality, providing an initial visual assessment of spatial dependence before the formal econometric estimation.

Figure 1. Spatial hotspot map of Gini ratio

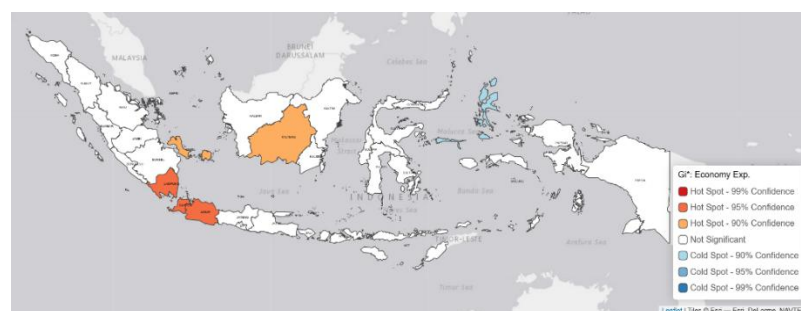


Source: Authors' calculation.

The map reveals that income inequality is not randomly distributed; provinces with high inequality tend to cluster adjacent to one another, forming distinct hot spots that signal strong positive spatial dependence in the Gini ratio.

Figure 2 displays the spatial concentration of local economic expenditure across provinces. The same hotspot procedure is applied to the economic expenditure allocation, allowing a direct visual comparison with the inequality map in Figure 1.

Figure 2. Spatial hotspot map of economy expenditure



Source: Authors' calculation.

The pattern indicates that economic spending is geographically clustered rather than evenly dispersed, with neighbouring provinces exhibiting similar allocation intensities that point to potential interjurisdictional spillovers.

Figure 3 presents the spatial distribution of local health expenditure. The map highlights provinces where health spending is significantly concentrated, offering a preliminary indication of whether fiscal effort in this sector follows a spatial pattern.

Figure 3. Spatial hotspot map of health expenditure



Source: Authors' calculation.

The clustering of high-allocation provinces suggests that health spending follows a regionally concentrated pattern, which may reflect uneven facility distribution and differing fiscal capacities across contiguous areas.

Figure 4 maps the spatial pattern of local education expenditure. Hot spots and cold spots are identified to reveal whether investment in human capital is geographically clustered across neighbouring provinces.

Figure 4. Spatial hotspot map of education expenditure

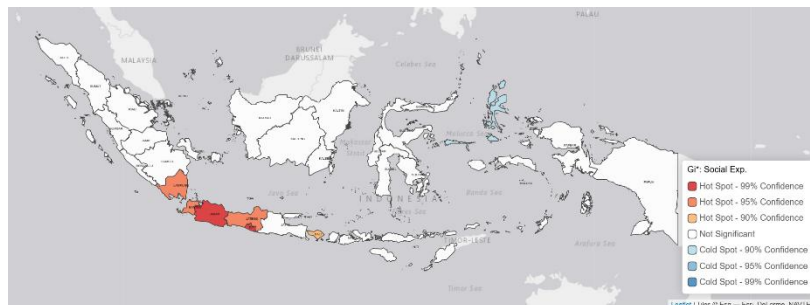


Source: Authors' calculation.

The map shows that educational spending is spatially clustered, with hot spots concentrated in particular regions, indicating that investment in human capital is geographically uneven across the archipelago.

Figure 5 illustrates the spatial distribution of social protection expenditure. The hotspot mapping shows where social assistance allocations are spatially concentrated, completing the set of fiscal indicators examined in this analysis.

Figure 5. Spatial hotspot map of social expenditure



Source: Authors' calculation.

The distribution exhibits geographical clustering of high- and low-allocation provinces, suggesting that social protection efforts are spatially correlated and may generate redistributive spillovers beyond administrative borders.

Taken together, the mapping outcomes (Figures 1–5) empirically demonstrated that regional income inequality and fiscal capacities in Indonesia are not randomly distributed across space. Instead, the distributions exhibited profound geographical clustering, forming distinct Hot Spots (clusters of extreme high values) and Cold Spots (clusters of extreme low values) across contiguous provinces.

4.2. Spatial Panel Diagnostics and Model Selection

To ascertain the most robust and efficient econometric specification, a rigorous diagnostic sequence was implemented. The outcomes of these model selection procedures are documented in Table 2 and Table 3.

