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Hidden Spillovers of Human Development: Enclave Panel Threshold SAR Evidence from West Java

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Abstract

This study examines the spatial spillover dynamics of the Human Development Index (HDI) in West Java Province, Indonesia, using the Enclave Panel Threshold Spatial Autoregressive (E-PT-SAR) model and panel data from 27 districts during 2021–2025. The model extends the conventional PT-SAR framework by incorporating enclave identification, distinguishing core prosperous regions, prosperous enclaves, and poor regions. The estimated poverty threshold ($\gamma = 8.5124\%$) separates West Java into 14 prosperous and 13 poor districts, while the enclavity index and a stationarity-constrained enclave threshold ($\tau = 0.7143$) identify a single prosperous enclave, Ciamis. The results reveal that spatial spillovers differ markedly across regimes. Crucially, the spillover among prosperous districts is insignificant in the conventional two-regime model ($\rho = 0.4656$, $p = 0.240$) but becomes significant once the isolated enclave is separated (core prosperous $\rho = 0.6344$, $p = 0.025$), consistent with the possibility that the standard threshold model masks part of the spillover among prosperous districts. A strong spillover is also found in the poor regime ($\rho = 0.9740$), whereas the enclave shows no statistically detectable spillover, which we interpret cautiously given its single-district sample rather than as confirmed evidence of isolation. The effects decomposition confirms that indirect (spillover) effects dominate in the poor regime. Because the enclave regime comprises only one district, its results are interpreted as exploratory. These findings imply that regional development policies should be tailored to different spatial regimes.

Keywords: Spatial Econometrics; E-PT-SAR; Enclave; Spatial Spillover; HDI; West Java

1. Introduction

West Java Province, Indonesia's most populous province, exhibits striking spatial disparities in human development. The northern region (Bekasi, Karawang, Purwakarta) has achieved high HDI, driven by industrialization and urban agglomeration, while the southern region (Cianjur, Sukabumi, Garut, Tasikmalaya) consistently shows lower HDI, characterized by agricultural dependence and limited infrastructure. This pattern reflects a broader phenomenon in regional data: development indicators often exhibit spatial dependence, so that regions with similar characteristics tend to cluster [1]. This raises a critical question: does prosperity in high-HDI regions spill over to neighboring areas, or do these regions develop independently?

A particularly interesting case is Ciamis. Although a relatively prosperous, low-poverty district, it is surrounded by neighbors with considerably higher poverty, so that most of its

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immediate neighbors belong to a different (poorer) regime. This configuration suggests an enclave phenomenon, a prosperous region spatially surrounded by poorer regions. The concept of an enclave was originally defined mathematically as a region isolated from others of its kind [2], and has since been applied in regional development studies to describe economically advantaged areas weakly connected to their surroundings [3]. In Poland, wealthy regions surrounded by poor regions acted as spatial outliers with no spillovers to poorer neighbors [4], and Farole found that Special Economic Zones sometimes develop as enclaves with limited local linkages, potentially worsening surrounding conditions [3]. Such evidence suggests enclaves may behave fundamentally differently from prosperous regions that form contiguous clusters.

This matters because it challenges the assumption that prosperous regions naturally drive growth in neighboring areas. Standard spatial models such as SAR assume a homogeneous relationship between neighbors [5], yet regional development is often heterogeneous: prosperous industrial clusters in northern West Java can generate strong spillovers through integrated labor markets and transport, whereas enclaves may remain isolated despite their advantages. Hansen addressed parameter homogeneity through the panel threshold model, later extended to spatial panels by Wei et al. in the Panel Threshold Spatial Durbin (PT-SDM) model [6, 7]. This improves on homogeneous models by letting spillovers differ between regimes (e.g., prosperous vs. poor), but it still assumes homogeneity *within* a regime, so it cannot distinguish contiguous prosperous clusters from spatially isolated enclaves.

This is a statistical, not merely descriptive, limitation: within a regime the spatial coefficient is a single pooled parameter, so districts whose neighbors belong overwhelmingly to the opposite regime contribute near-zero spatial interaction to the same average as strongly interacting clustered districts, attenuating the pooled estimate toward zero and inflating its standard error, so a genuine spillover may go undetected. This cannot be fixed by refining the poverty threshold, because what distinguishes an enclave is the regime of its *neighbors*, a dimension orthogonal to the threshold variable itself; capturing it requires a second, spatial-configuration partition.

This study applies the Enclave Panel Threshold Spatial Autoregressive (E-PT-SAR) model to HDI data from 27 districts in West Java, 2021–2025 (135 observations), with the open unemployment rate (TPT), log GRDP per capita (log PDRBK), and poverty rate as explanatory variables [8–11]. The objectives are: (i) identify the optimal poverty threshold separating prosperous and poor regions; (ii) identify prosperous enclaves via the enclavity index; and (iii) estimate and compare spillovers across core prosperous, prosperous enclave, and poor regimes. The contribution is twofold: it operationalizes the E-PT-SAR framework, whose derivation and asymptotics are set out in a companion paper [12], in an empirical setting; and it shows that failing to separate isolated prosperous districts can change the estimated spillover among prosperous regions, so enclave identification changes the substantive conclusion about prosperous regions, not merely their description.

2. Methodology

The analysis proceeds in six stages. We first select the appropriate panel data specification (Pooled OLS, Fixed Effects, or Random Effects) and construct the queen-contiguity spatial weight matrix. We then test for spatial dependence using Moran's I and Lagrange Multiplier statistics to determine whether a spatial autoregressive (SAR) specification is warranted. Building on the baseline panel SAR model, we introduce a poverty-based threshold to allow the spatial coefficient and covariate effects to differ between prosperous and poor regimes (PT-SAR), and subsequently extend this framework with an enclavity index that separates spatially isolated prosperous districts from prosperous districts that form contiguous clusters (E-PT-SAR). Finally, spillovers are decomposed into direct and indirect effects for interpretation. Each stage is detailed in the following subsections.

