Okun's Law and Spatial Regimes in Indonesia: A Machine Learning Approach

Abstract

We study how output growth translates into unemployment changes across districts in Indonesia, over the 2011–2020 period. Instead of imposing predetermined geographic groups, we apply a data-driven approach to identify districts with similar growth–unemployment dynamics. We find that the growth-unemployment relationship (Okun's law) varies markedly across districts: growth substantially reduces unemployment in some, while it is negligible or even reversed in others. To account for spatial dependence across districts, we estimate spatial models that decompose the total effect into each district's own response and spillovers from neighboring districts. These spillovers are both statistically significant and economically sizeable, suggesting that growth shocks diffuse well beyond individual district borders. Overall, our findings underscore the limitations of aggregate Okun estimates and the need for policies that are locally tailored and coordinated across neighboring regions.

Keywords: Okun's law, machine learning, Spatial Durbin Model, classify lasso, labor heterogeneity

JEL Classification: C33 , E24 , J21 , R11

Highlights

- Data-driven classification uncovers four spatial regimes across Indonesian districts
- Growth reduces unemployment in some districts but is negligible or reversed in others
- Growth shocks diffuse well beyond district borders through sizeable spatial spillovers
- Aggregate estimates and uniform employment policies overlook regional diversity
- Results call for locally tailored policies coordinated across neighboring regions

1 Introduction

Indonesia, the world's largest archipelago, comprises 514 districts whose economic structures and labor markets vary enormously—from diversified metropolitan areas to resource-intensive rural economies (Hill et al. (2008); Mendez and Siregar (2023)). This diversity poses a fundamental policy question: does economic growth translate into employment equally across all types of districts, or does the growth–unemployment relationship depend on local economic conditions? If the relationship differs substantially from one district to another, then uniform national employment policies may be ineffective—or even counterproductive—in large parts of the country. In macroeconomics, this empirical inverse relationship between economic growth and unemployment is formalized as Okun's law (Okun (1962); Elhorst and Emili (2022)).

This study asks two questions. First, can a data-driven, machine-learning classifier uncover labor-market regimes that outperform traditional geographic divisions in explaining the growth–unemployment relationship? Second, once those regimes are identified, how does the Okun effect differ across them—both within each district (the direct effect of its own growth) and through spillovers from neighboring districts (the indirect effect)—and what do these differences imply for region-specific policy design?

In his original formulation, Okun (1962) found that a 1 percentage point decrease in real gross national product was associated with a 0.3 percentage point increase in the unemployment rate. Since then, Okun's law has been extensively tested across diverse settings, and while many studies confirm the negative relationship, others find it statistically insignificant or even positive (Ball et al. (2013); Perman et al. (2015); Porras-Arena and Martín-Román (2023); Zidong et al. (2017)). A key finding from recent meta-analyses is that studies using subnational data tend to report smaller Okun coefficients than those using national data (Porras-Arena and Martín-Román (2023)). This is because local labor markets are heterogeneous: the growth–unemployment relationship may be strong in some regions and weak in others, and these differences can make the aggregate national relationship appear non-existent (Aginta et al. (2023); Basistha and Kuscevic (2017); Elhorst and Emili (2022); Maza (2022)).

A parallel strand of the literature shows that spatial spillovers are a critical feature of the growth–unemployment relationship: growth in one region affects unemployment not only locally but also in neighboring regions, and these indirect effects can be substantial—accounting, for example, for over 80 percent of the total unemployment change in US metropolitan areas (Pereira (2014); Palombi et al. (2017); Montero Kuscevic (2014); Basistha and Kuscevic (2017)). Elhorst and Emili (2022) traced the underlying mechanism, showing that for about two-fifths of output growth in a given region, production is displaced from other regions, and this complex output dynamic then transmits to unemployment through cross-region spillovers.

Despite this rich body of evidence, no study of Okun's law in Indonesia has explicitly accounted for spatial dependence across districts. The heterogeneity of Indonesia's economic structures and local labor markets has been widely discussed

(Aginta and Someya (2022); Hill et al. (2008); Manning (1997); Mendez and Siregar (2023); Miranti and Resosudarmo (2005)), and given the large number of regional divisions (currently 38 provinces comprising 514 districts), many studies classify districts into groups such as "East" and "West" (Aginta et al. (2023); Aurelia et al. (2022); Tjahja Nugraha and Prayitno (2020)) or by main islands (Aginta and Someya (2022); Hill et al. (2008); Manning (1997)). Using district-level data, Aginta et al. (2023) found a statistically non-significant Okun's coefficient when all districts were pooled; after estimating West and East Indonesia separately, the study found that Okun's law holds in West Indonesia but not in East Indonesia. However, large variations in economic and labor market characteristics exist even within the same group, and classifications based on observable characteristics assume that districts within a group behave similarly, ignoring the possibility of deeper, latent differences in labor market dynamics. Two gaps thus remain: no study of Okun's law in Indonesia accounts for spatial dependence, and no existing approach lets the data itself reveal which districts share similar labor-market dynamics.

To address these gaps, we take a two-step approach. In the first step, we apply a data-driven classification method—the classification-lasso (c-lasso) of Su et al. (2016)—that sorts districts into groups based solely on their estimated growth–unemployment relationship, without imposing assumptions about geographic similarity. In the second step, we embed these data-driven regimes in a Spatial Durbin Model (SDM) that allows the Okun's coefficient to vary across the groups identified by the c-lasso while capturing cross-district spillovers through spatial lags of both the dependent and independent variables (LeSage and Pace (2009); Elhorst et al. (2021)). This design allows us to quantify both the *direct* effect of output growth on a district's own unemployment within each latent regime and the *indirect* effect transmitted via neighboring districts—something neither non-spatial models nor ad-hoc regional splits can deliver.

Our results reveal four latent spatial regimes with markedly different Okun's coefficients. Group 1 collects Indonesia's thick labor markets—large metropolitan areas, industrial belts, and labor-intensive plantation districts—where growth is strongly unemployment-reducing. Group 2 captures districts where measured output expansions coincide with rising open unemployment, a pattern consistent with capital- and resource-intensive activity and weaker employment absorption. Groups 3 and 4 represent more transitional and peripheral labor markets where the growth–unemployment relationship is small or unstable, and adjustment is more likely to occur through underemployment and informality rather than measured open unemployment. These results demonstrate that traditional "West" and "East" or "main islands" classifications are insufficient to capture the variation in district-level labor market dynamics.

Our study advances the literature in three ways. First, to our knowledge, we are the first to integrate an unsupervised machine-learning classifier with a heterogeneous-slope SDM, demonstrating a practical route to combine latent grouping and spatial econometrics. Second, analyzing a balanced panel of 514 Indonesian districts over 2011–2020, we uncover four latent spatial regimes whose Okun's coefficients range from strongly negative to weakly positive. Third, we show that these regimes map to meaningful structural differences, from diversified metropolitan and manufacturing districts to capital- and resource-intensive areas and thin rural labor markets.

Beyond Indonesia, our methodological approach offers a replicable template for other large, diverse developing economies where conventional geographic divisions may mask important heterogeneity in regional labor markets. The integrated framework can be readily adapted to other macroeconomic relationships—such as regional Phillips curves or fiscal multipliers—where both latent regime structure and spatial interdependence are likely to be empirically relevant. Moreover, as our results confirm that spatial spillovers are significant, strategically targeting districts that transmit employment spillovers to their neighbors can amplify the impact of limited policy resources.

The remainder of this paper is organized as follows. Section 2 describes the data and methodology. Section 3 presents and discusses the main results. Section 4 confirms the robustness of our results. Finally, Section 5 concludes.