Table 2. Diagnostic tests for spatial model selection

Diagnostic Tests	Value	p-value
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Spatial Hausman test (χ^2)	8.829	0.1161
Nested LR test (SDM vs SAR)	16.735	0.0050
Nested LR test (SDEM vs SEM)	18.148	0.0027

Source: Authors' calculation.

Table 3. Akaike Information Criterion (AIC) comparison

Spatial Models	AIC Value	Rank
Spatial Durbin Model (SDM)	-2465.226	1
Spatial Autoregressive (SAR)	-2458.491	2
Spatial Durbin Error Model (SDEM)	-2453.044	3
Spatial Error Model (SEM)	-2444.896	4

Source: Authors' calculation.

The diagnostic evaluation was initiated by assessing the orthogonality of the unobserved individual-specific effects using the Spatial Hausman test. The procedure produced a statistic of 8.829 ($p=0.1161$), failing to reject the null hypothesis of no correlation between the unobserved heterogeneity and the explanatory variables. This statistical evidence firmly established that the RE specification provides consistent and relatively more efficient parameter estimates compared to the Fixed Effects approach (Mutl & Pfaffermayr, 2011).

Building upon the RE framework, nested Likelihood Ratio (LR) tests were deployed to evaluate the validity of simplifying the comprehensive models into more restrictive spatial forms. The analysis robustly rejected the null hypothesis that the SDM could be reduced to the SAR specification ($p=0.0050$). An equivalent diagnostic conclusion was reached when testing the SDEM against the SEM, with the proposed restriction being decisively rejected ($p=0.0027$). These rejections empirically justify the necessity of retaining spatially lagged independent variables to prevent structural misspecification.

As a final comparative measure, the AIC was utilized to rank the performance of the non-rejected models. The evaluation revealed that the SDM achieved the lowest information loss (-2465.226), thereby outperforming all alternative candidate specifications (Burnham & Anderson, 2004). Guided by this comprehensive diagnostic evidence, the SDM with Random Effects was conclusively designated as the optimal model for estimating the spatial impacts.

4.3. Marginal Impact Estimates

Due to the inherent spatial feedback loops within the SDM framework, point estimates cannot be directly interpreted as partial derivatives (J. LeSage & Pace, 2009). Consequently, the parameter estimates were analytically decomposed into Direct and Indirect (Spillover) effects. These marginal impacts were extracted via a Monte Carlo parametric bootstrap simulation utilizing 1,000 iterations (Arbia et al., 2020). The comparative results between the biased non-spatial classical Panel RE and the decomposed spatial impacts are presented in Table 4.

Table 4. Model comparison of the estimated direct and spillover effects

Variables	Baseline Panel RE	Extended Panel RE	Baseline SDM	Extended SDM
Direct Effects				
ln_Economy	-0.0082***	-0.0074***	0.0011	0.0004
ln_Health	0.0035*	0.0039*	0.0040*	0.0041
ln_Education	-0.0060***	-0.0053***	-0.0049***	-0.0033**
ln_Social	-0.0001	0.0002	-0.0010	-0.0016

In_GRDP (Control)	—	-0.0064	—	0.0040
Spillover Effects				
In_Economy	—	—	-0.0121***	-0.0059*
In_Health	—	—	-0.0008	-0.0042
In_Education	—	—	0.0011	0.0019
In_Social	—	—	-0.0066	0.0090*
In_GRDP (Control)	—	—	—	-0.0202**
Spatial Parameters				
Spatial autoregressive (λ/ρ)	—	—	0.3897***	0.4718***
Error variance (ϕ)	—	—	3.8678***	4.0947***

Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% levels. Source: Authors' calculation.

The spatial autoregressive parameter in the extended SDM was estimated at 0.4718 and proved to be highly statistically significant ($p < 0.01$). This confirms that regional inequality dynamics are heavily influenced by the economic trajectories of neighboring provinces.

Comparing the baseline and extended models reveals the critical importance of controlling for regional macroeconomic capacity. In the extended SDM, the direct effect of education expenditure remained statistically significant and negative (-0.0033, $p < 0.05$). This indicates that localized educational investment consistently compresses internal inequality, even after systematically neutralizing the scale bias associated with larger provincial economies.