2.1. Data and Variables

This study uses panel data from 27 districts and cities in West Java, 2021–2025 (135 observations), obtained from Statistics Indonesia (BPS). The dependent variable is HDI; explanatory variables are TPT, log PDRBK, and the poverty rate, the latter also serving as the threshold variable. Table 1 summarizes the variables.

Table 1: Variable Definitions and Descriptions

Variable	Symbol	Description	Unit
HDI	y	Composite measure of health, education, living standards	Index (0-100)
TPT	x_1	% labor force unemployed and seeking work	%
PDRBK	x_2	Total economic output per person	Thousand IDR
Poverty Rate	x_3	% population below poverty line	%

Note: ratio-scale variables, source BPS.

2.2. Panel Data Fixed Effects Model

Prior to spatial analysis, Pooled OLS, Fixed Effects (FE), and Random Effects (RE) are estimated:

$$y_{it} = \underline{x}'_{it}\underline{\beta} + \mu_i + \varepsilon_{it} \tag{1}$$

where μ_i are individual fixed effects and $\varepsilon_{it} \sim N(0, \sigma^2)$. Pooled OLS sets $\mu_i = 0$; FE allows μ_i to correlate with x_{it} (removed via within transformation); RE assumes no such correlation [13].

Chow test (H_0: Pooled OLS appropriate vs. H_1: FE appropriate) [14]:

$$F = \frac{(RSS_{Pooled} - RSS_{FE})/(N-1)}{RSS_{FE}/(NT - N - K)} \tag{2}$$

which follows $F(N-1,\, NT-N-K)$ under H_0; $p < 0.05$ favors FE [13].

Hausman test (H_0: $\text{Cov}(\mu_i, x_{it}) = 0$, RE consistent, vs. H_1: FE consistent) [15]:

$$H = (\hat{\underline{\beta}}_{RE} - \hat{\underline{\beta}}_{FE})'[\text{Var}(\hat{\underline{\beta}}_{FE}) - \text{Var}(\hat{\underline{\beta}}_{RE})]^{-1}(\hat{\underline{\beta}}_{RE} - \hat{\underline{\beta}}_{FE}) \tag{3}$$

which is $\chi^2(K)$ under H_0; $p < 0.05$ favors FE [13].

2.3. Spatial Weight Matrix (Queen Contiguity)

Two regions are neighbors if they share a border or vertex [1, 16–18]:

$$w_{ij} = \begin{cases} 1, & \text{if regions } i, j \text{ share a border or vertex} \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

with $w_{ii} = 0$. The contiguity structure follows official BPS boundaries, restricted to West Java's 27 districts/cities; several municipalities entirely enclosed by their parent regency (e.g., Kota Bogor, Kota Sukabumi) therefore have few neighbors. The matrix is row-standardized [16]:

$$w^*_{ij} = \frac{w_{ij}}{\sum_{j=1}^{N} w_{ij}} \tag{5}$$

so that $\sum_{j=1}^{N} w^*_{ij} = 1$ for each row i.

2.4. Spatial Autocorrelation: Moran's I

Moran's I is applied to (i) HDI and (ii) FE residuals [1, 16, 17]:

$$I_y = \frac{\sum_i \sum_j w_{ij}(y_{it} - \bar{y})(y_{jt} - \bar{y})}{\sum_t \sum_i (y_{it} - \bar{y})^2} \times \frac{N}{\sum_i \sum_j w_{ij}} \tag{6}$$

tested against $H_0 : I_y = E(I)$, with, under H_0 [1]:

$$E(I) = -\frac{1}{N-1} \tag{7}$$

Significance uses a 999-permutation bootstrap; $p < 0.05$ rejects H_0. On residuals $\hat{e}_{it}$ from the FE model [16]:

$$I_e = \frac{\sum_t \sum_i \sum_j w_{ij}\hat{e}_{it}\hat{e}_{jt}}{\sum_t \sum_i \hat{e}_{it}^2} \times \frac{N}{\sum_i \sum_j w_{ij}} \tag{8}$$

tested against $H_0 : I_e = 0$; rejection indicates a spatial model is required [16].

2.5. Lagrange Multiplier (LM) Tests

Standard and robust LM tests for panel data determine SAR vs. SEM [16–18]:

$$LM_{error} = \frac{[\underline{e}'(I_T \otimes W)\underline{e}/\hat{\sigma}^2]^2}{T \cdot \mathrm{tr}(W^2 + W'W)} \sim \chi^2(1) \tag{9}$$

$$LM_{lag} = \frac{\left[\underline{e}'(I_T \otimes W)\underline{y}/\hat{\sigma}^2\right]^2}{D} \sim \chi^2(1) \tag{10}$$

with $D = T \cdot \mathrm{tr}(W^2 + W'W) + T^2(WX\underline{\beta})'M(WX\underline{\beta})/\hat{\sigma}^2$, $M = I_N - X(X'X)^{-1}X'$. Robust versions correct for the presence of the other type of dependence [16]:

$$RLM_{lag} = \frac{\left[\underline{e}'(I_T \otimes W)\underline{y}/\hat{\sigma}^2 - \underline{e}'(I_T \otimes W)\underline{e}/\hat{\sigma}^2\right]^2}{T \cdot \mathrm{tr}(W^2 + W'W) - [\underline{e}'(I_T \otimes W)\underline{e}]^2 \,/\, (\hat{\sigma}^2 T \cdot \mathrm{tr}(W^2 + W'W))} \sim \chi^2(1) \tag{11}$$

$$RLM_{error} = \frac{\left[\underline{e}'(I_T \otimes W)\underline{e}/\hat{\sigma}^2 - \underline{e}'(I_T \otimes W)\underline{y}/\hat{\sigma}^2\right]^2}{T \cdot \mathrm{tr}(W^2 + W'W) - \left[\underline{e}'(I_T \otimes W)\underline{y}\right]^2 \,/\, (\hat{\sigma}^2 T \cdot \mathrm{tr}(W^2 + W'W))} \sim \chi^2(1) \tag{12}$$