2 Data and Methodology

2.1 Data

We use annual district-level data on the open unemployment rate and real gross regional domestic product (GRDP) to estimate Okun coefficients for all 514 Indonesian districts (*kabupaten* and *kota*). The primary source is Statistics Indonesia (*Badan Pusat Statistik*, BPS), complemented by administrative series from *Bappenas* to ensure consistent coverage in years where BPS district series are incomplete. We focus on districts because they are the main administrative units for local labor markets and the locus of fiscal decentralization in Indonesia (Aginta et al. 2023). The analysis covers 2011-2020, yielding a balanced panel of 5,140 district-year observations ($N = 514$, $T = 10$).

Constructing a consistent district panel in Indonesia requires addressing three practical challenges. First, administrative boundaries changed rapidly during the *pemekaran* period (administrative splitting of districts). The number of districts rose from 479 in 2010 to 514 by 2014, and comparisons over time require harmonizing observations to a consistent set of spatial units. We therefore assemble a panel using a consistent 514-district coding scheme and reconcile early-year observations for districts that had not yet split using data from the Indonesian Ministry of Development Planning (*Bappenas*).

Second, although higher-frequency data are available for national and provincial aggregates, district-level data for both GDP and the unemployment rate are only consistently available on an annual basis. BPS does not publish quarterly GDP for districts, and while the labor survey is conducted semi-annually during our period of study, only the August round is designed with a sample size sufficient to be representative at the district level. Utilizing annual data thus avoids the measurement errors and noise inherent in lower-representative survey rounds or interpolated quarterly estimates.

Third, national accounts series can exhibit methodological and base-year revisions. We measure output using GRDP in constant 2010 prices and compute GDP growth as the year-on-year percentage change in real GRDP to maintain a consistent price basis across the sample. Using a single constant-price base-year series helps avoid mechanical breaks in measured growth associated with rebasing. Similarly, the definition of ”unemployment” remained consistent throughout this period, following the ILO standard definition since 2011.

Finally, district-level unemployment rates for 2016 are not directly available in the BPS district series used here. Therefore, we rely on *Bappenas*-compiled district estimates for 2016 to preserve a balanced panel. Summary statistics are reported in Table 1.

Table 1: Summary statistics

Variable		Mean	Std. Dev	Min	Max	Obs
Unemployment rate (%)	Overall	5.124	2.818	0.053	19.242	N = 5140
	Between		2.442	0.597	13.237	n = 514
	Within		1.411	-0.825	15.454	T = 10
Real GDP growth (%, yoy)	Overall	5.086	4.212	-45.047	112.199	N = 5140
	Between		1.885	-5.878	30.608	n = 514
	Within		3.775	-34.082	108.439	T = 10

As an exploratory first step, we estimate the Okun relationship using national-level data from 2001–2020, presented in Appendix A. Average GDP growth increased from 4.8% during 2001–2009 to 5.4% during 2010–2019, while the unemployment rate declined from 9.3% to 6.1% over the same period. The COVID-19 shock in 2020 produced a sharp reversal, with GDP growth turning negative and the unemployment rate rising by 1.84 percentage points. A simple OLS regression yields an Okun coefficient of -0.192 ($R^2 = 0.641$), suggesting that a one percentage point increase in GDP growth is associated with a 0.19 percentage point decline in the unemployment rate. However, this aggregate result is heavily influenced by the 2020 outlier; excluding it, the relationship is weak during normal growth periods. Moreover, as discussed in Appendix A, the national series is subject to well-documented structural breaks in the Sakernas survey in 2001 and 2011 that limit its comparability across the full period. Together, these limitations motivate the district-level analysis that follows, where we exploit spatial and cross-sectional variation across 514 districts and explicitly account for spatial dependence.

2.2 Methodology

2.2.1 Estimating Okun’s Coefficient

Okun originally estimated the relationship between output and unemployment using three models: the difference model, the gap model, and a fitted trend model (Okun (1962); Porras-Arena and Martín-Román (2023)). As the estimates from these models yield similar results, we follow recent regional studies (Aginta et al. (2023)) and use the difference model, specified as:

$$\Delta U_{it} = \beta\,\Delta \text{GDP}_{it} + \gamma_i + \tau_t + \varepsilon_{it} \tag{1}$$

where ΔU_{it} is the annual change in the unemployment rate of district i at time t. ΔGDP_{it} is the annual GDP growth rate of district i at time t. Representing Okun's coefficient, β is our parameter of interest. γ_i is a district fixed effect, included to control for time-invariant, district-level trends, while τ_t is a year fixed effect, included to control for common shocks that affect all districts. Finally, ε_{it} is the error term. Equation 1 is estimated by OLS with two-way fixed effects.

Standard errors are clustered at the district level, making them robust to heteroskedasticity and within-district serial correlation. Standard diagnostic tests for the TWFE specification are reported in Appendix C.

More importantly, our exploratory spatial data analysis (ESDA) and spatial econometric model estimation results, which will be discussed in the upcoming sections, explicitly model spatial interaction rather than relying solely on residual-based diagnostics.

Another concern is the persistence of our variables, which may drive the estimates. Therefore, we check whether the pooled TWFE difference model in Equation 1 is sensitive to simple dynamic refinements and estimate a non-spatial ARDL(1,1) version with a one-year lag of Δu_{it} and a one-year lag of GDP growth. Our results, presented in Appendix C, indicate persistence in annual unemployment adjustments, but the GDP-growth terms remain statistically indistinguishable from zero. This reinforces our interpretation that a single national Okun coefficient (even with dynamics) is not informative for Indonesian districts, motivating the data-driven classification step that allows the growth-unemployment elasticity to differ across latent regimes.

2.2.2 Classification LASSO (c-lasso)

Because one of the main objectives of this paper is to propose the use of the c-lasso approach in classifying districts in Indonesia, we first estimate Equation 1 for all districts and then divide the sample into "West" and "East" as well as by main islands, as is commonly done in previous studies. Our results show, and will be discussed in more detail in Section 3, that the estimated Okun's coefficients are statistically insignificant, motivating a data-driven classification that does not rely on predetermined geographic boundaries.

Given these results, instead of classifying regions based on observable geographic characteristics, we allow the data to reveal clusters of districts that share similar Okun's Law dynamics. We follow the approach outlined in Huang et al. (2024). Our model is specified as follows.

$$\Delta U_{it} = \beta_i \Delta\text{GDP}_{it} + \gamma_i + \tau_t + \varepsilon_{it} \tag{2}$$

In Equation 2, we allow the responsiveness coefficient β to vary across districts β_i. Unlike OLS, which assumes a common β for all districts as in Equation 1, the c-lasso method assumes that β_i follows an unknown group pattern, formally expressed as:

$$\beta_i = \begin{cases} \alpha_1, & \text{if } i \in G_1, \\ \vdots & \vdots \\ \alpha_K, & \text{if } i \in G_K. \end{cases} \tag{3}$$

where K denotes the number of latent groups, α_k represents the slope coefficient specific to group k, and G_k denotes the set of district members in group k. The estimation of β, α, and group memberships G_k is done jointly via a penalized least squares (PLS) function.[1]

After the initial classification step, we re-estimate the group-specific Okun's coefficients using a post-lasso procedure (Huang et al. (2024)). Specifically, once the latent groups are identified based on their estimated β_i patterns, an ordinary least squares (OLS) regression is performed within each group without penalization. This second step corrects the bias introduced by the penalty term in the first stage and yields unbiased estimates of the Okun's coefficients for each latent group. By allowing β_i to vary across districts and refining the estimates through post-lasso, we capture the heterogeneous effects of GDP growth on unemployment changes in a data-driven way, avoiding arbitrary regional divisions.

