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A Spatial Truncated Autoregressive Regression Spline for Open Unemployment with Policy Thresholds and Spillovers in East Java

Dyah Putri Rahmawati [1,3,*], Tanzilal Mustaqim [1,3], Sri Hidayati [2,3]

[1] *Informatics Study Program, Surabaya Campus Directorate, Telkom University, Indonesia*
[2] *Data Science Study Program, Surabaya Campus Directorate, Telkom University, Indonesia*
[3] *Center of Excellence for Motion Technology for Safety, Health and Wellness, Research Institute of Sustainable Society, Telkom University, Indonesia*

Abstract High spatial variation is shown in East Java Open Unemployment Rates (OUR) variables, and there is a nonlinear relation with Regional Minimum Wages and Average Years of Schooling. However, two key features are often excluded from standard regression models, which are expressed policy thresholds and spatial dependency effects. They are excluded for a specific reason, namely that selecting knot locations jointly with the spatial parameter is a non-convex search that standard spatial packages do not implement, so that threshold locations in the regional policy literature are conventionally fixed at round numbers rather than estimated from the data. To address these challenges, this work introduces the Spatial Truncated Autoregressive Regression Spline (STARS) model that combines truncated spline flexibility to enable nonlinearities with a spatial autoregressive structure to measure regional dependence across regions. Knot locations are chosen using Generalized Cross Validation, but with the stipulation that candidate knots cannot occur in sufficiently sparse intervals, and parameters are estimated by concentrated Generalized Least Squares on the spatially filtered response. The analysis pools 2024 and 2025 data for the 38 regencies and cities of East Java into an estimation sample of 76 region year observations with a common year effect, and the spatial dependence is modeled by a row standardized weight matrix consisting of 5-nearest-neighbour. Two policy variables retain a threshold. The regional minimum wage bends upward at 20.2% above the provincial median, where the total effect of a wage increase rises from $+0.44$ to $+2.12$ percentage points, and average years of schooling bends at 7.97 years, where the total effect falls from $+0.59$ percentage points to a value indistinguishable from zero. The spatial autoregressive coefficient is $\rho = 0.395$ and indirect effects run at 0.604 of direct effects, so that roughly three eighths of the impact of a local policy is realized outside the jurisdiction that enacts it. STARS improves on a linear SAR benchmark in explanatory fit, in AICc and in leave one region out cross validation. A cluster bootstrap that re-runs the complete selection procedure in every replicate confirms that both thresholds are detected in a large majority of replicates, while showing that their locations are determined only within wide intervals, and we report both results.

Keywords Spatial Autoregressive Model, Truncated Spline, Policy Threshold, Spatial Spillover, Open Unemployment Rate, Generalized Cross Validation

AMS 2010 subject classifications 62H11, 62G08

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1. Introduction

1.1. Background and Problem Statement

The open unemployment rate (OUR) is an important indicator for measuring labor market dynamics and the impact of regional development policy. In East Java, the distribution of OUR across administrative units is wide and

*Correspondence to: Dyah Putri Rahmawati (Email: dyahputri1234@gmail.com). Informatics Study Program, Surabaya Campus Directorate, Telkom University, Jl. Ketintang No.156, Gayungan District, Surabaya, East Java, Indonesia (60231).

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persistent. In 2024 the rate ranged from 1.56% in Pacitan to 6.49% in Sidoarjo, and one year later the ordering of regions was almost unchanged, with a correlation of 0.94 between the two years across the 38 regencies and cities [1]. Whatever generates this dispersion is therefore structural rather than transitory. There is nothing unusual about this form of persistence. When an employment policy is enacted in one locality, it often spills over to nearby communities through labor market spillovers, supply chain connections and shifts in investment [2].

Two empirical features of OUR dynamics in East Java are commonly overlooked by traditional analytic approaches. Firstly, OUR is nonlinear with the policy variables. Positive but not excessive RMW is perceived as facilitating labor absorption, through the support of household purchasing power. Conversely, RMW in excess of regional productivity levels will trigger operational expenditure and normally elicit labor optimization steps that can unintentionally increase OUR [4]. A similar argument applies to schooling, since an additional year of education plausibly does something different in a regency where the workforce averages five years of education than in a city where it averages twelve. This type of threshold behavior cannot be fitted by linear regression models, which assume a constant relationship over the full range of data. Second, the 38 regencies and cities of East Java are not separate from each other. The interdependent nature of the economy as well as the mobility of population generates a dependence in space that violates the independence assumption on which classical statistical models are based [2]. Neglecting this spatial structure could cause a significant bias in the estimation of the parameters of interest and provide policy recommendations that do not acknowledge interactions between regions [20].

In order to address these shortcomings, various different approaches have been proposed. By contrast, GWR describes local heterogeneity explicitly but produces parameters that work less well for the derivation of coherent regional policy [5], and its multiscale extension refines the bandwidth without changing that character [8]. Meanwhile, Penalized-Spline SAR (PS-SAR) provides a nonparametric fit with spatial components [6], but its smoothing penalty implies that the locations at which the response bends are not recovered as parameters, and therefore are not immediately interpretable for practical policy use. Coming to these gaps, it leads us to propose our main question of this study: how can we construct an OUR model that jointly (1) identifies explicit and data supported policy thresholds at the provincial level in East Java, (2) estimates the spatial spillover effect across regions, and (3) reports how precisely each of those quantities is determined?

1.2. Problem-Solving Approach and Contributions

We formulate the Spatial Truncated Autoregressive Regression Spline (STARS) model as a solution to this problem. STARS merges the power of truncated splines for nonlinear relationships with a spatial autoregressive structure to deliberately capture interregional dependency. Compared to GWR, which produces parameters at smaller scales, and PS-SAR, where the penalty term absorbs structural breaks rather than reporting them, STARS is not localized, with only one equation covering all 38 regencies and cities. The identified policy thresholds are therefore consistent across the province, making them directly relevant to provincial planning frameworks.

We prefer using truncated splines, as these can map nonlinear dependencies and because knots are easily interpretable thresholds [7]. The estimated knot values allow us to explicitly map shifts in the direction or magnitude of policy variable effects on OUR [22]. This specification is augmented by a spatial autoregressive component, which captures the spillover effects of neighboring regions' unemployment levels on local outcomes, while allowing for independent measurement and approximation of indirect effects [14].

This work makes three main contributions. On a methodological note, we present the full mathematical details of STARS estimation by concentrated Generalized Least Squares, with knots optimally chosen via Generalized Cross Validation under a minimum support constraint, and a cluster bootstrap that re-runs the entire selection pipeline so that knot selection uncertainty enters the reported intervals rather than being conditioned away. Second, the study empirically identifies two thresholds on the policy variables that govern labor absorption, and quantifies how far the effect associated with each of them travels across regions. Third, the study documents that detecting the presence of a nonlinearity and locating it are inferentially distinct problems, and that at provincial sample sizes the first is considerably better determined than the second. We offer this last point as a caution to the applied spatial spline literature [19].

1.3. State of the Art and Research Gap

Nonparametric spatial modeling has been developed from GWR to MGWR, which allows for different bandwidths for individual predictors [8]. These approaches generate locally varying responses that are not easily translated into operational policy thresholds, even as they capture scale heterogeneity. Nonparametric components, such as those embedded in spatial autoregressive structures via PS-SAR [6] or Bayesian Spatial Spline approaches [9], provide better predictions than a parametric form, but the locations of their knots remain hidden behind smoothing penalties and thus offer no explicit decision points for public policy [12].

Despite this, spatial accuracy and policy interpretability remain diametrically opposed principles in the extant literature. The spatial threshold autoregressive model, abbreviated STAR by [11] and not to be confused with the STARS model proposed here, is an example of a parametric spatial threshold model that identifies policy regimes but imposes rigid functional forms. Most importantly, its regime boundaries are usually fixed exogenously by the researcher, for instance at round number wage or income levels, rather than estimated from the data. In this regard, STARS provides a remedy by determining knot locations endogenously, so that the process of setting a threshold reflects the empirical structure of the data rather than analyst discretion, while still being bound by the requirement that a candidate knot must fall within an interval actually populated by observations. On the other hand, while data driven GAMs fitted with spatial smoothers [12] are flexible, they tend to confound spatial and nonlinear effects, inhibiting the direct and indirect effect decomposition that is fundamental to many questions in spatial econometrics [13].

A further gap concerns the treatment of uncertainty. Studies in this area typically report knot locations as point estimates, conditioning all subsequent inference on those locations as though they were known in advance. Since the knots were themselves estimated from the same data, intervals constructed this way are too narrow, and the practice risks presenting a point on a flat criterion surface as a structural feature of the economy. Functional and semiparametric spatial models have begun to address estimation uncertainty more carefully [21], and resampling procedures designed for spatially dependent data are now available [16], but the two are rarely combined in applied regional work.