Decision rule [19]: significant RLM_{lag} only $\Rightarrow$ SAR; significant RLM_{error} only $\Rightarrow$ SEM; both significant $\Rightarrow$ consider SDM; neither $\Rightarrow$ FE suffices (critical value $\chi^2_{0.05,1} = 3.841$).

2.6. Spatial Autoregressive (SAR) Model

The Panel SAR model with fixed effects adds a spatially lagged dependent variable [5]:

$$y_{it} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \underline{x}'_{it}\underline{\beta} + \mu_i + \varepsilon_{it} \tag{13}$$

$\rho > 0$ (significant) indicates positive spillover, $\rho < 0$ negative, $\rho = 0$/insignificant none. Stability requires $|\rho| < 1$ [16], so the multiplier $(I_N - \rho W)^{-1}$ exists. Because Wy is endogenous [1], estimation uses ML or Spatial Two-Stage Least Squares (S2SLS) [20], with μ_i removed by the within transformation [16].

2.7. Panel Threshold SAR (PT-SAR) Model

Following Hansen and Wei et al. [6, 7], parameters vary across two poverty-based regimes:

$$y_{it} = \begin{cases} \rho_1 \sum_j w_{ij} y_{jt} + \underline{x}'_{it} \underline{\beta}_1 + \mu_i + \varepsilon_{it}, & \bar{q}_i \leq \gamma \\ \rho_2 \sum_j w_{ij} y_{jt} + \underline{x}'_{it} \underline{\beta}_2 + \mu_i + \varepsilon_{it}, & \bar{q}_i > \gamma \end{cases} \tag{14}$$

where $\bar{q}_i = \frac{1}{T} \sum_t q_{it}$ is time-averaged poverty and γ is estimated by grid search [6]:

$$\hat{\gamma} = \arg\min_{\gamma \in \Gamma} SSR(\gamma) \tag{15}$$

with Γ the trimmed candidate set.

2.8. Enclave Identification

A prosperous region may form a contiguous cluster or be spatially isolated (a prosperous enclave) [3]. The enclavity index E_i is the share of neighbors in the opposite regime [12]:

$$E_i = \frac{\sum_j w_{ij} \cdot I(r_j \neq r_i)}{\sum_j w_{ij}} \tag{16}$$

ranging 0 (cluster) to 1 (fully isolated) [2]. Prosperous regions split into **Core Prosperous** ($\bar{q}_i \leq \gamma$, $E_i \leq \tau$) and **Prosperous Enclave** ($\bar{q}_i \leq \gamma$, $E_i > \tau$); with the poor regime ($\bar{q}_i > \gamma$) this gives three mutually exclusive regimes. τ is selected by grid search subject to $|\rho| < 1$ (stationarity), choosing the stationary candidate with the lowest SSR; a district exactly at $E_i = \tau$ is core prosperous. Full derivation in [12].

2.9. Enclave PT-SAR (E-PT-SAR) Model

The three-regime model is:

$$y_{it} = \begin{cases} \rho_1 \sum_j w_{ij} y_{jt} + \underline{x}'_{it} \underline{\beta}_1 + \mu_i + \varepsilon_{it}, & \bar{q}_i \leq \gamma, \ E_i \leq \tau \\ \rho_2 \sum_j w_{ij} y_{jt} + \underline{x}'_{it} \underline{\beta}_2 + \mu_i + \varepsilon_{it}, & \bar{q}_i \leq \gamma, \ E_i > \tau \\ \rho_3 \sum_j w_{ij} y_{jt} + \underline{x}'_{it} \underline{\beta}_3 + \mu_i + \varepsilon_{it}, & \bar{q}_i > \gamma \end{cases} \tag{17}$$

Fixed effects are removed via within transformation; estimation is by S2SLS with instruments $H = [X, WX, W^2X]$ [20]. Complete derivation, estimation, and asymptotics in the companion paper [12].

2.10. Spatial Spillover Decomposition

Because Wy makes the model non-linear, coefficients are not marginal effects. Following LeSage and Pace [5], let $P = \text{diag}(\rho_{r(i)})$ and $S = (I_N - PW)^{-1}$. For variable k, $M_k = S \cdot \text{diag}(\beta_{k,r(i)})$; the average direct effect (ADE) is the mean diagonal of M_k within regime r, the average total effect (ATE) the mean row sum, and $AIE = ATE - ADE$. S is well defined when the spectral radius of PW is below one, guaranteed by $|\rho| < 1$ (Section 2.8).

3. Results and Discussion

This section proceeds from descriptive evidence toward the model that motivates our main contribution. We begin with descriptive statistics and preliminary spatial diagnostics, then estimate the baseline panel SAR model. We next identify the poverty threshold and estimate the two-regime PT-SAR model, which motivates the enclave identification step; the resulting three-regime E-PT-SAR model is then estimated, decomposed into direct and indirect effects, and compared against its nested alternatives. The section closes with a discussion that interprets these results jointly and states their limitations.