2.2.3 Spatial Connectivity and Spatial Models

The c-lasso estimates already reveal striking regime heterogeneity, but they may be biased: if GDP growth and unemployment changes are spatially correlated across districts — as previous studies and our own ESDA suggest — non-spatial models misattribute neighbor-driven variation to a district's own growth, biasing the estimated Okun coefficient. For that reason, before moving to spatial regression models, we first ask a simple diagnostic question, which is whether or not changes in the unemployment rate and GDP growth of neighboring districts *move together.*

To answer that question, we need an explicit definition of "neighbors." We encode spatial connectivity in a row-standardized weights matrix $W = [w_{ij}]$, where $w_{ij} > 0$ if district j is considered a neighbor of district i, and $w_{ij} = 0$ otherwise, with each row scaled to sum to one. Our baseline neighbor definition is queen contiguity, where two districts are considered neighbors if they share a common border.

However, Indonesia's archipelagic geography implies that contiguity based on the original administrative polygons can leave many districts (especially on smaller islands) effectively neighborless. To avoid disconnected units while preserving a geography-based definition of proximity, we follow Santos-Marquez et al. (2022) and Miranti and Mendez (2023) and construct queen contiguity on Thiessen (Voronoi) polygons generated from district centroids (Appendix B). This produces a fully connected and interpretable neighborhood structure that combines contiguity with centroid distance in a transparent way.

We begin with an exploratory spatial data analysis (ESDA) using *global* Moran's I, the standard summary measure of global spatial autocorrelation. Intuitively, Moran's

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[1] A detailed description of the estimation procedure can be seen in Huang et al. (2024).

I compares each district's deviation from the national mean to a weighted average of deviations among its neighbors. The value of Moran's I is positive when similar values cluster in space (high values with high values and low values with low values), close to zero under spatial randomness, and negative when neighboring values are dispersed (high values with low values, and vice-versa). Formally, for a variable x observed across N districts, define $z_i = x_i - \bar{x}$ and $S_0 = \sum_i \sum_j w_{ij}$. Moran's I is

$$I \;=\; \frac{N}{S_0} \, \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} z_i z_j}{\sum_{i=1}^{N} z_i^2}. \qquad (4)$$

We compute Moran's I for both GDP growth and unemployment-rate changes using the baseline W.

In addition to global Moran's I, we use Local Indicators of Spatial Association (LISA), most commonly implemented through the *local* Moran statistic, to locate clusters and spatial outliers. The local statistic decomposes global spatial association into district-specific contributions, allowing us to identify statistically significant "hot spots" and "cold spots." In practice, the LISA cluster map classifies each district into standard categories based on the sign of its deviation z_i and the sign of the spatial lag Wz_i: *High-High* (high values surrounded by high values/HH), *Low-Low* (LL), and spatial outliers *High-Low* (HL) and *Low-High* (LH).

The ESDA results for 2020 are reported in Figures 1 and 2 (with the full 2011-2020 evolution in Appendix D). In our data, GDP growth displays clear global spatial clustering, while unemployment-rate changes exhibit weaker but statistically significant spatial association.

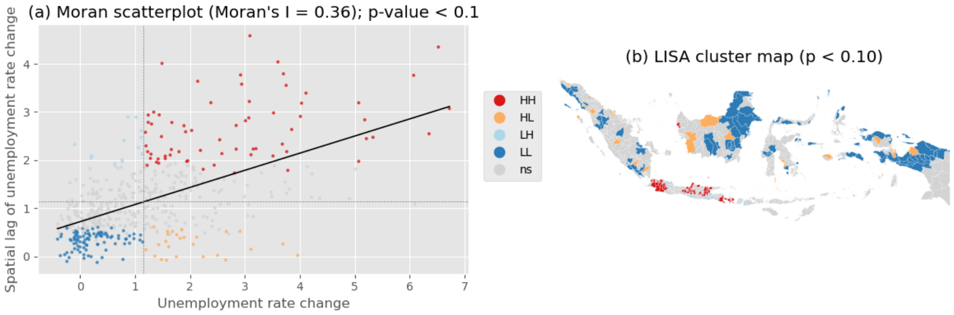


Fig. 1: Spatial dependence and local clusters of regional unemployment rate change in 2020

These findings are consistent with the idea that growth shocks propagate geographically and that labor-market outcomes may inherit spatial dependence partly through those output spillovers. The upward slope of the Moran scatterplots indicates positive global spatial autocorrelation, meaning that districts with above-average values of GDP growth and unemployment rate changes tend to be surrounded by neighbors with above-average values of those outcomes and vice

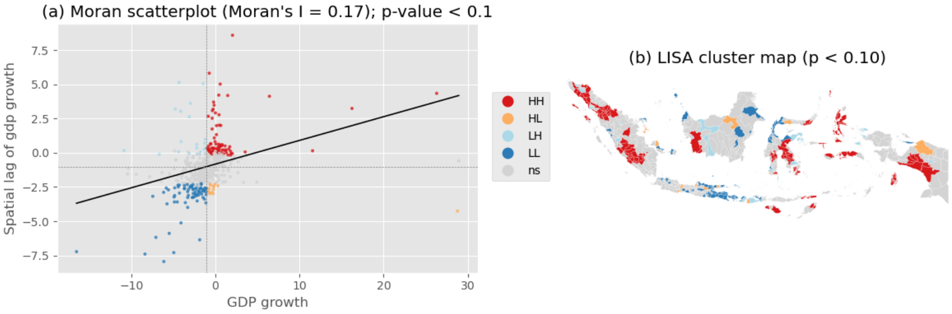


Fig. 2: Spatial dependence and local clusters of regional GDP growth in 2020

versa. This spatial clustering underscores the need for a regression framework that explicitly accounts for cross-district interdependence rather than treating each district as an isolated unit.

The LISA cluster maps complement the global Moran's I statistics by locating where clustering is concentrated. The maps show that spatial dependence is not uniform across Indonesia, but is driven by localized pockets of HH and LL clusters, alongside a few HL and LH outliers. For GDP growth, the presence of HH clusters is consistent with geographically linked growth corridors, where shocks co-move across neighboring districts through supply-chain linkages, shared factor markets, and common exposure to commodity or industry-specific cycles. For unemployment-rate changes, the weaker but still significant spatial association suggests that labor-market adjustment is partly local and partly spatially transmitted.

Therefore, the ESDA evidence motivates a regression framework that allows unemployment changes to respond to neighboring unemployment changes (feedback and diffusion). Furthermore, it is also plausible to consider the possibility of neighboring districts' GDP growth affecting local unemployment (spillovers in the Okun channel). For that reason, we employ the Spatial Durbin Model (SDM), which includes both a spatial lag of the dependent variable and spatially lagged regressors.

Unlike the Spatial Lag (SAR) or Spatial Error (SEM) models, the SDM *simultaneously* incorporates a spatial autoregressive term in the dependent variable and spatial lags of the regressors, thereby capturing both feedback effects and omitted neighbor-level covariates (LeSage and Pace 2009; Elhorst et al. 2021). Importantly, the SDM nests the SAR and SEM as restricted cases, so conventional Wald or LR tests can confirm whether those simpler models are adequate. We report the results of these tests in Appendix E. In what follows, we further embed the c-lasso regimes in the SDM by allowing the growth elasticity (and its spillover component) to vary by latent group, so that we can distinguish regime-specific *direct* and *indirect* Okun effects in a fully spatial setting.