STARS attempts to fill this void by bringing an explicit truncated power basis into the SAR framework. The locations of knots are selected through GCV optimization, resulting in piecewise linear response functions with measurable thresholds. STARS offers two main advantages: first, provinces apply policy in exactly the same way, as all regions are subject to similar thresholds, and second, spatial effects can be decomposed without confounding nonlinearities, using the multiplier matrix $(\boldsymbol{I}_n - \rho \boldsymbol{W})^{-1}$, consistent with the LeSage and Pace framework [14] and recent calls for interpretable nonparametrics in regional policy analysis [15]. Overall, STARS indicates a departure from black box nonparametric spatial modeling toward policy aware spatial modeling that combines functional nonlinearities, spatial dependence, and operationalizable intervention thresholds within a single framework.

2. Methodology

2.1. Mathematical Specification of the STARS Model

The STARS model is constructed to simultaneously account for predictor nonlinearity and spatial dependence. Let y_i be the Open Unemployment Rate for region $i = 1, 2, \ldots, n$. Spatial interactions are modeled by an autoregressive structure among cases, whereas nonlinear relations with policy variables x_{ij} $(j = 1, \ldots, p)$ are approximated using truncated spline functions.

2.1.1. Truncated Spline Function and Basis Vectors For each predictor x_j, the association with y is smoothed as a linear spline with m_j knot points $\tau_{j1} < \tau_{j2} < \cdots < \tau_{jm_j}$. The functional form is

$$f_j(x_{ij}) = \alpha_{j0} + \alpha_{j1} x_{ij} + \sum_{k=1}^{m_j} \gamma_{jk} (x_{ij} - \tau_{jk})_+, \tag{1}$$

where $(u)_+ = \max(0, u)$ is the truncation operator. Here α_{j1} is the baseline slope, and γ_{jk} determines how much the slope changes after crossing knot τ_{jk}. These knots are seen as explicit policy thresholds.

2.1.2. Matrix Formulation and Estimation The whole STARS model in matrix notation is

$$\boldsymbol{y} = \rho \boldsymbol{W}\boldsymbol{y} + \boldsymbol{B}\boldsymbol{\theta} + \boldsymbol{\varepsilon}, \qquad \boldsymbol{\varepsilon} \sim N(0, \sigma^2 \boldsymbol{I}_n), \tag{2}$$

where $\boldsymbol{y}$ is the $n \times 1$ vector of OUR observations, ρ is the spatial autoregressive coefficient, $\boldsymbol{W}$ is an $n \times n$ row standardized spatial weight matrix, $\boldsymbol{B}$ is the $n \times K$ design matrix with spline basis columns for all predictors, $\boldsymbol{\theta}$ is a $K \times 1$ vector of spline parameters, and $\boldsymbol{\varepsilon}$ is the error vector. Writing $\boldsymbol{A}(\rho) = \boldsymbol{I}_n - \rho \boldsymbol{W}$, the equation is transformed as

$$\boldsymbol{A}(\rho)\, \boldsymbol{y} = \boldsymbol{B}\boldsymbol{\theta} + \boldsymbol{\varepsilon}. \tag{3}$$

Equation (3) makes the estimator transparent. Conditional on ρ, the filtered response $\boldsymbol{A}(\rho)\boldsymbol{y}$ is linear in $\boldsymbol{\theta}$ with spherical errors, so that

$$\widehat{\boldsymbol{\theta}}(\rho) = \left(\boldsymbol{B}^\top \boldsymbol{B}\right)^{-1} \boldsymbol{B}^\top \boldsymbol{A}(\rho)\, \boldsymbol{y}. \tag{4}$$

It is important to note that only the response is filtered, and the design matrix is not. Filtering both sides, that is regressing $\boldsymbol{A}(\rho)\boldsymbol{y}$ on $\boldsymbol{A}(\rho)\boldsymbol{B}$, is the Generalized Least Squares estimator appropriate to a spatial error model, in which the dependence lies in $\boldsymbol{\varepsilon}$ rather than in $\boldsymbol{y}$, and it is not consistent for the spatial lag structure of Equation (2). Fitted values follow from the reduced form,

$$\widehat{\boldsymbol{y}} = \boldsymbol{A}(\rho)^{-1} \boldsymbol{B}\, \widehat{\boldsymbol{\theta}}, \tag{5}$$

which uses no observed response and is therefore a genuine prediction rather than a spatial interpolation.

The parameter ρ is estimated by profiling. Since $\boldsymbol{W}\boldsymbol{y}$ is endogenous with respect to $\boldsymbol{\varepsilon}$ due to simultaneity, ordinary least squares on the untransformed equation does not provide ρ. Instead, we conditionally estimate the model via Equation (4) for each candidate ρ on a grid, and select ρ via the criterion in Equation (6) jointly with knot selection. For a given ρ this is the conditional least squares estimator of the spatial lag model, and it coincides with conditional maximum likelihood under normality up to the log Jacobian term $\ln |\boldsymbol{I}_n - \rho \boldsymbol{W}|$, which profiling by Equation (6) replaces with a complexity penalty. The procedure therefore avoids the inconsistency that would result from treating $\boldsymbol{W}\boldsymbol{y}$ as an exogenous regressor, while selecting ρ on predictive rather than likelihood grounds, which is the criterion the knot search also uses.

2.1.3. Optimal Knot Selection via Generalized Cross Validation The number and location of the optimal knots $\boldsymbol{\tau}^*$ are determined by minimizing the Generalized Cross Validation criterion

$$\mathrm{GCV}(\rho, \boldsymbol{\tau}) = \frac{n^{-1} \|\boldsymbol{y} - \widehat{\boldsymbol{y}}(\rho, \boldsymbol{\tau})\|^2}{\left[1 - n^{-1} K\right]^2}, \tag{6}$$

where $\widehat{\boldsymbol{y}}(\rho, \boldsymbol{\tau})$ are the model predictions and K is the number of columns of $\boldsymbol{B}$. GCV achieves a trade-off between model fit and complexity without the need to explicitly estimate the error variance, and it has been shown to behave stably relative to competing criteria in truncated spline settings [27].

The criterion alone, however, is not sufficient. A truncated term $(x - \tau)_+$ carries information only through the observations lying above τ, so that a knot placed near the edge of a predictor's range is identified by a handful of points, and its associated slope change coefficient is estimated almost entirely from them. In the limit, a knot positioned inside a gap in the empirical distribution is not identified at all, however favorable the criterion value it attains. We therefore restrict candidate knots to cut points that leave at least ten observations in every segment they create, and we emphasize that the constraint applies to segments rather than merely to each side of a single knot, since two nearly coincident knots can otherwise isolate a single observation while satisfying a per knot rule. Figure 3 displays the resulting admissible region for each predictor against the observed data.

Within the admissible region the search is coordinate-wise. Starting from the purely linear specification, the knot set of one predictor at a time is optimized with the others held fixed, and the sweep is repeated until no single

change lowers the criterion. The spatial parameter ρ is re-optimized at every evaluation, so that knots and spatial dependence are selected jointly rather than sequentially. We allow at most one knot per predictor, and Section 3.5 reports what happens when that restriction is lifted.

2.1.4. Spatial Effect Decomposition Policy impacts on unemployment are decomposed via partial derivatives of the Leontief inverse matrix $\boldsymbol{S} = (\boldsymbol{I}_n - \rho \boldsymbol{W})^{-1}$. The marginal effect of a change in x_j at location k on y_i is

$$\frac{\partial y_i}{\partial x_{kj}} = S_{ik} \cdot \frac{\partial f_j(x_{kj})}{\partial x_{kj}}. \tag{7}$$

Two properties deserve emphasis. Because $f_j(\cdot)$ is only piecewise linear and not globally linear, the derivative $\partial f_j(x_{kj})/\partial x_{kj}$ is regime specific, since it equals the local slope of the segment in which region k's observed value falls rather than a single global derivative. Reported effects therefore average S_{ik} against each region's own regime appropriate local slope. In addition, $\boldsymbol{S}$ is not symmetric under a nearest neighbour weight matrix, because region k may be among region i's neighbours without the converse holding, and influence therefore flows through w_{ik} rather than w_{ki}.

Direct effects are calculated as the average of the diagonal elements S_{ii}, indirect or spillover effects as the average of the off-diagonal row elements, and total effects as their sum [14]. The spillover ratio is described as

$$\text{Spillover Ratio} = \frac{\text{Average Indirect Effect}}{\text{Average Direct Effect}}. \tag{8}$$

2.1.5. Inference Conventional standard errors treat knot locations as known, whereas in this framework they are estimated from the same data. We therefore use a cluster bootstrap over regions, in which the complete pipeline, namely candidate generation under the support constraint, knot selection, and the search over ρ, is re-run on every replicate. Both years of a region are resampled together, which preserves the within region correlation. Intervals constructed in this way are wider than conditional intervals, and they are the ones we report throughout. Resampling schemes of this type are standard practice for spatially dependent data [16].

2.2. Design, Data, and Variables

We use an explanatory quantitative design with a nonparametric spatial modeling approach. The analytical units are the 38 regencies and cities of East Java Province, observed in 2024 and 2025 and pooled into an estimation sample of 76 region year observations with a common year effect. Data were obtained from Statistics Indonesia (BPS) [1]. Pooling two years doubles the number of observations available to identify a slope change without requiring the relationships themselves to differ between years, and the year effect absorbs any province wide shift in OUR between the two periods that is common to all regions. Panel extensions of this kind are increasingly common in Indonesian regional work [28]. These variables are summarized in Table 1.