3.1. Descriptive Statistics

Table 2 presents descriptive statistics, 2021–2025.

Table 2: Descriptive Statistics (2021–2025)

Variable	N	Mean	Median	SD	Min	Max
HDI	135	74.12	73.27	4.40	67.16	84.66
TPT (%)	135	7.49	7.65	2.29	1.52	13.07
log PDRBK	135	10.57	10.47	0.98	8.12	12.64
Poverty Rate (%)	135	8.28	8.46	2.71	2.31	13.13

Source: BPS Jawa Barat.

HDI ranges from 67.16 (Cianjur) to 84.66 (Kota Bandung); poverty from 2.31% (Kota Depok) to 13.13% (Kota Tasikmalaya). Figure 1 maps HDI for 2025, showing a clear north-south divide: high-HDI northern/metropolitan districts versus lower-HDI southern districts. Ciamis, a low-poverty district surrounded predominantly by poorer neighbors, is visually a candidate enclave, motivating the analysis below. The pattern is stable across 2021–2025.

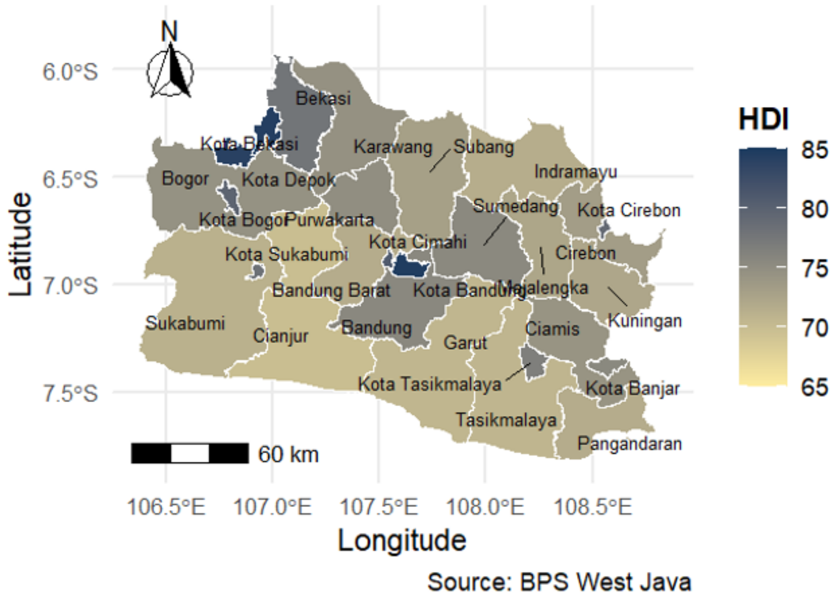

Fig. 1: Thematic map of HDI in West Java, 2025.

3.2. Panel Data Model Selection

Before estimating the spatial panel model, model selection tests were conducted to determine the appropriate baseline panel specification. The Chow test was used to compare the pooled model and the fixed effects model, while the Hausman test was used to compare the random effects and fixed effects models. The results of these tests are presented in Table 3.

Table 3: Panel Model Selection Tests

Test	Hypothesis	Statistic	p	Decision
Chow	H_0: Pooled, H_1: FE	$F = 1070.67$	< 0.001	Choose FE
Hausman	H_0: RE, H_1: FE	$\chi^2 = 1318.04$	< 0.001	Choose FE

As shown in Table 3, both tests reject their null hypotheses decisively [13]. Therefore, the fixed effects model is selected as the baseline panel specification because it controls for time-invariant district-level heterogeneity, such as geography, historical characteristics, and institutional differences.

3.3. Spatial Dependence Test

Moran's I on HDI is positive and significant every year (Table 4), confirming spatial clustering [1].

Table 4: Moran's I on HDI (2021–2025)

Year	Moran's I	p
2021	0.283	0.0107**
2022	0.281	0.0112**
2023	0.277	0.0121**
2024	0.275	0.0127**
2025	0.284	0.0105**

The within transformation removes time-invariant, mostly between-district spatial clustering, so in a short panel ($T = 5$) FE residuals have low power to detect residual spatial dependence ($I = 0.167$, $p = 0.072$). Pooled OLS residuals retain this cross-sectional variation and better test whether a spatial specification is needed at all: Moran's I = 0.2615 ($z = 4.03$, $p = 2.78 \times 10^{-5}$), firmly rejecting no spatial autocorrelation. LM tests on FE residuals (Table 5) confirm this: Robust LM Lag exceeds Robust LM Error, favoring SAR over SEM [19].

Table 5: Lagrange Multiplier Tests

Test	Statistic	p
LM Lag	23.79	$< 0.001^{***}$
LM Error	2.75	0.097
Robust LM Lag	41.57	$< 0.001^{***}$
Robust LM Error	20.54	$< 0.001^{***}$

Both robust statistics are significant, which under the strict decision rule of Anselin and Rey [19] would nominally point toward a spatial Durbin (SDM) specification. We nonetheless retain SAR for three reasons. First, the magnitude of the two statistics is not comparable: Robust LM Lag (41.57) is roughly double Robust LM Error (20.54), so lag dependence dominates error dependence even though both clear the $\chi^2_{0.05,1} = 3.841$ threshold; the non-robust LM Error is, in fact, insignificant ($p = 0.097$), and only becomes significant in its robust form because it partly absorbs the strong lag dependence that the robust correction does not fully net out. Second, our research question concerns whether prosperity in one district diffuses to its neighbors through the outcome itself (i.e. a lag mechanism, $\rho \sum_j w_{ij} y_{jt}$), which is the object the enclave identification in Section 2.8 is designed to test; an SDM specification would additionally require regime-specific spatially lagged covariates (WX) for every one of the three E-PT-SAR regimes, which the available sample (five annual observations per district, and only one district in the enclave regime) cannot support without severe over-parameterization. Third, this choice follows the same SAR-based approach used in the companion methodological paper [12] from which the E-PT-SAR estimator is derived, ensuring consistency between the theoretical framework and its empirical application here. We flag SDM as a natural extension once longer panels or additional enclave districts become available, and note this explicitly as a limitation in Section 3.11.