Specification of the SDM

Let G_j ($j = 1, \ldots, 4$) denote the latent regimes uncovered by c–lasso. We interact the output growth variable and its spatial lag with these regime dummies, allowing the

Okun coefficient and its spillover to vary by group while keeping a single spatial-autoregressive parameter ρ:

$$\Delta U_{it} = \rho W \Delta U_{it} + \sum_{j=1}^{4} \beta_j \big(\Delta \text{GDP}_{it}\, \mathbb{1}_{\{i \in G_j\}}\big) + \sum_{j=1}^{4} \theta_j \big(W \Delta \text{GDP}_{it}\, \mathbb{1}_{\{i \in G_j\}}\big) + \gamma_i + \tau_t + \varepsilon_{it} \tag{5}$$

where W is the row-standardized queen contiguity matrix based on the Thiessen polygons. The parameters of interest are β_k which shows the *direct* (within-district) growth–unemployment elasticity for regime k, θ_k which shows the *indirect* (spillover) elasticity—how neighbors' growth influences unemployment in regime k districts, and ρ which shows the feedback of neighboring unemployment changes on the focal district.

We estimate Equation (5) by quasi–maximum likelihood (QMLE) with two-way fixed effects following Belotti et al. (2017).

In addition to the static SDM, we estimate a dynamic SDM that includes a one-year lag of the focal district's unemployment changes, a one-year lag of neighboring regions' unemployment changes, or both. The inclusion of these time lags are intended to capture persistence in labor-market adjustments. As we will show later, we treat the specification with a one-year lag of the focal district's unemployment rate changes ("Lag Y") as our benchmark model and report alternative dynamic specifications and spatial-weight matrices as robustness checks.

Interpreting the coefficients

Because spatial lags generate feedback loops, the raw coefficients (β_k, θ_k) do not equal marginal effects. Following LeSage and Pace (2009), we therefore report regime-specific *direct*, *indirect*, and *total* effects computed from the reduced-form impact matrix. In the static SDM of Equation (5), the contemporaneous (one-period) impact of growth in regime k is

$$S_k = (I - \rho W)^{-1} (\beta_k I + \theta_k W), \tag{6}$$

which maps a change in ΔGDP into ΔU after accounting for spatial feedback through $(I - \rho W)^{-1}$. We summarize S_k into the standard average effects:

$$\begin{aligned} \text{SR Direct}_k &= \frac{1}{N}\, \text{tr}[S_k]\,, \\ \text{SR Indirect}_k &= \frac{1}{N} \mathbf{1}^\top S_k \mathbf{1} - \text{SR Direct}_k, \\ \text{SR Total}_k &= \text{SR Direct}_k + \text{SR Indirect}_k. \end{aligned} \tag{7}$$

Here, the *direct* effect is the average of the diagonal elements of S_k (the within-district impact, including spatial feedback that returns to the origin), while the *indirect* effect captures spillovers to and from other districts through the off-diagonal elements.

In our benchmark dynamic SDM ("Lag Y"), we add a one-year lag of unemployment changes,

$$\Delta U_{it} = \phi\, \Delta U_{i,t-1} + \rho W \Delta U_{it} + \cdots,$$

so that contemporaneous spatial impacts also propagate forward over time. With annual data, the *short-run* effects are the within-year (impact) effects defined above. Under dynamic stability (with $|\phi| < 1$), the *long-run* (steady-state) effects scale up the short-run impacts by the persistence multiplier:

$$\begin{aligned} \text{LR Direct}_k &= \frac{1}{1-\phi}\text{SR Direct}_k, \\ \text{LR Indirect}_k &= \frac{1}{1-\phi}\text{SR Indirect}_k, \\ \text{LR Total}_k &= \frac{1}{1-\phi}\text{SR Total}_k. \end{aligned} \tag{8}$$

Intuitively, if ϕ is close to one, unemployment adjustments are persistent, and a growth shock has larger cumulative effects over subsequent years. In contrast, if ϕ is small, the long-run and short-run impacts are similar. We compute regime-specific standard errors for both short-run and long-run effects by Monte Carlo simulation of the estimated variance-covariance matrix.

Why heterogeneous slopes matter

If spatial dependence were the only source of bias, imposing a common Okun coefficient across Indonesia might suffice. Yet our c–lasso classification shows that districts differ not merely in the *level* of their unemployment responses but even in the sign. While there are regions with the expected negative Okun's relationship, others display increased unemployment rate changes during periods of high growth (positive β_k). As such, embedding these latent regimes in the SDM achieves two goals at once. First, it corrects for spatial spillovers and, second, it preserves district-level heterogeneity that would otherwise be averaged out. The evidence from our ESDA results supports our choice of a heterogeneous-slope SDM as an informative specification for Indonesian district-level data.

3 Results and Discussion

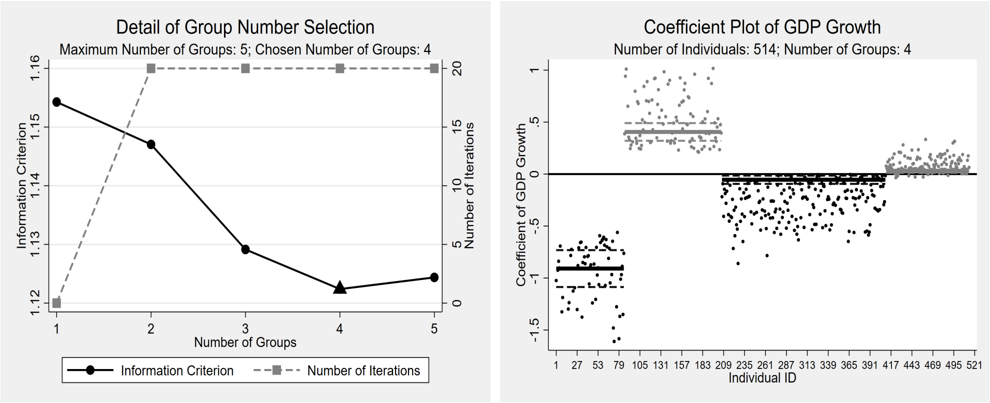
3.1 TWFE estimation results

We begin with a conventional benchmark that mirrors much of the Indonesia Okun's-law literature: a two-way fixed effects (TWFE) regression estimated on pooled districts and on coarse geographic partitions (West-East and main islands). Table 2 presents our estimation results by using the TWFE estimator, with column (1) showing the results for the whole sample, columns (2) and (3) for districts in the West and East, and columns (4) to (10) for districts based on their main islands, respectively. As the results suggest, when all districts are pooled in the estimation, the obtained Okun's coefficient is indistinguishable from zero (column (1)). Dividing the sample into West and East, and based on their main islands, results in nonsignificant Okun's coefficients, except for Java-Bali and Nusa Tenggara, which have contrasting results.

A natural (but misleading) reading of those results would be that Okun's law is largely absent outside a few regions. However, this conclusion is premature because it implicitly assumes that districts share a common growth-unemployment elasticity within each broad geographic bin. If, instead, districts differ systematically in how labor markets adjust to growth, then pooled TWFE estimates will average over opposing slopes and wash out the underlying relationship. This is exactly the setting for classify-lasso (c-lasso): it allows the Okun coefficient to vary by district but constrains these coefficients to come from a small number of latent groups.

3.2 C-lasso Results: Four regional groups in the Okun relationship

We therefore apply classify-lasso as in Equation 2, allowing the Okun coefficient to differ across districts but to follow an unknown latent group structure. Figure 3 summarizes the group selection and the resulting heterogeneity. Panel (a) uses the information criterion to choose the number of regimes, which is $K = 4$. Panel (b) then plots district-specific Okun coefficient estimates (represented by the dots) alongside group means (represented by the solid horizontal bars) and confidence intervals (represented by the dashed horizontal bars), with districts ordered by their latent assignment.