Table 1. Variable Definitions and Data Sources

Variable	Symbol	Description	Source
Open Unemployment Rate (%)	y	Response variable	BPS
Regional GDP Growth (%)	x_1	Regional economic growth rate	BPS
LFPR (%)	x_2	Labor Force Participation Rate	BPS
Relative RMW	x_3	log(RMW) minus log(provincial median RMW)	BPS
AYS (years)	x_4	Average Years of Schooling	BPS
Industry (%)	x_5	% of workforce in industrial sector	BPS
Coordinates (lat, lon)	n.a.	Spatial information for weight matrix	BPS

On the measurement of the minimum wage: The regional minimum wage enters the model relative to the provincial median of its own year, rather than in nominal rupiah. The reason is practical. The median nominal

minimum wage in East Java rose by 6.5% between 2024 and 2025, so a threshold expressed in rupiah loses its meaning within a single planning cycle, and a region may cross it without any change in its position relative to the rest of the province. Measured relative to the median, the same cut point applies in both years and can be restated in rupiah for whichever year a policymaker requires. We regard this as the natural scale for a threshold that is intended to inform wage setting.

On the exclusion of HDI: The Human Development Index is reported in the descriptive statistics but excluded from the model. HDI is a composite index that takes mean years of schooling as one of its three components, so that the two are correlated at 0.977 in this sample. Entering both produces variance inflation factors above 30, together with large and mutually offsetting slope estimates that cannot be interpreted separately. With HDI excluded every variance inflation factor falls below 2, as reported in Section 3.6. Since a threshold that cannot be attributed to a single variable is of no use to policy, we regard this as the correct trade.

2.3. Baseline Model: Linear SAR

As a benchmark, we also estimate the standard linear SAR model, with specification

$$\boldsymbol{y} = \rho \boldsymbol{W}\boldsymbol{y} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \tag{9}$$

where $\boldsymbol{X}$ consists of linear terms only and the same year effect. Estimation follows the same concentrated GLS steps as STARS, which guarantees a fair comparison.

2.4. Spatial Weight Matrix Construction

For the spatial weight matrix $\boldsymbol{W}$, we use a 5-nearest-neighbours approach with row standardization,

$$w_{ij} = \begin{cases} 1/5 & \text{if } j \in \mathcal{N}_i^{(5)}, \\ 0 & \text{otherwise}, \end{cases} \qquad \sum_{j=1}^{n} w_{ij} = 1, \tag{10}$$

extended block diagonally across the two years, so that a region's neighbours are its neighbours within the same year. Among the alternatives evaluated in Section 3.6 this specification attains the highest explanatory fit, but the case for adopting it is substantive rather than numerical.

A contiguity matrix encodes the assumption that labor market interaction requires a shared land boundary. In East Java that assumption fails in a specific and consequential way. Under Queen contiguity the four regencies of Madura, namely Bangkalan, Sampang, Pamekasan and Sumenep, form a connected component of their own, joined to the rest of the province by nothing at all, because the island shares no land boundary with the mainland. A pure contiguity matrix therefore asserts that no labor market interaction exists between Surabaya and Bangkalan. Daily commuting across the Suramadu bridge makes that assertion untenable, and the local cluster analysis reported in Section 3.7 places Bangkalan in the same high unemployment cluster as Surabaya, Gresik and Kota Pasuruan in both years. A nearest neighbour matrix represents this connection, whereas a contiguity matrix cannot. Section 3.6 reports the estimates under both, and under a contiguity matrix augmented with the single Suramadu link.

The same reasoning sets the lower end of the range of k that we examine. Because $\boldsymbol{W}$ is row standardized, a region transmits to its neighbours only through the rows that list it, so what matters for Madura is how many mainland regions treat a Madura regency as a neighbour, and not how many neighbours Madura itself has. At $k = 3$ and $k = 4$ that count is zero for Sampang, Pamekasan and Sumenep, and Bangkalan is the only regency of the island that any mainland region lists at all. Three of the four regencies would then be able to receive unemployment from the mainland while being unable to transmit it back, which reproduces in a milder form the very asymmetry that recommends a nearest neighbour matrix over contiguity in the first place. At $k = 5$ Sampang and Sumenep acquire mainland links as well, so that three of the four regencies participate in the network in both directions. The comparison in Section 3.6 therefore varies k from 5 to 8.

2.5. Validation and Diagnostics

Given the moderate sample size, we validate the model in four ways: (1) a cluster bootstrap over regions with $B = 200$ replicates, re-running the complete selection pipeline, to determine the uncertainty of the parameters and

of the selected knots; (2) Moran's I tests on the residuals, to establish whether spatial autocorrelation remains; (3) decomposition of the spatial effect according to the LeSage and Pace framework [14]; and (4) leave one region out cross validation, in which both years of a region are withheld simultaneously so that no information about a held out region reaches the model through its other year.

3. Results and Discussion

3.1. Descriptive Statistics and Spatial Exploration

Table 2 presents the descriptive statistics for the pooled sample. OUR ranges from 1.33% to 6.49%, with a mean of 3.911%. Average years of schooling ranges from 5.08 to 12.12 years, and the relative minimum wage ranges from 0.081 log points below the provincial median to 0.696 log points above it, which corresponds to 7.8% below and 100.6% above in proportional terms. Both spans are wide enough that imposing a single slope across them is a strong assumption. Figure 1 shows the distribution across regions in both years, which makes the persistence of the ranking visible, since the province wide level falls by 0.26 percentage points between the two periods while the relative position of regions barely moves.

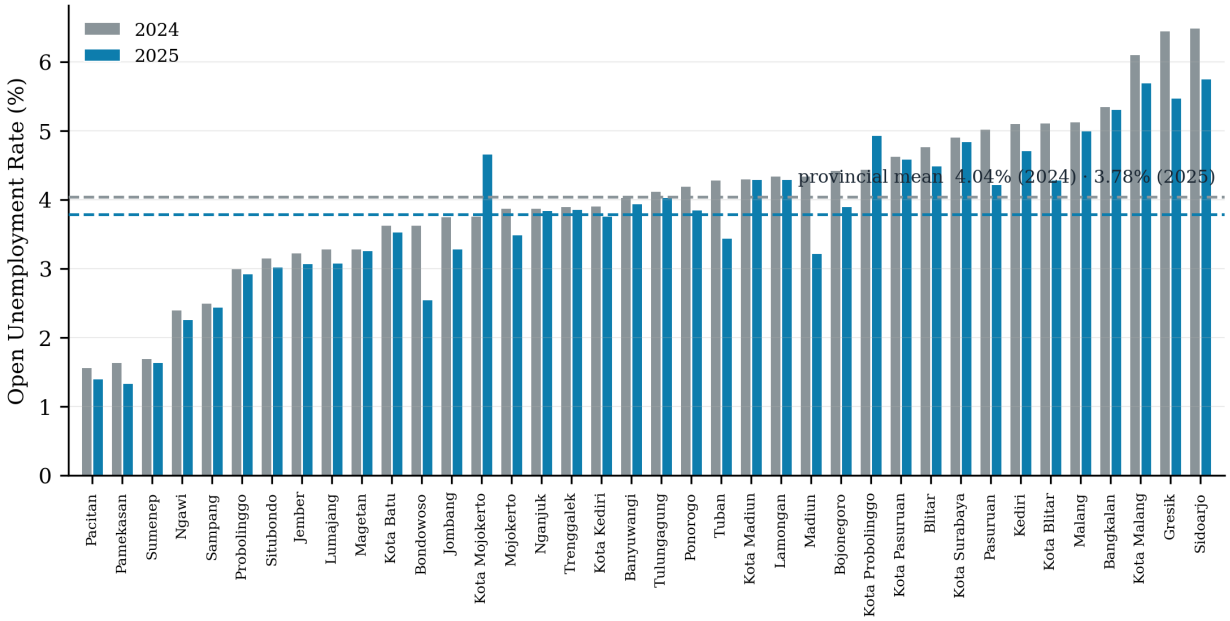


Figure 1. Open Unemployment Rate by regency/city, East Java, 2024 and 2025, ordered by the 2024 rate.

A significance test of Moran's I applied to OUR yields 0.329 for 2024 and 0.330 for 2025, both with permutation p-values of 0.0004 over $9{,}999$ permutations, which provides evidence of significant positive spatial autocorrelation that warrants SAR modeling. The near identical values across the two years are worth noting, since they indicate that the spatial pattern is not a feature of one year's data but a stable property of the province, and that stability is what justifies pooling the two years under a common spatial structure. Figure 2 shows the corresponding Moran scatterplots.