3.4. Baseline SAR Model

After the fixed effects specification and SAR structure were supported by the preliminary tests, the baseline SAR model was estimated to examine the overall spatial dependence in HDI before introducing threshold and enclave regimes. The estimation results and spatial effect decomposition are presented in Table 6.

Table 6: Baseline SAR Model: Estimates and Effects

Parameter	Coef.	SE	p	ADE	AIE
ρ	0.5306	0.0712	$< 0.001^{***}$	–	–
TPT	−0.0062	0.0186	0.739	−0.0068	−0.0064
log PDRBK	6.0367	1.0108	$< 0.001^{***}$	6.5995	6.2601
Poverty	0.0305	0.0564	0.589	0.0333	0.0316

ADE/AIE = direct/indirect effects (HDI points per unit change) from $S = (I - \rho W)^{-1}$. Total = ADE+AIE.

As reported in Table 6, the spatial autoregressive coefficient is positive and statistically significant, with $\rho = 0.5306$ and $p < 0.001$. This confirms the presence of strong positive spatial spillover in HDI across districts. Only log PDRBK is statistically significant, indicating that economic performance plays an important role in explaining HDI differences.

3.5. Poverty Threshold Identification

The threshold variable $\bar{q}_i = \frac{1}{T}\sum_t q_{it}$ ranges 2.428–12.178% (mean 8.282%, median 8.454%). Following Hansen's grid search over the trimmed [15%,85%] range [4.850%, 11.325%] (100 candidates), the SSR is minimized at $\gamma^* = 8.5124\%$ (min SSR = 3.2747; Figure 2), classifying 14 districts prosperous and 13 poor. Prosperous districts concentrate in the northern industrial belt and metropolitan areas; poor districts in the southern agricultural areas, matching Figure 1. Prosperous (14): Kota Depok, Kota Bandung, Kota Bekasi, Kota Cimahi, Bekasi, Kota Banjar, Kabupaten Bandung, Kota Bogor, Sukabumi, Bogor, Kota Sukabumi, Karawang, Purwakarta, Ciamis. Poor (13): Pangandaran, Kota Cirebon, Subang, Sumedang, Garut, Cianjur, Tasikmalaya, Bandung Barat, Majalengka, Cirebon, Kota Tasikmalaya, Kuningan, Indramayu.

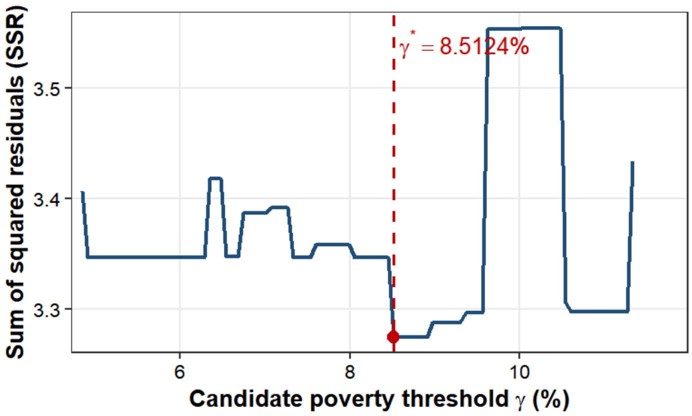

Fig. 2: Hansen grid search: $SSR(\gamma)$ for the poverty threshold.

3.6. PT-SAR Model (Two Regimes)

After identifying $\gamma = 8.5124\%$, the PT-SAR model is estimated by S2SLS after the within transformation (SEs from the S2SLS asymptotic covariance matrix). Table 7 reports estimates and effects (computed from the joint multiplier $S = (I - PW)^{-1}$, $P = \text{diag}(\rho_{regime})$, since a per-regime shortcut $\beta/(1-\rho)$ is unstable near $\rho \approx 0.97$).

Table 7: PT-SAR Estimation by Regime: Coefficients and Effects

Regime	**Param.**	**Coef.**	**SE**	p	**ADE**	**AIE**
Prosperous	ρ (N=14)	0.4656	0.3963	0.240	–	–
Prosperous	TPT	0.0272	0.0325	0.404	0.0304	0.0119
Prosperous	log PDRBK	6.2664	5.0937	0.219	7.0147	5.8079
Prosperous	Poverty	−0.1321	0.1116	0.237	−0.1479	0.0722
Poor	ρ (N=13)	0.9740	0.1488	$< 0.001^{***}$	–	–
Poor	TPT	−0.0110	0.0274	0.688	−0.0167	−0.0029
Poor	log PDRBK	1.8909	1.9746	0.338	2.8683	17.9132
Poor	Poverty	0.2416	0.0837	0.004^{**}	0.3665	0.8028

Spillover is strong and significant in the poor regime ($\rho = 0.974$) but weak and insignificant among prosperous districts ($\rho = 0.4656$, $p = 0.240$)—a first sign of internal heterogeneity motivating enclave analysis. No covariate is significant among prosperous districts; among poor districts only poverty is (0.2416, $p = 0.004$). The GRDP total effect is far larger in the poor regime (20.78, dominated 86% by the indirect component) than the prosperous regime (12.82, direct/indirect more balanced), reflecting the poor regime's near-unity spatial coefficient. This asymmetry motivates the finer partition via enclave identification.