(a) Detailed group selection

(b) Coefficient plot of groups

Note: In Panel (b), the dots represent the first-stage penalized district coefficients (β in Eq. 3, while the solid bars represent the post-lasso group coefficients (α in Eq. 3

Fig. 3: Selected number of groups

Table 2: Estimation Results: OLS

		West/East		Main Islands						
VARIABLES	Total	West	East	Sumatera	Java-Bali	Nusa Tenggara	Kalimantan	Sulawesi	Maluku	Papua
Δ GDP_{it}	-0.000	-0.046	0.009	0.000	-0.095***	0.017***	0.058	-0.003	0.058	0.008
	(0.007)	(0.027)	(0.005)	(0.028)	(0.036)	(0.004)	(0.045)	(0.005)	(0.047)	(0.014)
Constant	-0.061	0.167	-0.136***	-0.092	0.468***	-0.059***	-0.337	-0.108***	-0.550	-0.071
	(0.037)	(0.126)	(0.031)	(0.124)	(0.172)	(0.017)	(0.206)	(0.036)	(0.268)	(0.086)
Observations	5,140	2,820	2,320	1,540	1,280	320	560	810	210	420
R-squared	0.099	0.137	0.081	0.101	0.275	0.102	0.108	0.130	0.120	0.050

Notes: District-level and year fixed effects included in all models. Standard errors in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

We observe the following three patterns that stand out from Panel (b). First, the mean values of the four groups are sharply separated relative to the within-regime scatter. The most negative regime (Group 1) clusters near -0.91, while the shallowest negative regime (Group 3) sits around -0.05 (refer to Table 3 for the estimated Okun's coefficient by groups). Similarly, Group 2 exhibits a positive Okun's coefficient of 0.367, while Group 4's coefficient is 0.03. Although both are positive and statistically significant, the districts are separated into different groups, given the stark difference in the average magnitudes of the coefficients of the two groups. This is precisely what the shrinkage step is designed to do, namely, to bundle districts that share similar growth-unemployment elasticities into common regimes.

Second, the regimes are not tiny edge cases. With each group containing a sizable share of districts, as shown in Table 3, heterogeneity is economically meaningful rather than merely statistical noise. Out of our sample, roughly 16% belong to Group 1, 24% belong to Group 2, 40% to Group 3, and the remaining 20% to Group 4. The group means range from a strong negative elasticity (–0.91) to a positive coefficient (+0.40). Pooling these districts or dividing them into West versus East Indonesia would flatten these extremes and hide the fact that growth shocks can raise unemployment in a non-trivial share of Indonesia's districts (as shown in Table 2).

Third, the ordering in Panel (b) makes the key point visually. Panel (b) orders districts by their assigned regime based on their estimated Okun behavior. The coefficients cluster into four separate 'bands' with minimal overlap, showing that the algorithm is not fitting arbitrary labels, but is grouping districts with similar growth–unemployment elasticities.

Table 3: Heterogeneous effects of GDP growth on unemployment rate

Variable	**Group 1**	**Group 2**	**Group 3**	**Group 4**
Δ GDP$_{it}$	-0.909***	0.405***	-0.054***	0.032***
	(0.091)	(0.043)	(0.020)	(0.010)
Constant	4.664***	-2.118***	0.214**	-0.238***
	(0.481)	(0.221)	(0.105)	(0.075)
Observations	850	1,210	2,040	1,040

Note: District-level and year fixed effects are included in all models. Robust standard errors in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$

What the four regimes look like in the first-stage (non-spatial) estimates

As mentioned previously, Table 3 reports the group-specific TWFE post-lasso slopes. Two regimes display the textbook negative Okun relationship (Groups 1 and 3), while the remaining two regimes exhibit a positive association between GDP growth and unemployment changes (Groups 2 and 4). At this stage, we intentionally avoid discussing the magnitudes of the coefficient because the specification in Table 3 ignores spatial dependence. As such, these coefficients may mix local effects with spillovers and are biased. However, the *sign pattern* is informative and motivates the deeper spatial analysis presented in the upcoming sections.

Where are the district members of the regimes? Everywhere

Figure 4 overlays the four groups onto a map of Indonesia. The immediate takeaway is that each regime is geographically dispersed. Every group contains districts from multiple islands and both sides of the country, meaning that the spatial patterns of labor market responsiveness to economic growth do not align well with traditional geographic divisions. This highlights the limitations of traditional regional classifications and also explains why our results presented in Table 2, as well as other studies that use the traditional classifications, tend to find statistically non-significant Okun's coefficient estimates, as they are unable to capture the presence of hidden heterogeneity in regional labor market dynamics.

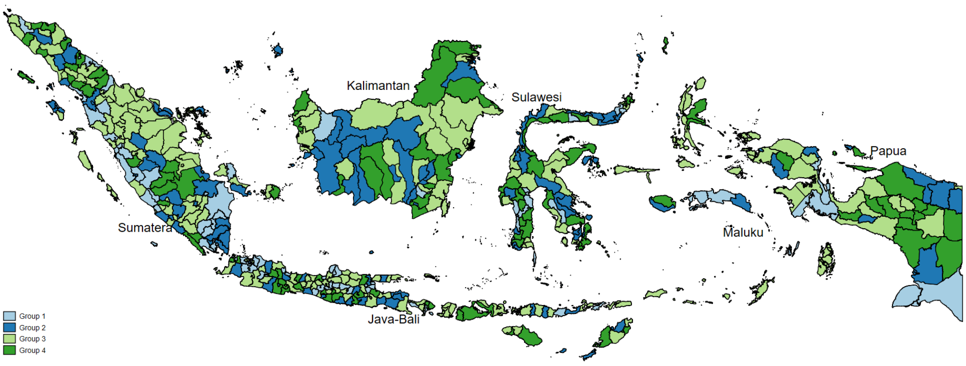


Fig. 4: Geographic distribution of c-lasso groups across Indonesian districts

Note: Districts are colored based on their latent group membership estimated through the c-lasso method using the relationship between GDP growth and unemployment rate changes. Major regional divisions based on the main islands are labeled for reference.

To better understand the economic intuition behind the four latent groups identified by c-lasso, we explore the structural characteristics of the districts in each group. While the classification is based purely on statistical patterns in the data, the resulting groupings align with meaningful differences in regional economic structures, labor market behavior, and economic sectoral composition. Table 4 presents key labor market statistics, namely unemployment, employment, and labor market metrics of each group.

Group 1: metropolises and labor-absorbing districts

Group 1 is the regime where growth is most strongly associated with falling unemployment in the first-stage estimates. As shown in Table 4, this group boasts the highest average GDP, the largest district populations, and the highest baseline unemployment rates.

Table 4: Unemployment, employment intensity, and labor-force intensity by regime

	Group 1	**Group 2**	**Group 3**	**Group 4**
GDP	29,853.11	15,566.91	18,658.71	10,221.65
Unemployment rate (mean)	0.064	0.050	0.049	0.047
Employment per capita (mean)	0.451	0.463	0.468	0.471
Underemployment per capita (mean)	0.140	0.173	0.174	0.180
Labor force per capita (mean)	0.480	0.486	0.490	0.492
Population (mean)	724,109	417,774	525,006	372,719

Notes: Means computed over district-years (2011-2020). Because district-level working-age population data are unavailable, we scale employment and labor force by total population.

This group comprises Indonesia's large metropolitan labor markets and industrial belts, including Kota Jakarta Utara, Kota Depok, Kota Bandung, Kota Semarang, Kota Medan, and Kota Makassar, as well as manufacturing and logistics corridors such as Kabupaten Bekasi, Kabupaten Bogor, Kabupaten Karawang, and Kabupaten Tangerang. These places combine thick labor markets with many firms and many workers, with labor-intensive activity. Therefore, it is plausible that in this group, economic expansions translate quickly into hires. The districts in this group are also more populated compared to other groups (Table 4). Interestingly, 70% of the districts in Group 1 are in the western part of Indonesia, as shown in Figure 4 and Appendix F, which supports the findings of Aginta et al. (2023) that western Indonesia has a more significant Okun's law, though we also find that Okun's law is significant in other districts in eastern Indonesia. Note that many of the districts included in Group 1 are urban or semi-urban districts with high concentrations of manufacturing, logistics, and trade activities.