Table 2. Descriptive Statistics of Research Variables ($n = 76$)

Variable	Mean	Std. Dev.	Min	Max	Unit
OUR	3.911	1.145	1.330	6.490	%
GDP Growth	4.931	0.922	1.670	6.350	%
LFPR	74.006	3.713	67.520	86.620	%
Relative RMW	0.135	0.245	−0.081	0.696	log points
AYS	8.509	1.692	5.080	12.120	Years
Industry	22.479	6.059	13.120	37.170	%
HDI (descriptive only)	75.688	4.743	66.720	85.650	Index

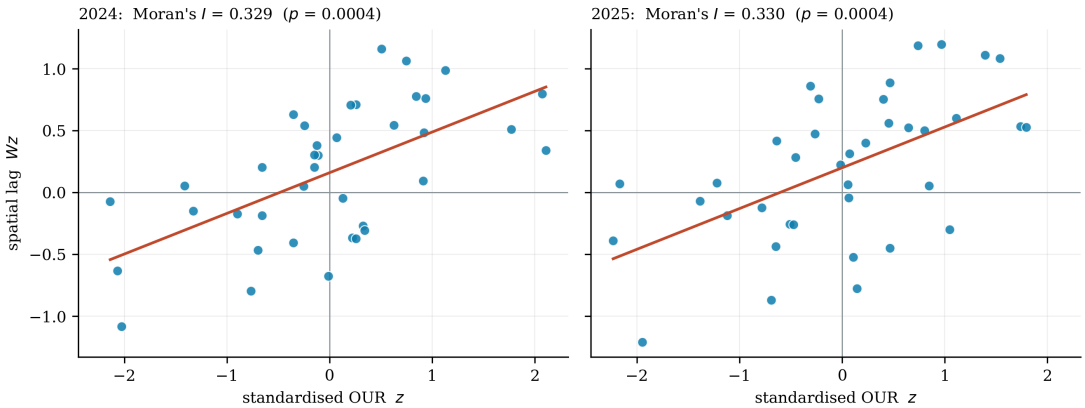


Figure 2. Moran scatterplots for both years. A positive slope indicates that regions with high OUR tend to neighbour regions with high OUR.

3.2. The Estimated STARS Model

Applying the selection procedure of Section 2.1.3 to the pooled sample retains two knots, one on the relative minimum wage at 0.184 log points and one on average years of schooling at 7.97 years. All other predictors enter linearly. The resulting specification has nine parameters and a GCV-optimal spatial parameter $\rho = 0.395$. Table 3 reports the estimates, and Figure 3 shows the admissible knot region that constrained the search.

The year effect of -0.07 percentage points is the part of the province wide decline that remains once the movement in the predictors has been accounted for, and it is therefore much smaller than the raw fall of 0.26 percentage points reported in Section 3.1. The slope change coefficients are read together with their baselines. For the relative minimum wage the slope below the knot is $+0.266$ and above it is $0.266 + 1.014 = +1.281$, so that the association becomes almost five times stronger once the threshold is crossed. For average years of schooling the slope below the knot is $+0.357$ and above it is $0.357 - 0.348 = +0.009$, which is effectively zero. Section 3.3 discusses both, and Section 3.4 converts them into direct, indirect and total effects.

Table 3. Estimated STARS Model Coefficients (pooled 2024 and 2025, $n = 76$, $\rho = 0.395$)

Parameter	**Estimate**
Intercept	2.5650
Relative RMW slope change at the knot (γ)	1.0141
AYS slope change at the knot (γ)	-0.3476
GDP Growth baseline slope (β)	-0.0295
LFPR baseline slope (β)	-0.1550
Relative RMW baseline slope (β)	0.2664
AYS baseline slope (β)	0.3569
Industry baseline slope (β)	-0.0065
Year 2025 (δ)	-0.0661
R^2	0.6418
RMSE	0.6809
MAPE	17.40%
AICc	183.37

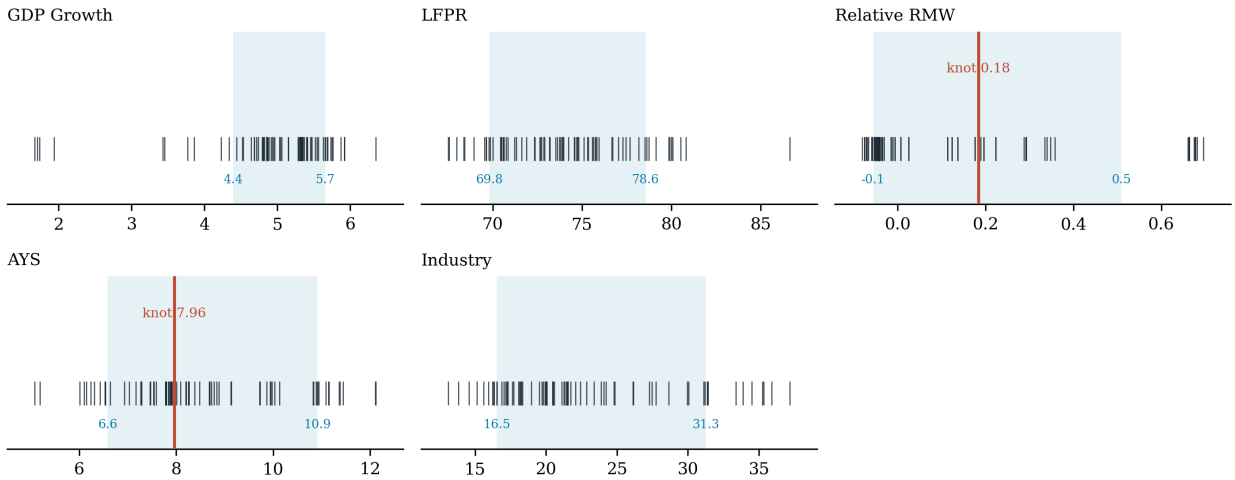


Figure 3. Admissible knot region for each predictor under the minimum support constraint. Ticks are the 76 pooled region year observations, and the shaded band holds the candidate knots leaving at least ten observations in every segment.

3.3. Identified Policy Thresholds

Figure 4 displays the fitted STARS function for each predictor, holding the remaining predictors at their sample means. The picture makes the estimated structure immediate. Three of the five response functions are straight lines, which is the model's own verdict that the data do not support a change of slope for GDP growth, for the labor force participation rate or for the industry share. All three carry a negative slope, at -0.030 for GDP growth, -0.155 for the labor force participation rate and -0.007 for the industry share, so that faster growth, wider participation and a larger industrial base are each associated with lower unemployment across the whole range of the data. Their magnitudes are modest beside the spline terms, and the industry share in particular is close to zero once the other predictors are held fixed, which suggests that its influence operates through the wage and schooling channels rather than independently of them. Two functions bend, and each bends once.

The wage threshold: The relative minimum wage function is nearly flat until the wage reaches 20.2% above the provincial median, and rises steeply thereafter. Expressed in rupiah, the threshold corresponds to Rp 2.83 million in

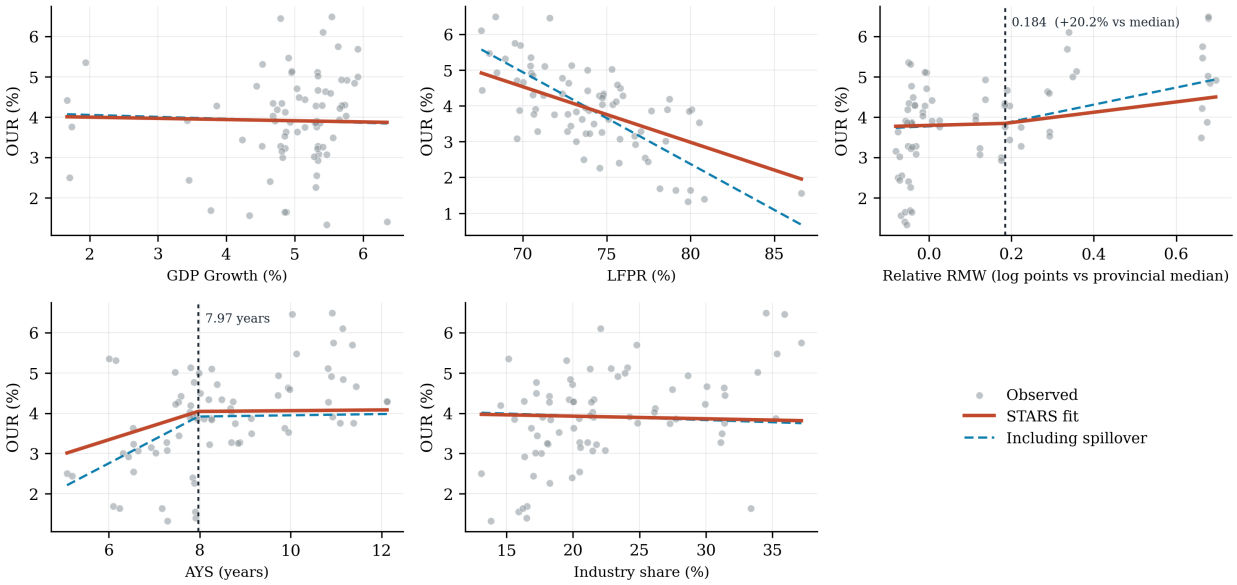


Figure 4. Fitted STARS function for each predictor. The solid line is the within region response and the dashed line adds the spatial multiplier, so the vertical distance between them is the spillover. The dotted vertical lines mark the estimated knots.