3.7. Enclave Identification

For each prosperous district, E_i is the share of poor neighbors (Table 8; poor-regime enclaves are not evaluated as their maximum E, 0.667, is below any admissible threshold).

Table 8: Enclavity Index for Prosperous Districts

District	**Neighbors**	**Poor Nbrs**	E	**Class**
Ciamis	6	5	0.8333	Enclave
Bandung	7	5	0.7143	Core
Purwakarta	5	3	0.6000	Core
Kota Bandung	3	1	0.3333	Core
Kota Cimahi	3	1	0.3333	Core
Sukabumi	3	1	0.3333	Core
Karawang	4	1	0.2500	Core
Bogor	8	1	0.1250	Core
Bekasi, Kota Banjar, Kota Bekasi, Kota Bogor, Kota Depok, Kota Sukabumi	–	0	0.0000	Core

A district is an enclave if $E_i > \tau$ (strict criterion); τ is chosen by grid search subject to stationarity ($|\rho| < 1$; Table 9).

Table 9: Enclave Threshold Grid Search

τ	**SSR**	**# Enclaves**	$\rho_{enclave}$	**Stationary**
0.1250	3.2566	7	0.2941	Yes
0.2500	3.2649	6	0.3855	Yes
0.3333	3.2599	3	1.9536	No
0.6000	3.1950	2	1.6490	No
0.7143	3.2432	1	0.1358	Yes (Selected)
0.8333	–	0	–	–

Three of the six candidate thresholds are stationary ($\tau = 0.1250, 0.2500, 0.7143$); the two mid-range candidates ($\tau = 0.33, 0.60$) are inadmissible because they yield explosive, non-stationary enclave coefficients ($\rho = 1.95, 1.65$). Among the stationary candidates, $\tau^* = 0.7143$ is selected because it attains the lowest SSR (3.2432), and it happens to isolate Ciamis alone ($E = 0.8333$); Kabupaten Bandung, at $E = 0.7143$ exactly, remains core under the strict criterion. We emphasize that $\tau^* = 0.7143$ is the best-fitting member of a small stationary candidate set rather than the unique admissible specification: $\tau = 0.1250$ and $\tau = 0.2500$ are also stationary, with SSR values (3.2566 and 3.2649) close to that of τ^*, though they classify substantially more districts (seven and six, respectively) as enclaves. We report $\tau^* = 0.7143$ as our preferred specification on SSR grounds, and revisit the sensitivity of the main result to this choice in Section 3.9. Under the selected threshold, the final partition is 13 core prosperous, 1 enclave (Ciamis), 13 poor (Figure 3). Ciamis sits in the south-east, surrounded by Kuningan, Majalengka, Tasikmalaya, and Pangandaran, structurally explaining its isolation from the northern/central prosperous cluster. With only one district (five observations), enclave-specific estimates below are exploratory and should be read as illustrative of the E-PT-SAR framework rather than as conclusive evidence about Ciamis itself.

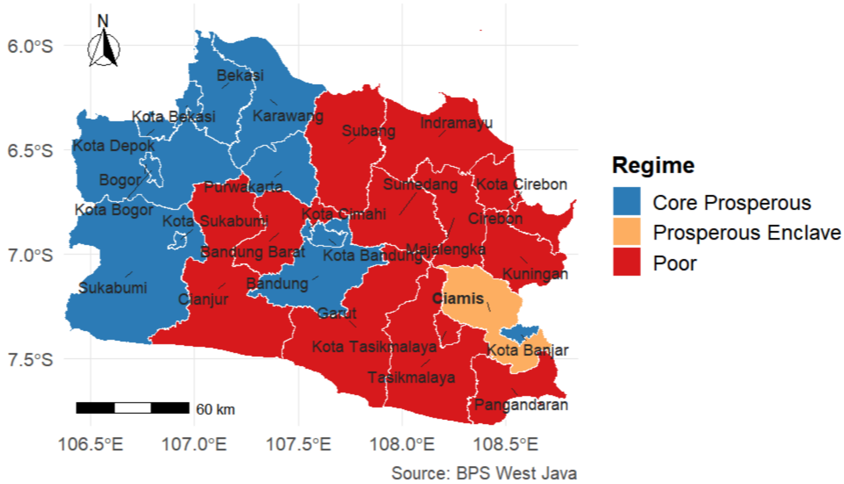

Fig. 3: Three-regime classification (Core Prosperous, Prosperous Enclave, Poor).

3.8. E-PT-SAR Model

The three-regime model (core prosperous 13, enclave 1, poor 13) is estimated by S2SLS after the within transformation (Table 10).