Another interesting observation is that Group 1 also includes many districts that rely on smallholder plantations, mostly in Sumatra, such as Kabupaten Mandailing Natal, Kabupaten Tapanuli Tengah, Kabupaten Labuhan Batu, Kabupaten Serdang Bedagai, and Kabupaten Pesisir Selatan. These economies depend on palm, rubber, coffee, and cocoa plantations that require intensive manual labor. The strong negative Okun's coefficient estimated for Group 1 likely reflects the labor-intensive nature of their economies and their ability to quickly absorb labor in response to economic expansion. The key point is not that Group 1 is "Java" or "West," but that it captures districts where growth is plausibly labor-absorbing.

Group 2: districts with unemployment-increasing growth and weak employment absorption

Group 2 is the regime that looks most puzzling as it displays a positive Okun coefficient, as shown in Table 3. Unlike Group 1, Group 2 is characterized by high capital intensity and high value-added sectors that do not heavily rely on labor absorption to drive growth. This group is a mix of resource- and capital-intensive districts such as Kota Balikpapan, Kota Samarinda, Kabupaten Seruyan, and Kabupaten Ketapang, but also many rural and secondary districts in Java and Sumatra (e.g., Jember, Bondowoso, Situbondo, Garut, Subang, Langkat, Nias) and several peripheral districts in eastern Indonesia (e.g., NTT and Papua). The common element is therefore not location per se, but a shared *adjustment pattern* where output expansions coincide with rising open unemployment.

There are two plausible mechanisms driving this positive Okun relationship. First, for the resource and financial hubs, output surges are decoupled from local labor demand. Growth in districts like Kota Balikpapan or Central Jakarta is driven by capital investments in machinery or high-value tertiary services, respectively (Awaludin et al. (2024)). The transition toward high-productivity but low-labor-elasticity service sectors often generates high GDP growth without mass employment creation, a phenomenon consistent with premature deindustrialization and service-led growth patterns (Rodrik (2016)). Furthermore, Ngadi (2013) shows that the private and state-owned corporate plantations, which are prevalent in districts in this group, absorb significantly less labor per hectare (0.34–0.37 persons) compared to the smallholders in Group 1.

This transition from labor-intensive smallholders to mechanized corporate production is supported by recent empirical data. Recent Agricultural Census evidence points to a consolidation of farming units over our study period. BPS reports that the total number of agricultural holdings (dominated by individual/family-run units) fell by 7.42% between 2013 and 2020, while the number of corporate agricultural entities increased by 35.54% (from 4,209 to 5,705) (Badan Pusat Statistik (2023)). These shifts are consistent with a growing role for larger-scale, corporate agriculture and weaker labor absorption per unit of output in some areas—an interpretation that aligns with the positive Okun slopes and the weak employment-intensity response we document for Group 2.

Second, for the highly rural districts in this group, the mechanism is tied to the informal sector. In districts with pervasive agricultural informality, a localized, capital-intensive growth shock can disrupt traditional labor networks. As capital deepens and agricultural technologies improve, labor is often displaced from traditional farming (Bustos et al. (2016)). Workers leave unpaid family work or informal agriculture to search for formal wage employment. However, due to search frictions and skill mismatches in the formal sector, these transitioning workers enter the labor force as openly unemployed, mechanically driving up the measured unemployment rate even as regional GDP rises (Rothenberg et al. (2016); Zenou (2008)).

Another plausible mechanism, which is consistent with our earlier exploratory spatial evidence, is the movement of labor. If growth shocks propagate geographically mainly through output linkages, then booms in Group 2 may coincide with (or even help trigger) stronger growth in more labor-absorbing districts (e.g., Group 1), inducing labor movements that raise measured unemployment locally in Group 2 while jobs are created elsewhere. We test this mechanism in the upcoming section and show that in Group 2, the increase in unemployment rate changes is unlikely to be due to increased absorption in employment or the labor force.

Group 3: transitional and secondary centers

Group 3 shows a statistically significant but small negative slope in Table 3. This group comprises transitional economies or secondary urban centers where the empirical relationship between economic growth and unemployment is relatively weak. While districts in this group exhibit GDP levels and unemployment rates comparable to those in Group 2, many are undergoing structural transformation—either through early-stage industrialization or a sectoral shift from agriculture to services, such as Kabupaten Cilacap, Kabupaten Indramayu, and Kabupaten Malang and also districts tied to export platforms or enclaves (e.g., Kota Batam, Kabupaten Mimika) where output movements can be decoupled from local hiring because production is capital intensive, relies on non-local labor, or is integrated into wider supply chains. In these districts, part of the labor adjustment may occur through hours (underemployment) and informality rather than unemployment, which is consistent with their higher underemployment intensity relative to Groups 1 and 2 in Table 4.

Group 4: peripheral and thin labor markets

Lastly, Group 4 is composed predominantly of rural or geographically isolated districts, such as those in Papua (Kabupaten Dogiyai and Kabupaten Intan Jaya), East Nusa Tenggara (Kabupaten Alor and Kabupaten Lembata), and parts of Sulawesi and Maluku. Group 4 has the lowest GDP and unemployment rate among the groups but the highest underemployment intensity, suggesting that labor slack is absorbed mainly through low-hours and informal work rather than open joblessness. Economic growth in these regions does not meaningfully translate into lower unemployment, partly due to low market integration and limited labor mobility. Limited connectivity slows the spillover of new demand into non-farm services. The positive and small Okun's coefficient found for this group may reflect how increased output in these districts often comes from capital projects or external transfers, rather than expansion of wage employment.

Together, these findings highlight the diversity of Indonesia's district-level labor markets. The classifications of the districts by c-lasso prove to offer further insights into the heterogeneous nature of Indonesian districts, which cannot be achieved by the simple "West versus East" or "main islands" classifications widely used in previous research. What it cannot do, by construction, is disentangle local effects from spatial spillovers. Our exploratory spatial evidence suggests that both unemployment and GDP growth are spatially dependent. As such, output spillovers are likely to be a key channel linking neighboring labor markets. The next section, therefore, embeds these regimes into an SDM and reports the marginal effects.

Mechanism: why unemployment can rise with growth in some regimes

To unpack the counterintuitive positive Okun slopes, especially that of Group 2, we examine which adjustment margin drives unemployment changes. Specifically, the equations we estimate are as follows. Let E_{it} denote employment, LF_{it} the labor force, and Pop_{it} total population in district i and year t. Define employment intensity and labor-force intensity as

$$e_{it} \equiv \frac{E_{it}}{Pop_{it}}, \qquad \ell_{it} \equiv \frac{LF_{it}}{Pop_{it}}.$$

Open unemployment can be written as $u_{it} = 1 - \frac{E_{it}}{LF_{it}}$, so changes in unemployment may reflect weak employment absorption (changes in e_{it}) and/or shifts in labor-force intensity (changes in ℓ_{it}). [2]

Using the c-lasso regime assignment $G(i) \in \{1, 2, 3, 4\}$, we estimate regime-specific TWFE regressions of the form:

$$\Delta u_{it} = \sum_{g=1}^{4} \beta_g^u \, \Delta GDP_{it} \, \mathbb{1}\{G(i) = g\} + \gamma_i + \tau_t + \varepsilon_{it}^u, \tag{9}$$

$$\Delta e_{it} = \sum_{g=1}^{4} \beta_g^e \, \Delta GDP_{it} \, \mathbb{1}\{G(i) = g\} + \gamma_i + \tau_t + \varepsilon_{it}^e, \tag{10}$$

$$\Delta \ell_{it} = \sum_{g=1}^{4} \beta_g^\ell \, \Delta GDP_{it} \, \mathbb{1}\{G(i) = g\} + \mu_i + \tau_t + \varepsilon_{it}^\ell, \tag{11}$$

where γ_i and γ_t are district and year fixed effects. Standard errors are clustered by district. The estimated regime-specific slopes β_g^u, β_g^e, and β_g^ℓ are reported in Table 5. Together, they indicate whether unemployment responses to growth operate primarily through changes in employment intensity (labor absorption) or through shifts in labor-force intensity.