2024 and Rp 3.02 million in 2025, and twelve regions lie above it in each year, with every region on the same side of the threshold in both years. The regions above the threshold are the industrial and urban core of the province, namely Gresik, Sidoarjo, Kota Surabaya, Mojokerto, Kota Mojokerto, Pasuruan, Kota Pasuruan, Malang, Kota Malang, Kota Batu, Jombang and Tuban.

The shape is exactly what conventional minimum wage theory predicts and what the Indonesian evidence on wage floors has suggested [4]. While the wage floor remains near the provincial median, it is within the range that regional productivity can absorb, and raising it carries only a weak association with unemployment. Once the floor runs well ahead of the median, the same increase is associated with a much larger rise in measured unemployment, because firms respond through labor optimization rather than through absorption. The practical reading is that a uniform province wide wage increase does not carry a uniform employment consequence, since it acts on the twelve regions above the threshold quite differently from the twenty six below it.

The schooling threshold: The schooling function rises steeply up to 7.97 years and is flat above it. Sixteen regions lie below the threshold in 2025 and nineteen in 2024, with thirty five of the thirty eight regions on the same side in both years. They concentrate in Madura and the eastern *Tapal Kuda* arc, with an inland extension through Bojonegoro, Ngawi and Ponorogo and two north coast cases at Tuban and Pasuruan.

The estimated sign below the threshold deserves comment, because it runs opposite to what a human capital argument would predict. The explanation lies in what the open unemployment rate measures. A person engaged in subsistence agriculture or unpaid family work is counted as employed and not as unemployed, whereas a person who has left that activity to search for wage employment is counted as unemployed. In regions below the threshold a large share of the workforce sits in the first category, and rising schooling moves people into the second. Measured open unemployment therefore rises not because opportunities have contracted, but because participation in the formal labor market has widened. Above the threshold that transition is largely complete, and further schooling no longer shifts the measured rate. This reading is consistent with the broader Indonesian evidence on vocational supply and labor absorption [29].

Figure 5 maps the two regimes side by side, and the comparison is instructive in itself. The two thresholds divide the province along almost opposite lines. The regions above the wage threshold are the metropolitan corridor, whereas the regions below the schooling threshold are the agrarian periphery, and only Pasuruan and Tuban appear on the policy relevant side of both. A province wide instrument therefore acts on two largely disjoint groups of

regions depending on which threshold it operates through, which is the central practical implication of estimating the two jointly rather than separately.

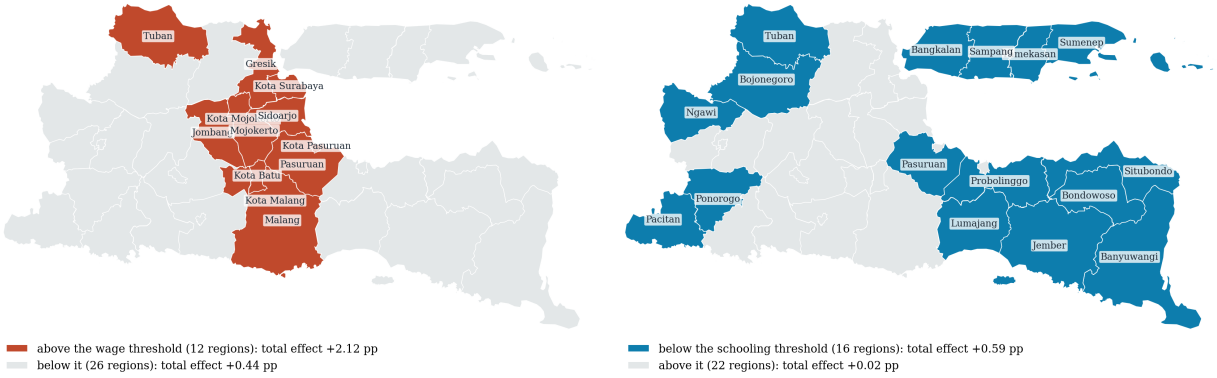


Figure 5. Regions on either side of the two estimated thresholds, based on 2025 values. Effects shown in the legend are total effects, direct plus spillover, per unit of the predictor.

3.4. Spatial Effect Decomposition and Spillover Analysis

Based on the spatial impact matrix $\boldsymbol{S} = (\boldsymbol{I}_n - \rho \boldsymbol{W})^{-1}$, policy effects are decomposed explicitly in Table 4, following the framework set out in Section 2.1.4.

Table 4. Spatial Effect Decomposition by Regime (percentage points per unit of the predictor)

Predictor	**Regime**	**Direct**	**Indirect**	**Total**
Relative RMW	below the threshold (0.184)	$+0.2745$	$+0.1658$	$+0.4403$
	above the threshold	$+1.3195$	$+0.7969$	$+2.1164$
AYS	below the threshold (7.97 years)	$+0.3678$	$+0.2221$	$+0.5899$
	above the threshold	$+0.0096$	$+0.0058$	$+0.0154$
Spillover ratio				0.604

Spillover Ratio Interpretation: A 0.604 ratio indicates that indirect effects are somewhat more than three fifths of direct effects. It represents the indirect spillover effect brought by the policy, and read as an average, roughly three eighths of the total effect of a policy in this province is realized outside the jurisdiction that enacts it. Even when these spillover effects are included, the direct impact generated locally still accounts for the majority of the total impact. The spillover effect calculated here, although smaller than the local component, remains a non-negligible part of the total impact and not a statistical error that can be ignored. This result also concretely confirms that the various labor markets in East Java are not isolated islands operating independently, but an integrated whole connected across regions, which is consistent with earlier moment based evidence on spatial spillovers in Indonesian regional data [20].

How the multiplier operates in practice: Averages understate how uneven the propagation is, so it is useful to trace two concrete cases through the estimated $\boldsymbol{S}$. Suppose mean years of schooling rises by one year in Sampang, a region below the schooling threshold. The model implies that Sampang's own OUR rises by 0.362 percentage points, and that a further 0.116 points appear elsewhere in the province, which is 32% of the local effect, concentrated in Pamekasan ($+0.034$), Sumenep ($+0.032$) and Kota Probolinggo ($+0.029$).

The same intervention in Jember propagates considerably further. Jember's own rate rises by 0.369 points and a further 0.210 points appear elsewhere, which is 57% of the local effect, spread across Banyuwangi ($+0.041$),

Situbondo (+0.039) and Bondowoso (+0.039). The difference between the two cases is geography rather than policy. Sampang sits on an island whose neighbours are few and are themselves peripheral, whereas Jember sits inside a dense chain of mutually adjacent regencies along the eastern arc. Under the estimated structure, a given change in schooling in Jember is therefore associated with close to twice as much movement outside the regency as the same change in Sampang, and this has a direct implication for how the costs of such programs might reasonably be shared between neighbouring administrations.

The wage channel carries the same asymmetry with larger magnitudes. For a region above the wage threshold, a one log point increase in the relative minimum wage carries a direct effect of $+1.32$ percentage points and an indirect effect of $+0.80$ points, so that the spillover alone exceeds the entire total effect of the same policy applied below the threshold. Since the twelve regions above the threshold form a contiguous industrial corridor from Tuban through Gresik and Surabaya to Malang, their spillovers fall largely on one another, and a coordinated wage decision across that corridor therefore has a materially different aggregate consequence from twelve independent decisions.

Which regions transmit and which receive: The two cases traced above concern transmission, namely how far a policy enacted in one place travels outward, which is governed by the column sums of $\boldsymbol{S}$. Reception is a separate quantity, governed by the row sums, and it is what Figure 6 maps. Keeping the two apart matters, because under a nearest neighbour weight matrix they are distributed very differently. The matrix $\boldsymbol{W}$ is not symmetric, since region i counting j among its five nearest neighbours does not oblige j to count i, and the asymmetry is what separates the two measures.