Table 10: E-PT-SAR Estimation by Regime

Regime	Parameter	Coef.	SE	p
Core Prosperous	ρ	0.6344	0.2826	0.0248*
Core Prosperous	TPT	0.0232	0.0318	0.4659
Core Prosperous	log PDRBK	4.3178	3.7275	0.2467
Core Prosperous	Poverty	−0.0934	0.1053	0.3748
Prosperous Enclave	ρ	0.1358	2.5642	0.9578
Prosperous Enclave	TPT	0.0752	0.1564	0.6308
Prosperous Enclave	log PDRBK	9.1952	30.3730	0.7621
Prosperous Enclave	Poverty	−0.2964	1.3991	0.8322
Poor	ρ	0.9740	0.1505	9.8×10^{-11}***
Poor	TPT	−0.0110	0.0277	0.6909
Poor	log PDRBK	1.8909	1.9974	0.3438
Poor	Poverty	0.2416	0.0847	0.0043**

The central result: once Ciamis is separated out, the core prosperous coefficient rises from an insignificant $\rho = 0.4656$ ($p = 0.240$, pooled PT-SAR) to a significant $\rho = 0.6344$ ($p = 0.025$). We describe this as the estimated core-prosperous spillover becoming detectable once the isolated enclave is removed from the pooled prosperous group; Section 3.9 reports a formal test of whether the two estimates differ from one another before we draw any stronger conclusion. The enclave itself shows $\rho = 0.1358$ with a very large SE ($p = 0.958$), which reflects insufficient data (one district, five observations) and should not be read as evidence that the enclave truly has no spillover. The poor regime is essentially unchanged ($\rho = 0.974$, $p < 0.001$); only poverty remains significant there (0.2416, $p = 0.004$), indicating HDI differences are transmitted mainly spatially rather than via covariates.

3.9. Spillover Decomposition and Robustness

Effects are decomposed via $S = (I - PW)^{-1}$; the spectral radius of PW is 0.8370 (< 1), so the decomposition is valid (Table 11).

Table 11: Spillover Decomposition (E-PT-SAR)

Regime	Variable	ADE	AIE	ATE
Core Prosperous	TPT	0.0275	0.0259	0.0534
Core Prosperous	log PDRBK	5.1325	8.0611	13.1937
Core Prosperous	Poverty	−0.1110	0.0794	−0.0316
Enclave	TPT	0.0828	−0.0040	0.0788
Enclave	log PDRBK	10.1299	1.4446	11.5746
Enclave	Poverty	−0.3266	0.1254	−0.2011
Poor	TPT	−0.0163	0.0230	0.0067
Poor	log PDRBK	2.8082	16.8562	19.6643
Poor	Poverty	0.3588	0.6579	1.0167

For log GRDP, the indirect effect dominates in the poor regime (86% of total, six times the direct effect) and is substantial in the core prosperous regime (1.6× direct). In the enclave, the indirect effect is small relative to the direct effect (ratio 0.14): the point estimates are consistent with Ciamis benefiting from its own gains while transmitting or receiving comparatively little through the spatial channel, although with a single district in this regime we treat this pattern as suggestive rather than conclusive.

To assess whether the difference between the pooled prosperous spillover ($\rho = 0.4656$) and the core-prosperous spillover ($\rho = 0.6344$) is itself statistically supported, we conducted a district-level bootstrap ($B = 200$, resampling districts with replacement within regime, re-estimating the PT-SAR and E-PT-SAR spatial coefficients each iteration) and computed the bootstrap distribution of the difference $\rho_{core} - \rho_{pooled}$. The resulting 95% percentile interval for this difference is $[-0.04, 0.41]$, which includes zero; the shift in point estimates and p-values is therefore directionally consistent with, but not conclusively confirmed by, a formal difference test, and we present it as such throughout. The same bootstrap gives 95% CIs excluding zero for the core prosperous spillover taken on its own [0.146, 1.190] and for the poor regime [0.109, 1.405], while the enclave CI [0.000, 0.136] contains zero, consistent with its single-district sample rather than with a confirmed absence of spillover.

As a further sensitivity check on the threshold choice, we re-estimated the E-PT-SAR model under the two other stationary candidates from Table 9 ($\tau = 0.1250$ and $\tau = 0.2500$, classifying seven and six districts as enclaves respectively). Under both alternative thresholds the core-prosperous spillover remains higher than the pooled two-regime estimate (0.58–0.61 versus 0.4656) and remains nominally significant, suggesting the qualitative pattern is not an artefact of selecting $\tau^* = 0.7143$ specifically, though the magnitude and composition of the enclave group differ across specifications. Configurations with τ in the mid-range (0.33, 0.60) remain inadmissible, producing explosive, non-stationary coefficients ($\rho = 1.65$–1.95), and are excluded from consideration on stationarity grounds alone.

3.10. Model Comparison and Diagnostics

Two nested LR tests are reported to assess whether the added regime structure improves fit beyond what added parameters alone would predict. Because PT-SAR and E-PT-SAR are estimated by S2SLS rather than full-information maximum likelihood, no exact likelihood is available; we therefore compute a residual-based pseudo-log-likelihood, $\ell(\hat{\theta}) = -\frac{NT}{2}\left[\ln(2\pi) + \ln(\widehat{RSS}/NT) + 1\right]$, evaluated at the S2SLS residuals under an assumption of (conditional) Gaussian errors, and use it purely as a common, comparable fit criterion across the three nested specifications (SAR, PT-SAR, E-PT-SAR); it is not a genuine ML likelihood and the associated LR statistics should be read as an approximate, asymptotically-motivated diagnostic rather than an exact test. With this caveat, the nested comparisons are: SAR vs. PT-SAR, $LR = 13.90$ (df 3, critical 7.81), $p = 0.003$; SAR vs. E-PT-SAR, $LR = 15.13$ (df 7, critical 14.07), $p = 0.034$. Both reject their nulls; the incremental gain of E-PT-SAR over PT-SAR is modest, as would be expected for a regime built from a single district, so we treat its value as substantive (offering a more granular partition of the prosperous group) rather than as a demonstrated improvement in overall fit.