Table 5: Mechanism regressions: GDP growth and unemployment components by regime

	Group 1	**Group 2**	**Group 3**	**Group 4**
Δu_{it}	-0.166^{***}	0.109^{***}	-0.040^{**}	0.029^{***}
	(0.028)	(0.019)	(0.017)	(0.008)
$\Delta(E/Pop)_{it}$	0.00112^{*}	-0.00099^{*}	-0.00064	0.00020
	(0.00062)	(0.00054)	(0.00065)	(0.00022)
$\Delta(LF/Pop)_{it}$	0.00051	-0.00070	-0.00079	0.00031
	(0.00062)	(0.00054)	(0.00066)	(0.00023)

Notes: Entries are group-specific slopes from TWFE regressions of each outcome on district GDP growth interacted with regime dummies (district and year fixed effects; standard errors clustered by district). Employment and labor force are scaled by total population (district-year working-age population is unavailable), so coefficients should be interpreted as changes in employment and labor-force intensity. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The results in Table 5 provide suggestive evidence that these margins differ sharply across regimes. In Group 1, GDP growth significantly reduces unemployment (-0.166) and is accompanied by a (weakly) positive employment-intensity response. This is consistent with labor-absorbing expansions in metropolitan and industrial districts, where output gains translate into local hiring. Conversely, Group 2 exhibits the opposite pattern where GDP growth increases unemployment

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[2] District-year working-age population is unavailable, so we scale by total population. We interpret e_{it} and ℓ_{it} as intensity measures rather than exact employment-to-population and participation rates.

(0.109) while employment intensity *falls* (slope -0.0010, $p < 0.10$). Labor-force intensity does not rise significantly, suggesting that the positive Okun slope is driven primarily by weak employment absorption rather than a participation-driven expansion of the labor force. Groups 3 and 4 show smaller and less precisely estimated responses in employment and labor-force intensity, consistent with labor-market adjustment occurring through underemployment and informality rather than measured open unemployment.

The SDM results in the next subsection suggest whether these regime-specific patterns are primarily local (direct) or transmitted through neighboring districts (indirect).

3.3 SDM Results: Regime-specific spatial dependence

Building on the exploratory spatial analysis and the latent regimes uncovered by the c-lasso estimation, we now examine whether and how the Okun relationship exhibits spatial dependence that varies across these regimes. We estimate a heterogeneous-slope SDM in which both the direct (within-district) and indirect (spillover) effects of growth differ across the four latent groups. This allows us to quantify not only whether unemployment changes are spatially correlated but also how the intensity and direction of spatial spillovers depend on the regime-specific labor-market structure. Table 6 presents the direct, indirect, and total effects, while the raw coefficients are reported in Appendix G. We take the dynamic SDM with a one-year lag of the dependent variable (Lag Y) as our benchmark specification. This specification captures persistence in unemployment adjustments while remaining parsimonious. The selection of our benchmark specification is also justified by its AIC, which is the lowest among alternative dynamic structures, as reported in Appendix G.

The results from our SDM with regime-specific slopes estimation confirm the heterogeneity in district-level Okun's law and refine the magnitudes found from our c-lasso regression. The highly significant spatial ρ, shown at the bottom of Table 6, indicates that unemployment rate changes are strongly correlated across districts. This also confirms the earlier findings from our ESDA estimation, which was positive (0.18) and statistically significant. The positive and statistically significant spatial autoregressive parameter ($\rho = 0.135$, $p < 0.01$) suggests that the unemployment rate changes of districts tend to move in the same direction as their neighbors after fixed effects and covariates are controlled for. This finding motivates modelling Okun's law in a spatial framework that separates local effects from spillovers.

We now turn our discussion to the differences in Okun's coefficient by each Group. In Group 1, the OLS slope of -0.9 (Table 3) highly overstates the effect of GDP growth on unemployment rate changes because it loads region-wide spillovers onto the local regressor. Once spillovers are modeled separately, the total long-run elasticity is still strongly negative but less extreme (-0.189). Decomposing the total effects into direct and indirect effects, we can see that both direct and indirect effects are negative and statistically significant. The expected negative relationship of GDP growth on unemployment rate changes is stronger within districts (direct effects = -0.112), but it also spills over to other districts (indirect effects = -0.077).

Table 6: Spatial Durbin Model with Spatial Regimes

	Direct Effects	Indirect Effects	Total Effects
Short Run			
Δ GDP G_1	-0.138***	-0.101*	-0.239***
	(0.028)	(0.052)	(0.056)
Δ GDP G_2	0.088***	0.086	0.174***
	(0.020)	(0.055)	(0.063)
Δ GDP G_3	-0.029**	-0.006	-0.035
	(0.014)	(0.027)	(0.030)
Δ GDP G_4	0.016***	-0.034	-0.018
	(0.005)	(0.034)	(0.035)
Long Run			
Δ GDP G_1	-0.112***	-0.077*	-0.189***
	(0.023)	(0.041)	(0.045)
Δ GDP G_2	0.071***	0.066	0.137***
	(0.017)	(0.043)	(0.050)
Δ GDP G_3	-0.024**	-0.004	-0.028
	(0.011)	(0.022)	(0.024)
Δ GDP G_4	0.013***	-0.027	-0.014
	(0.004)	(0.027)	(0.028)
Spatial ρ			0.135***
			(0.023)
Observations			4626
AIC			16809.89
Within R^2			0.115

Notes: The table above presents the marginal effects of our SDM with heterogeneous slopes (Equation 5). The specification includes both the spatial and the time lags of Δ unemployment rate in addition to district and year fixed effects. Reported effects are LeSage-Pace average marginal effects. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Similarly, the magnitude of the Okun's coefficient of Group 2 was also overestimated when spatial dependence was ignored. Our SDM estimation results indicate that a rise in a district's GDP growth by 1 ppt is expected to increase the change in the unemployment rate of that district and its neighboring districts by 0.137 ppts, which, although statistically significant, is lower than our naive estimation of 0.405 (Table 3).

The rise in the change in the unemployment rate is expected to come mostly from the focal district (direct effect = 0.071), while the increase in neighboring districts is statistically nonsignificant. This pattern implies that, for Group 2 districts, higher output growth is associated with an *increase* in open unemployment changes, and this relationship is primarily local rather than spillover-driven in our benchmark specification. This result also links back to the ESDA maps (Figures 1 and 2), where the presence of statistically significant HL/LH districts indicates that some locations systematically diverge from their neighbors, which is consistent with localized booms that do not translate into proportional local hiring and with labor reallocation across borders.