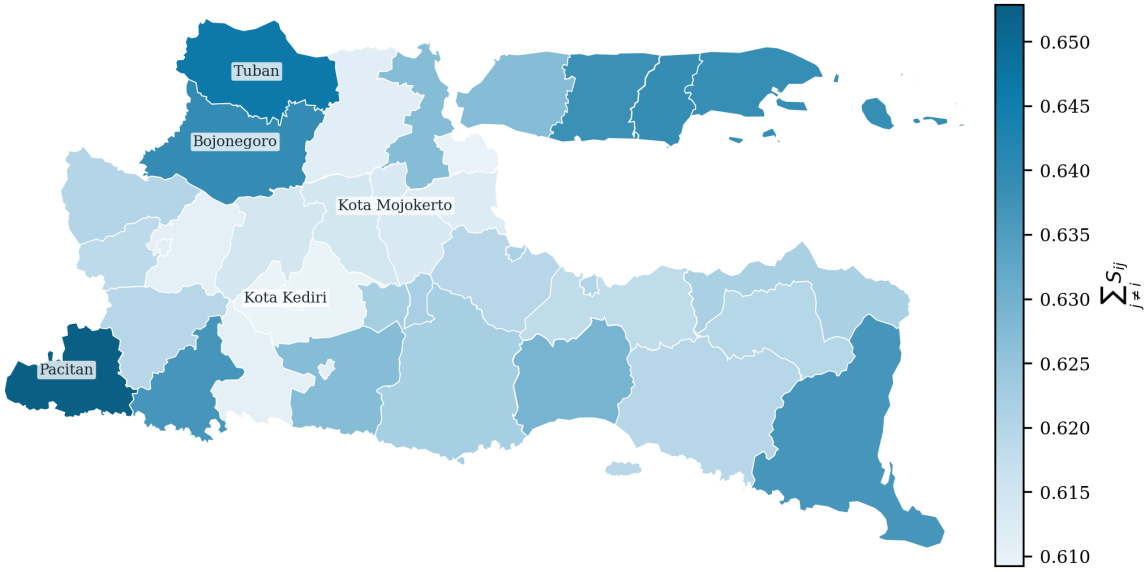


Figure 6. Reception of spillovers across East Java, computed as the row sum of the off-diagonal elements of $\boldsymbol{S} = (\boldsymbol{I}_n - \rho \boldsymbol{W})^{-1}$ at $\rho = 0.395$. This measures how much each region absorbs from elsewhere, and is distinct from how much it transmits, which is discussed in the text.

Reception is remarkably even. Exposure to changes occurring elsewhere runs only from 0.609 to 0.653, a spread of just over seven percent, so that every regency absorbs about the same share of what happens around it. Its ordering also runs counter to economic weight. The most exposed are Pacitan, Tuban and Bojonegoro, peripheral regencies whose nearest neighbours lie further away, so that row standardization spreads their weight over a longer reach, while the least exposed are Kediri, Kota Kediri and Kota Mojokerto, which sit packed among close neighbours.

Transmission is not even at all. Measured relative to a region's own direct effect, it runs from 0.00 in Pacitan, which no other regency counts among its five nearest neighbours, to 1.13 in Kota Mojokerto, whose influence

outside its own boundary exceeds the effect inside it. Here the ordering follows economic weight rather than opposing it, since Kota Mojokerto, Kota Surabaya, Probolinggo and Sidoarjo transmit most, and Pacitan, Tuban, Pamekasan, Bojonegoro and Sumenep transmit least. The regencies that generate province wide spillovers are therefore the urban and industrial centres, and they are largely the same regions that lie above the wage threshold of Section 3.3. A wage decision taken in the Surabaya corridor propagates across the province, whereas the same decision taken in Madura or in Pacitan stays close to where it is made. This also explains the Sampang and Jember contrast above, since Jember transmits at 0.57 and Sampang at 0.32 while the two receive almost identically.

Both measures average to the same 0.604, which is why the aggregate ratio is a property of ρ and $\boldsymbol{W}$ alone and is identical for every predictor and every spline regime. The average conceals the asymmetry, and it is the asymmetry that carries the policy content.

3.5. Model Performance: STARS vs. Linear SAR

GCV optimization identifies the optimal STARS configuration with $\rho = 0.395$. The linear SAR baseline yields $\rho = 0.315$. Table 5 compares three specifications estimated on the same pooled sample, namely the linear SAR benchmark, the selected STARS specification, and a deliberately over-parameterised STARS specification in which the limit of one knot per predictor is lifted, so that eight knots are distributed across five predictors while the minimum support constraint is still enforced.

Table 5. Model Performance Comparison across Specifications ($n = 76$)

Specification	K	ρ	R^2	**MAPE**	**AICc**	**LORO** R^2
Linear SAR	7	0.315	0.6032	18.66%	185.75	0.4384
STARS, selected knots	**9**	**0.395**	**0.6418**	**17.40%**	**183.37**	**0.4424**
STARS, unrestricted	15	0.425	0.7097	14.84%	185.82	0.4314

LORO R^2 denotes leave one region out cross validated R^2, in which both years of a region are withheld simultaneously.

The comparison is instructive in both directions, and Figure 7 displays it. The selected specification improves on the linear benchmark on every criterion, raising R^2 from 0.6032 to 0.6418, lowering MAPE from 18.66% to 17.40%, lowering AICc by 2.38 units and raising cross validated R^2 from 0.4384 to 0.4424. The nonlinearity is therefore real and modeling it pays, and it pays after the cost of two additional parameters has been charged.

The over-parameterised specification tells the other half of the story. It attains by far the highest in-sample R^2 of the three, at 0.7097, and the lowest MAPE, yet its AICc is worse than the linear benchmark and its cross validated R^2 is the lowest of the three. Its additional flexibility is therefore spent on features of the estimation sample that do not survive the removal of a single region. This is the concrete cost of selecting knots on fit alone at this sample size, and it is what the limit of one knot per predictor, imposed in Section 2.1.3, is designed to prevent. The minimum support constraint alone does not prevent it, since every segment of this specification still carries at least ten observations. Support and parsimony are therefore separate disciplines, and both are required.

Another methodological finding is that the estimated spatial parameter changes after introducing nonlinear components, rising from 0.315 in the linear SAR model to 0.395 in STARS. This shift implies that failing to account for the nonlinear relations can lead to a misrepresented estimate of spatial dependence, since variation that the spline components ought to explain may instead be absorbed into the residual structure of the linear model. In summary, these results indicate that the STARS specification with a disciplined complexity penalty is a more appropriate model of the nonlinear, spatial nature of OUR than either a purely linear specification or an unconstrained spline.

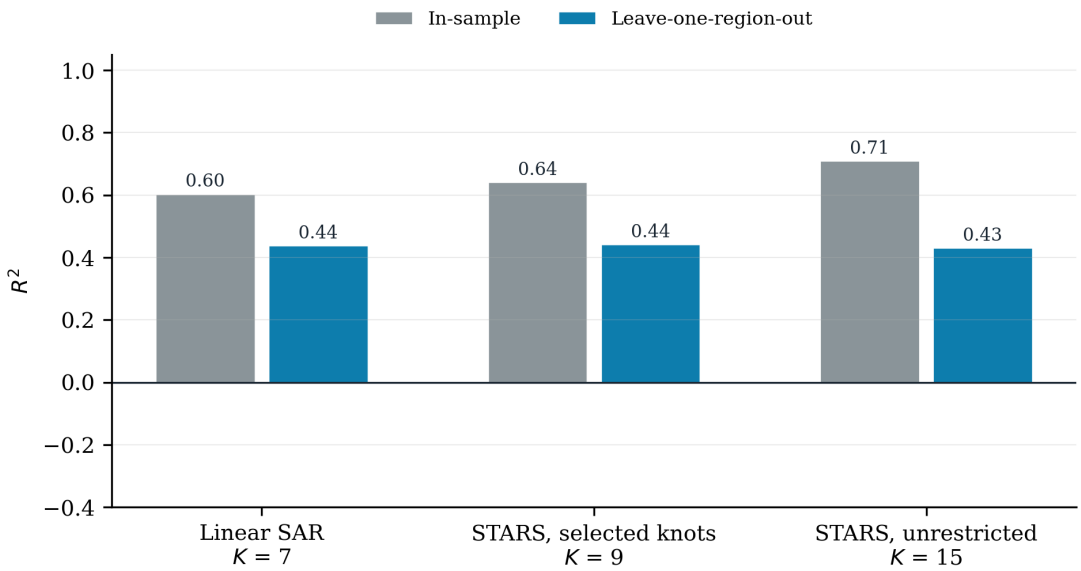


Figure 7. Explanatory and predictive performance across specifications. Cross validation removes both years of a region at a time and re-estimates ρ on the remaining sample.

3.6. Model Diagnostics and Validation

Multicollinearity: With the five model predictors the variance inflation factors are 1.25 for GDP growth, 1.43 for LFPR, 1.86 for the relative minimum wage, 1.60 for AYS and 1.95 for the industry share, all comfortably below the commonly used rule of thumb of 5. This is the direct consequence of excluding HDI, as discussed in Section 2.2.
Residual structure: Moran's I on the residuals is $+0.146$ ($p = 0.049$) for 2024 and $+0.019$ ($p = 0.597$) for 2025. The 2025 residuals show no remaining spatial structure, whereas the 2024 residuals retain a weak positive autocorrelation that sits at the margin of conventional significance and that the model does not fully absorb. We record this in Section 4.3 rather than treat it as resolved. Diagnostic tests on the residuals support the classical distributional and variance assumptions, since the Jarque-Bera test gives a p-value of 0.115 and the Breusch-Pagan test gives a p-value of 0.934, so that neither test rejects normality or homoskedasticity at conventional significance levels.
Sensitivity to the spatial weight matrix: Re-estimating the selected specification under seven weight matrices, varying the neighbourhood size from $k = 5$ to $k = 8$ and adding three non nearest neighbour alternatives, gives ρ between $+0.025$ and $+0.570$, as reported in Table 6 and displayed in Figure 8, with R^2 between 0.6164 and 0.6418. The explanatory fit is therefore insensitive to the choice of $\boldsymbol{W}$, but the point estimate of ρ is not robust in the strong sense. Queen contiguity, which severs Madura from the mainland, returns ρ close to zero, whereas inverse distance weighting returns 0.570. Augmenting Queen contiguity with the single Suramadu link raises ρ from 0.025 to 0.330, which is close to the nearest neighbour estimate. That one edge moves the estimate this far is itself evidence that the connection matters for this province, and that a land contiguity assumption is the wrong one here, as argued in Section 2.4.
Precision of the selected knots: Figure 9 and Table 7 report the cluster bootstrap with $B = 200$, in which the whole selection procedure is re-run on every replicate so that knot selection uncertainty enters the intervals rather than being conditioned away. The two predictors retained in Table 3 are also the two selected most often across replicates, namely average years of schooling in 90% and the relative minimum wage in 77%, while no other predictor exceeds 57%. The evidence that these two relationships change is therefore strong, and it is strong for these two in particular rather than for the set of predictors generally.