Table 12: Model Comparison

Model	Param.	LogLik	AIC	BIC	RMSE
SAR	5	73.99	−137.98	−123.46	0.1399
PT-SAR	8	80.94	−145.89	−122.65	0.1329
E-PT-SAR	12	81.56	−139.12	−104.25	0.1322

The LogLik, AIC, and BIC values in Table 12 are derived from the same residual-based pseudo-likelihood described above and should be interpreted only as relative, within-study comparisons across the three nested S2SLS-estimated specifications, not as figures comparable to ML-based AIC/BIC from other studies. On this basis, PT-SAR attains the lowest AIC; SAR the lowest BIC (which penalizes extra regime parameters more heavily); E-PT-SAR the lowest RMSE. Together with the LR tests, these support the threshold/multi-regime specifications while confirming that the enclave extension is a parsimonious, substantively motivated refinement rather than one primarily justified by improved fit.

The decay sequence ρ^m [21] shows the spatial reach of each regime (Table 13): the poor regime's influence is still 0.88 at order 5 (near-global reach within the poor cluster); the core prosperous regime decays moderately; the enclave's influence falls below 0.02 already at order 2. Given the enclave regime's single-district basis, this decay pattern is again reported as descriptive of the point estimate rather than as confirmed evidence of confinement.

Table 13: Decay Effect (ρ^m) by Regime

Order (m)	Core Pros.	Enclave	Poor
1	0.6344	0.1358	0.9740
2	0.4025	0.0184	0.9486
3	0.2554	0.0025	0.9239
4	0.1620	0.0003	0.8999
5	0.1028	0.0000	0.8765

3.11. Discussion

Three findings emerge from the results reported above. First, spatial dependence in HDI is real but highly heterogeneous across regimes: very strong in the poor regime ($\rho = 0.974$, mostly indirect impact), moderate but significant in the core prosperous regime ($\rho = 0.634$), and not statistically detectable in the single-district enclave regime. Second, separating the isolated enclave from the pooled prosperous group is associated with a shift in the estimated prosperous spillover from insignificant to significant; while the bootstrap difference test in Section 3.9 does not by itself confirm that the two coefficients differ, the pattern is consistent across the SSR-preferred threshold and the two alternative stationary thresholds, which we take as suggestive evidence that pooling spatially isolated and clustered prosperous districts can attenuate the estimated spillover among the latter. Third, this refinement is better characterized as substantive than as fit-driven: both LR tests (computed on the residual-based pseudo-likelihood described in Section 3.10) are significant, but the enclave regime's incremental fit is modest given its single district; its main value lies in offering a more granular partition of the prosperous group rather than in improving overall model fit.

Practically, the strong, far-reaching poor-regime spillovers are consistent with a case for coordinated, cluster-level interventions rather than isolated district-level efforts. For a spatially isolated prosperous district such as Ciamis, the point estimates are consistent with limited two-way diffusion with its surroundings, so trickle-down expectations should be treated with caution in such cases; we note this as a tentative implication given the exploratory nature of the enclave estimates, rather than as an established policy conclusion.

Limitations: the enclave regime rests on a single district (five observations), so all associated estimates, decompositions, and decay patterns are exploratory despite the reported robustness checks, and should not be interpreted as confirming either the presence or the absence of spillover for spatially isolated prosperous districts in general; the panel is short (2021–2025); the LM diagnostics in Section 3.3 nominally admit an SDM specification, which future work with longer panels could pursue; the analysis relies on queen contiguity (alternative weight matrices merit future testing); and the study is confined to West Java, so external validity and generalizability to settings with more enclaves remain open questions.

4. Conclusions

Applying the E-PT-SAR framework to HDI in 27 West Java districts (2021–2025), an endogenous poverty threshold ($\gamma^* = 8.5124\%$) and a stationarity-constrained enclave threshold selected as the lowest-SSR candidate among the stationary options ($\tau^* = 0.7143$) yield three regimes: 13 core prosperous districts, one enclave (Ciamis), and 13 poor districts. Spillovers are strongly regime-dependent: very strong among poor districts ($\rho = 0.9740$), moderate among core prosperous districts ($\rho = 0.6344$), and not statistically detectable in the single-district enclave regime. The central contribution is that the prosperous spillover, insignificant when pooled ($\rho = 0.4656$, $p = 0.240$), becomes significant once the isolated district is separated ($\rho = 0.6344$, $p = 0.025$); a bootstrap test of the difference between these two estimates does not by itself confirm the shift, so we present this as suggestive evidence, consistent across alternative stationary thresholds, that pooling an enclave with clustered districts can bias the group estimate toward zero, rather than as a definitively established result. Because the enclave regime rests on a single district, all of its associated estimates remain exploratory; future work should apply E-PT-SAR to longer panels and provinces with more isolated districts, formally test the prosperous-spillover difference with a larger sample, and examine whether these patterns persist under alternative spatial weight specifications and under an SDM specification.

CRediT Authorship Contribution Statement

Nidia Ayu: Conceptualization, Methodology, Formal Analysis, Software, Writing-Original Draft. **Henny Pramoedyo**: Supervision, Validation, Writing-Review & Editing. **Suci Astutik**: Supervision, Validation, Writing-Review & Editing. **Friansyah Gani**: Writing-Review & Editing.

Declaration of Generative AI and AI-assisted Technologies

Generative AI technology (ChatGPT, OpenAI) was used during manuscript preparation for language refinement, grammar checking, code exploration, and LaTeX formatting assistance.

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The authors declare no competing financial or personal interests.

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Data and Code Availability

Data are publicly available from Statistics Indonesia (BPS) Provinsi Jawa Barat. The R code supporting the findings is available from the corresponding author upon reasonable request.

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