Regarding economic expenditure, the extended SDM estimates demonstrated that the direct impact of economic spending on local inequality was statistically insignificant (0.0004). However, its indirect (spillover) impact remained significant and negative (-0.0059, $p < 0.10$). This metric confirms that a 1% expansion in economic expenditure within a specific province is systematically associated with a 0.0059% reduction in income inequality across its interconnected neighboring provinces. Furthermore, the spatial spillover effect of the GRDP control variable itself was significantly negative (-0.0202, $p < 0.05$), empirically validating its inclusion to prevent simultaneous bias.

To ensure the reliability of these empirical findings, a robustness check was conducted by estimating the SDM under alternative spatial weight matrices, specifically varying K-Nearest Neighbors ($k=4$, $k=5$, and $k=6$), Inverse Distance Weighting (IDW), and Queen contiguity specifications. The comparative results of the total spatial impacts and the spatial parameters are presented in Table 5.

Table 5. Robustness Check of Estimated Total Spatial Impacts Under Alternative Weight Matrices

Variables	KNN (k=4)	KNN (k=5)	KNN (k=6)	IDW	Queen
In_Economy	0.0029	0.0007	-0.0002	0.0022	0.0021
In_Health	0.0067	0.0074	0.0068	0.0075*	0.0049
In_Education	-0.0074***	-0.0059**	-0.0056*	-0.0060**	-0.0060***
In_Social	-0.0028	-0.0029	-0.0044	-0.0021	-0.0004
Spatial Parameter					
Spatial autoregressive (λ/ρ)	0.4462***	0.4718***	0.4850***	0.4207***	0.3030***

Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Across all alternative spatial configurations, the spatial autoregressive parameter (λ/ρ) remained highly stable and positive (ranging from 0.3030 to 0.4850). Furthermore, the core marginal impacts demonstrated consistent stability; the total spatial impact of educational expenditure remained significantly negative across all weight matrices. This structural consistency confirms that the primary redistributive findings of the study are robust and strictly not sensitive to the arbitrary selection of spatial proximity definitions.

4.4. Discussion

The empirical estimations validated the theoretical premise that regional income inequality does not operate within an isolated geographical vacuum (Rahman et al., 2024). The significant spatial autoregressive parameter calculated in this study confirmed that economic disparities in one province systematically influence inequality formations in contiguous areas (Medeiros et al., 2022). This finding highlights the limitation of traditional non-spatial models, demonstrating that localized fiscal policies actively reshape economic trajectories across borders through interjurisdictional policy mimicry and agglomeration externalities (De Siano & D'Uva, 2017; Khan et al., 2026). Consequently, treating adjacent archipelagic regions as independent entities obscures the spatial feedback loops governing regional wealth distribution.

Decomposing the marginal policy impacts revealed that localized educational expenditures significantly compressed income inequality within the originating provinces. This outcome addresses the theoretical ambiguity surrounding short-term human capital investments in developing archipelagos, indicating that public schooling functions as an economic equalizer when structurally supported (Hamza & Cochrane, 2026; Jiang & Yin, 2026). The negative direct impact aligns with the macroeconomic consensus that human capital democratization compresses wage gaps and minimizes economic vulnerability among marginalized demographics (Mbewe et al., 2025; Sylwester, 2002). It implies that despite the logistical challenges inherent in geographically fragmented nations, persistent local funding directed at educational facility improvements yields tangible egalitarian benefits.

Conversely, the spatial econometric estimations revealed that health expenditures exhibited a positive direct correlation with the Gini ratio. While the precise causal mechanisms require future micro-level validation, this dynamic suggests that localized health investments may inadvertently favor urban centers or higher-income brackets. This phenomenon is potentially driven by the unequal geographical distribution of advanced healthcare facilities, which remain heavily concentrated in metropolitan areas, thereby limiting access for marginalized rural populations (Cortés, 2021; Yin et al., 2026). Such structural segregation implies that central and local governments must deliberately integrate targeted public service improvements with inclusive spatial planning to prevent localized welfare disparities from widening during rapid regional development (Sun et al., 2017; Yuan et al., 2024). It demonstrates that simply increasing sectoral budgets without resolving the underlying spatial inequality of healthcare facilities fails to adequately protect vulnerable demographics.