Table 6. Spatial Weight Matrix Robustness Comparison

Weight Matrix	Optimal ρ	R^2
KNN, $k = 5$ (adopted)	**0.395**	**0.6418**
KNN, $k = 6$	0.420	0.6397
KNN, $k = 7$	0.385	0.6312
KNN, $k = 8$	0.335	0.6267
Inverse Distance	0.570	0.6233
Queen Contiguity	0.025	0.6164
Queen + Suramadu link	0.330	0.6337

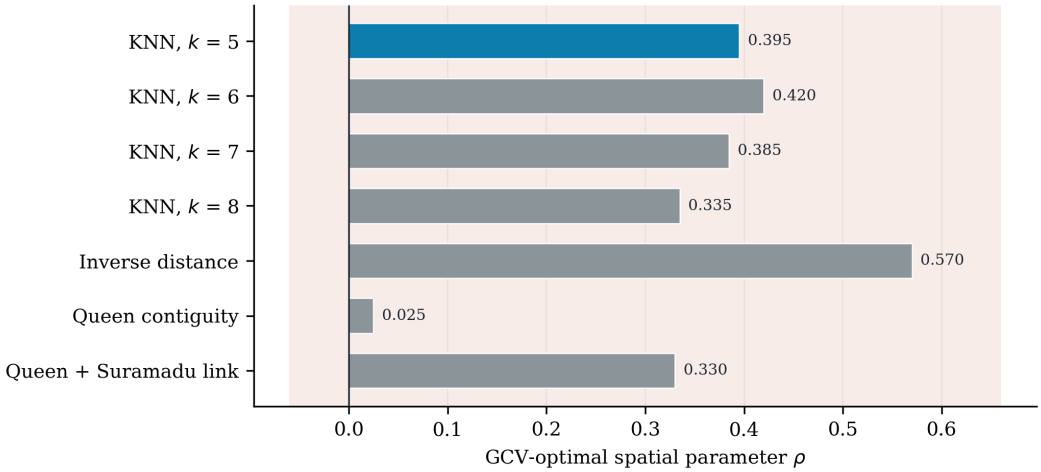


Figure 8. Sensitivity of the spatial parameter to the weight matrix. The shaded band is the 95% cluster bootstrap interval for ρ, which propagates knot selection uncertainty.

The evidence for where they change is weaker. The 95% interval for the schooling knot runs from 6.59 to 10.91 years, a span of more than four years, and the interval for the wage knot runs from -0.056 to 0.509 log points, which covers most of the observed range of that variable. The bootstrap medians reinforce this reading rather than the point estimates, since the median wage knot falls at 0.006 log points and the median schooling knot at 8.32 years, neither of which coincides with the selected value. The wage interval is also pressed against the lower edge of the admissible region, which begins at -0.058 log points, so the replicates are placing the knot as low as the support constraint permits about as often as they place it high. We therefore report the thresholds as evidence that the relationships change somewhere in the indicated part of the distribution, and not as calibrated triggers.

Table 7. Cluster Bootstrap Stability of the Selected Knots ($B = 200$)

Variable	Selected as nonlinear	Median knot	95% interval
AYS	**90%**	**8.320**	**[6.590, 10.915]**
Relative RMW	**77%**	**0.006**	**[−0.056, 0.509]**
LFPR	57%	74.745	[69.820, 78.560]
Industry	46%	23.120	[16.540, 31.275]
GDP Growth	40%	5.105	[4.390, 5.655]

The spatial parameter behaves in a similar way. Its cluster bootstrap median is $+0.330$ and it is positive in 94% of replicates, but the 95% interval, $[-0.060, +0.660]$, includes zero once knot selection uncertainty is propagated. Conventional intervals that condition on the selected knots exclude zero, and we report the wider interval because the knots were estimated from the same data.

We draw a general conclusion from this pair of results. Detecting the presence of a change in slope and locating that change are distinct inferential problems with very different data requirements. At the scale of a single province, namely 38 administrative units and 76 observations pooled over two years, the first is comfortably within reach while the second is not. Studies that report spline knots as policy thresholds without quantifying their sampling variability therefore risk presenting a point on a flat criterion surface as a structural feature of the economy, and this caution applies to the wider class of knot selection procedures used in applied nonparametric regression [22, 26].

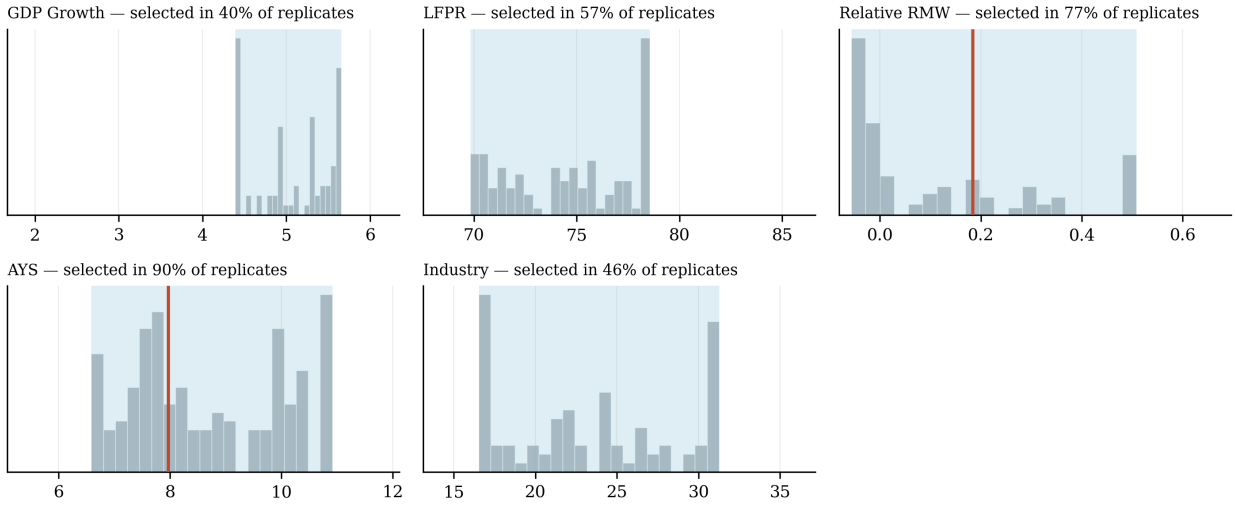


Figure 9. Sampling variability of the GCV-selected knot locations. Bars give the distribution of selected knot locations, the shaded band its 95% interval, and the vertical line the knot retained in the estimated specification.

3.7. Spatial Clusters and Regional Implications

Local Moran statistics identify where the global dependence reported in Section 3.1 is concentrated [3]. Figure 10 displays the result. At the five percent level, five regions cluster significantly in 2024 and eight in 2025. The High-High cluster is stable across both years and comprises Kota Surabaya, Gresik, Kota Pasuruan and Bangkalan, joined in 2025 by Lamongan. This traces the industrial corridor west and south of Surabaya and extends across the Suramadu bridge to Bangkalan. Sumenep forms a Low-Low cluster in both years, joined by Situbondo in 2025, while Tuban appears as a Low-High outlier in 2025.

Two points follow. Firstly, the High-High cluster is a labor market corridor rather than a contiguous block, since Bangkalan belongs to it despite sharing no land boundary with any other member, and this corroborates from an entirely independent direction the weight matrix argument of Section 2.4. Second, three of the four regions that form the stable High-High cluster, namely Kota Surabaya, Gresik and Kota Pasuruan, also lie above the wage threshold identified in Section 3.3, while Bangkalan does not. The core of the corridor where a further wage increase carries the strongest association with unemployment is therefore also the part of the province whose unemployment is most tied to that of its neighbours, which is a finding with a direct bearing on how wage policy in the Surabaya corridor should be coordinated.

We note finally that spatial dependence in this province is a level phenomenon concentrated in a small number of places. It does not support a partition of all 38 regions into distinct spatial regimes, and we do not propose one. A rule based classification applied to thresholds estimated as imprecisely as those in Table 7 would assign regions according to the accident of where a knot happened to fall.

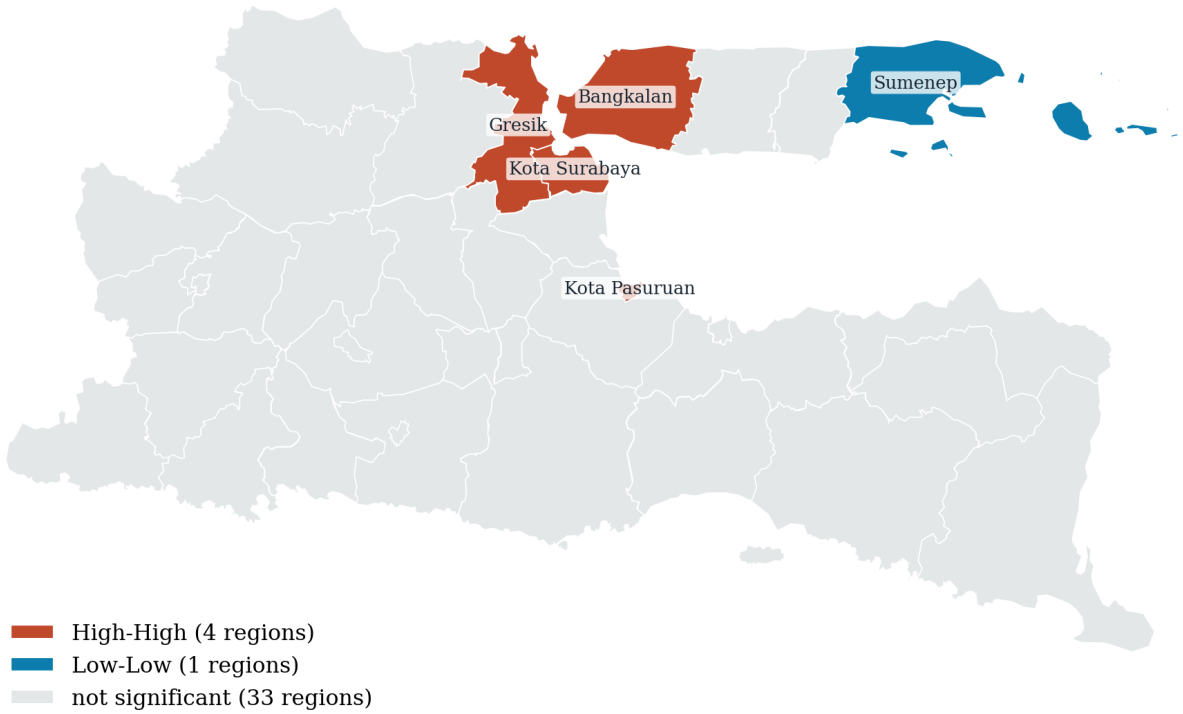


Figure 10. Local clusters of open unemployment, based on Local Moran's I with conditional permutation inference (9,999 permutations, $\alpha = 0.05$).

4. Conclusions and Recommendations

4.1. Conclusions

The STARS model successfully combines truncated spline based nonlinear modeling with spatial dependence, and provides a specification that improves on the linear SAR benchmark in explanatory fit, in a complexity penalized criterion and in cross validation at the same time. Applied to the 38 regencies and cities of East Java over 2024 and 2025, the framework yields three findings.

Firstly, two policy variables carry a threshold. The relative minimum wage bends upward at 20.2% above the provincial median, where the total effect of a wage increase rises from $+0.44$ to $+2.12$ percentage points, and average years of schooling bends at 7.97 years, where the total effect falls from $+0.59$ percentage points to a value indistinguishable from zero. The two thresholds divide the province along almost opposite lines, since the regions above the wage threshold form the metropolitan corridor while the regions below the schooling threshold form the agrarian periphery.

Second, spatial dependence is substantial, and its presence is established more firmly than its magnitude. The spatial autoregressive parameter is 0.395, indirect effects run at 0.604 of direct effects, and Moran's I is essentially unchanged between the two years, although the magnitude of ρ varies across weight matrices and its bootstrap interval is wide. The reach of a given intervention depends on where it is undertaken, since the worked examples of Section 3.4 show the same schooling policy spilling over at 32% of its local effect in Sampang and 57% in Jember. Reception is near uniform across the province while transmission is not, and the regencies that transmit most are the urban and industrial centres.

Third, and cutting against the first two, knot locations are estimated imprecisely. Both thresholds are detected in a large majority of bootstrap replicates, at 90% for schooling and 77% for the wage, but their locations are determined

only within wide intervals, and the interval for ρ includes zero once knot selection uncertainty is propagated. The framework therefore establishes that the thresholds exist more securely than it establishes where they lie.

4.2. Policy Recommendations

We separate recommendations that follow directly from the estimates from broader contextual considerations that do not.

Implications from the estimates: A uniform province wide minimum wage increase does not carry a uniform employment consequence, since the association is almost five times stronger in the twelve regions already paying more than 20% above the provincial median. Wage adjustment in those regions should therefore be accompanied by measures that raise productivity, whereas in the twenty six regions below the threshold the same adjustment carries a much weaker association. In regions below the schooling threshold, rising schooling is associated with a higher measured OUR rather than a lower one, and monitoring frameworks should allow for that pattern rather than read it as programme failure. Because spillovers run at three fifths of the strength of direct effects, evaluation of labor market policy at the single jurisdiction level will understate its impact, and since the spillover share varies with geography, the case for cost sharing across jurisdictions is strongest along the dense eastern arc and along the Surabaya corridor, and weakest in Madura.

Contextual considerations: The wider literature suggests that absorption capacity, including industrial structure, infrastructure and the match between vocational training and local demand, governs whether an expanded labor supply is taken up [29]. Our estimates are consistent with that view but do not test it, and we therefore flag these considerations as context rather than as results. We also note that the mathematical foundation, the estimated thresholds, the spillover multipliers and the cluster assignments reported here can be integrated into a regional monitoring dashboard combining periodic BPS releases with STARS based outputs, following the dashboard designs the authors have applied in other domains [17, 18], which would enable periodic updates of the regional picture and early detection of regions approaching either threshold.

Because the wage threshold is expressed relative to the provincial median rather than in nominal rupiah, it can be carried forward without revision as nominal wages rise, and restated in rupiah for whichever planning year is required. We regard this as a practical advantage of the specification for use inside a planning cycle.

4.3. Limitations and Future Research Directions

The current study uses observational data covering two years. The spatial lag addresses simultaneity in the outcome, but nothing in the design separates the associations reported here from reverse causation or from omitted regional characteristics that drive both sides, so all relationships reported here are associations rather than causal effects. Seventy-six observations across 38 units support nine parameters comfortably, but not the richer specifications that the framework can express, and the over-parameterised specification in Table 5 illustrates that failure mode directly.

The 95% interval for the schooling knot spans 6.59 to 10.91 years and the interval for the wage knot spans most of the observed range of that variable, so both thresholds should be read as evidence that the relationships change somewhere in the indicated part of the distribution rather than as calibrated policy triggers. The spatial parameter ranges from $+0.025$ to $+0.570$ across the weight matrices examined, and although the qualitative conclusion of positive spatial dependence with substantial indirect effects holds throughout, the magnitude does not transfer between weight matrices. Weak positive residual spatial autocorrelation also remains in the 2024 cross section. In addition, the Human Development Index is excluded because it is collinear with average years of schooling by construction, and a specification separating the health and income components of HDI from its education component would allow the non education dimensions of human development to enter without that collinearity. As with any study that analyses administrative units, the findings are sensitive to how those units are drawn, since the estimated thresholds, the spillover magnitudes and the spatial parameter are all conditional upon existing administrative boundaries and upon the nearest neighbour aggregation scheme, which is the modifiable areal unit problem in its standard form. A final limitation concerns the outcome itself. The open unemployment rate counts anyone who is searching for work, and it does not separate a school leaver entering the labor market by choice from a worker displaced from an existing job. The two carry very different welfare consequences, and the interpretation of the schooling threshold in Section 3.3 rests on that distinction without being able to measure it. A measure that

separates the two, such as unemployment by reason or by previous employment status, would allow the mechanism proposed there to be tested directly rather than inferred.

The most direct route past the precision limits documented here is a longer panel. Two years of data doubled the observations available to identify a knot, and a five or ten year panel with region and year effects would permit knot locations to be estimated with intervals narrow enough to serve the policy purpose that this framework was designed for, while allowing the change in slope to be identified from within region variation rather than from cross sectional differences alone [28]. Extensions to spatial panel specifications such as pooled OLS, fixed effects and random effects frameworks would demonstrate temporal dynamics that the present design cannot. Beyond that, mixed estimator approaches that combine spline components with kernel or Fourier series terms [10, 23, 24, 25] could relax the piecewise linear form where the data support it, and endogenous network specifications [21] could allow weight matrices based on known economic flows rather than geographic proximity alone.

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