A critical insight from the adopted spatial framework emerged from the indirect impacts generated by economic expenditures. While localized economic spending did not alter internal inequality, it produced a negative spatial spillover that systematically reduced income disparities across neighboring provinces. This empirical evidence supports the existence of positive agglomeration externalities originating from public infrastructure developments (Hakim & Rosini, 2022; Ou et al., 2026). Regional spending on physical infrastructure networks

actively reshapes economic trajectories in adjacent territories by lowering cross-border logistical costs, stimulating commuter labor absorption, and promoting interjurisdictional industrial cooperation (Luo & Fu, 2020).

Interestingly, the extended spatial framework revealed that social protection allocations produced a positive spatial spillover effect on inequality. This unexpected dynamic suggests that localized social safety nets might inadvertently trigger poverty-driven migration; vulnerable demographics may migrate toward adjacent provinces with superior social assistance programs, thereby unintentionally concentrating poverty and widening the Gini ratio in interconnected areas. Conversely, the robust negative spillover generated by the GRDP control variable underscores that overarching regional macroeconomic capacity serves as a fundamental anchor in driving interregional redistributive resilience. Ultimately, these combined empirical insights establish that modern fiscal evaluations must incorporate spatial econometric architectures to capture the multidimensional feedback loops governing territorial wealth redistribution across interconnected archipelagos (Runge, 2023).

5. Conclusion and Suggestion

This study investigated the spatial dynamics of sectoral local government expenditures and their impact on regional income inequality across 33 Indonesian provinces. The empirical results confirmed that different fiscal functions produce distinct distributive outcomes. Educational expenditures directly compressed internal income inequality, functioning as a structural economic equalizer. Conversely, health allocations inadvertently widened the local Gini ratio, reflecting uneven spatial facility distributions. Additionally, the analysis revealed that economic infrastructure expenditures generated substantial negative spatial spillovers, effectively reducing income disparities in contiguous provinces despite showing no significant direct internal impact.

By empirically distinguishing between direct local fiscal effects and indirect neighboring spillovers, this study demonstrates that central and local governments must transition from isolated fiscal strategies toward coordinated interregional planning. Policymakers are explicitly advised to synchronize physical infrastructure expansions across provincial borders to efficiently leverage these negative inequality spillovers. Furthermore, intergovernmental fiscal transfers must formally safeguard educational budgets in lagging regions while reallocating health expenditures to prioritize primary care access for marginalized rural communities. This collaborative approach ensures that positive agglomeration externalities are leveraged efficiently and vulnerable demographics remain protected during periods of rapid spatial economic integration.

6. Limitations and Future Research

While this study provides a robust empirical foundation for spatial fiscal policy, several methodological and data limitations must be acknowledged. First, the utilization of macro-level provincial panel data precludes the observation of localized economic variations. Because fiscal decentralization authority in Indonesia is primarily delegated to the district and municipal levels, provincial aggregates might mask significant intra-provincial fiscal disparities and micro-level welfare dynamics. Second, the adopted spatial econometric framework relies on a predetermined geographical weight matrix. In a fragmented archipelagic nation, geographic proximity does not always perfectly correlate with actual economic connectivity. Variations in maritime logistics and inter-island trade networks

suggest that economic or infrastructure distance matrices might provide a different perspective on spatial spillovers. Third, the current model primarily examines linear interdependencies, which may not fully capture potential saturation points or diminishing marginal returns in regional fiscal capacity over the long term.

To address these constraints, future research must integrate granular intra-regional microdata at the district or municipal level to evaluate fiscal policy impacts more accurately. Additionally, exploring the nonlinear threshold effects of fiscal decentralization and testing alternative spatial weight configurations based on trade flows or infrastructure connectivity will further advance the understanding of territorial wealth redistribution. Finally, this study acknowledges the inherent risk of endogeneity and reverse causality, as regional inequality levels may simultaneously dictate the strategic allocation of public expenditure. Although preliminary robustness checks utilizing time-lagged fiscal variables (t-1) were conducted to explicitly mitigate simultaneity bias, these predetermined regressors do not completely substitute for a fully dynamic spatial panel estimation. Consequently, the causal interpretations presented in this study must be approached with caution. Future research should formally incorporate dynamic spatial panel models or instrumental variables to comprehensively address potential reverse causality and provide deeper insights into the long-term temporal relationship between sectoral public expenditure and regional income inequality

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Declaration of AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used Scopus AI in order to identify relevant literature. After using this tool, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the publication.

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