Economically, this is consistent with the structural profile of Group 2 districts discussed earlier. Resource- and capital-intensive production can generate large measured output gains without proportional labor demand, particularly when growth reflects commodity-price movements, capital deepening, or enclave activities with limited downstream integration. In such settings, growth can coincide with rising measured unemployment if expansions attract job seekers from nearby districts (or induce local workers to enter search) faster than firms expand payroll employment. This mobility-and-search interpretation is also consistent with our mechanism regressions, where GDP growth in Group 2 is associated with falling employment intensity and no significant rise in labor-force intensity (Table 5). Taken together, the ESDA outliers, the mechanism evidence, and the SDM decomposition point to a regime in which output expansions are "jobless" locally and may trigger cross-district labor-market adjustment rather than immediate within-district employment absorption.

Lastly, for Groups 3 and 4, the estimated long-run total effects are small and statistically nonsignificant (-0.028 and -0.014, respectively). Direct effects retain the expected sign for Group 3 (negative) and remain positive for Group 4, but the overall totals are imprecise once spillovers and dynamics are incorporated. This pattern is consistent with the descriptive evidence that labor-market adjustment in these districts may occur less through measured unemployment and more through underemployment and informal work, weakening the link between output fluctuations and open unemployment. It also suggests that, relative to Group 1, growth shocks in Group 3 and Group 4 do not produce reliably detectable unemployment responses at the district level over our sample period.

Comparing short-run and long-run totals shows that the impact effects are generally larger in magnitude than the long-run effects. This pattern reflects the temporal adjustment captured by the lagged dependent variable in the dynamic SDM, which is that unemployment changes exhibit persistence and partial reversal over time. Therefore, the cumulative long-run response is smaller than the immediate impact response.

The relatively modest within R^2 in Table 6 warrants a discussion, though it is not surprising in our setting. We model *annual changes* in district unemployment, Δu_{it}, which are inherently noisy at the district level and reflect short-run shocks and adjustment frictions. Moreover, two-way fixed effects absorb most of the systematic cross-district and common time variation, so the within R^2 is computed on the remaining within-district year-to-year fluctuations. For that reason, our interpretation focuses on the regime-specific direct and indirect marginal effects and the statistically significant spatial dependence parameter ρ.

Taken together, our three estimation strategies yield a coherent picture. The results from our TWFE estimator suggest the absence of the Okun relationship at all. Once latent regimes are allowed, districts separate into unemployment-reducing and unemployment-increasing growth responses. Embedding these regimes in a dynamic SDM refines magnitudes and separates local effects from spillovers: in labor-absorbing districts (Group 1), both direct and (modest) spillover channels reduce unemployment, while in resource- and capital-intensive districts (Group 2), output growth is associated with rising open unemployment primarily through the local channel. For transitional and peripheral districts (Groups 3 and 4), total effects are weak and imprecisely estimated, consistent with adjustment occurring through underemployment and informality rather than measured unemployment. This layered approach uncovers that Okun's law in Indonesia is heterogeneous and spatially interconnected instead of statistically nonsignificant, as found by previous literature.

4 Robustness Tests

To test the robustness of our results, we conduct two additional analyses. First, we apply the classification Lasso to Okun's law using data at the province-level. This approach helps verify whether the observed spatial clusters hold consistently across different spatial scales. Specifically, using province-level data as a robustness test is superior for several reasons, such as addressing potential issues related to the modifiable areal unit problem (MAUP) (see e.g. Resende (2011)) as well as capturing broader interactions that might be missed at the district level (see e.g. Zheng and Wu (2024)). Second, to avoid the risk of tautology, we classify the districts based on a simple Kaldor-Verdoorn relationship before estimating the district-level Okun's law with heterogeneous slopes.

4.1 Province-level Okun's Law

The results of our province-level estimations are shown in Table 7 and plotted in Figure 5. Based on the information criterion, the number of groups selected is 3 (Appendix I). Similar to our district-level findings, the latent groupings transcend traditional "West versus East" and main island classifications (Figure 5). Group 1 comprises 15 provinces, Group 2 consists of 10 provinces, and Group 3 contains the remaining 9 provinces. As expected, the Okun's coefficients differ significantly across these regimes (Table 7). Group 1 displays a robust, statistically significant negative coefficient of -0.262. Group 2 shows a positive yet statistically non-significant coefficient, while Group 3 yields a small but significant negative slope of -0.033.

Table 7: Heterogeneous effects of GDP growth on unemployment rate, province-level

Variable	**Group 1**	**Group 2**	**Group 3**
Δ GDP$_{it}$	-0.262***	0.122	-0.033**
	(0.059)	(0.054)	(0.014)
Constant	0.186***	-0.665**	0.049
	(0.290)	(0.293)	(0.120)
Observations	165	110	99

Note: Province-level and year fixed effects are included in all models. Robust standard errors in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$

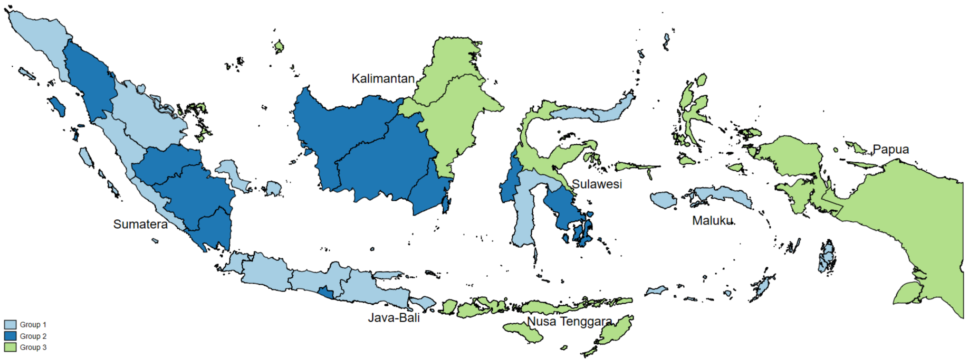

Fig. 5: Geographic distribution of c-lasso groups across Indonesian provinces

Note: Provinces are colored based on their latent group membership estimated through the c-lasso method using the relationship between GDP growth and unemployment rate changes.

The three latent provincial clusters also tell a coherent story in line with our main findings. Group 1 includes provinces in Java-Bali, the export-oriented manufacturing centers of Sumatra's east coast (e.g., Riau), and South Sulawesi. These provinces are characterized by three key traits. First, they possess diversified sectoral bases where manufacturing, trade, and transport account for roughly 50% of real regional GDP (BPS (2024b)). Second, they dominate inter-provincial trade; Java alone handles approximately 60% of total domestic trade flows, signaling dense supply-chain linkages (BPS (2024a)). Third, they support massive internal consumer markets, contributing roughly 80% of Indonesia's total household consumption in 2024. This combination of labor-intensive manufacturing and strong domestic demand ensures that growth shocks are rapidly absorbed by the labor market, resulting in a steep, negative Okun coefficient.

In contrast, Group 2 reflects a structural transition zone, encompassing the primary plantation heartlands of Sumatra and Kalimantan (e.g., North Sumatra, Jambi, Central Kalimantan) and parts of Sulawesi. These provinces are heavily reliant on corporate agriculture and mid-tier commodities. The statistically weak and positive Okun estimate in this group suggests that while global CPO or rubber prices drive measured output, the resulting growth does not translate into proportional formal hiring. This is consistent with the land consolidation and mechanization trends identified at the district level, where corporate agricultural holdings often displace informal labor without a commensurate increase in formal labor demand.

Lastly, Group 3 collects the commodity-frontier provinces and resource-rich enclaves of Kalimantan and Eastern Indonesia (e.g., East Kalimantan, Papua, North Maluku), alongside the thin labor markets of Nusa Tenggara. In many of these provinces, mining or heavy industry accounts for more than 35% of GDP (BPS (2024b)). For instance, in East Kalimantan, commodities such as coal, LNG, and crude palm oil constitute over 85% of merchandise exports. These ”enclave” economies are characterized by high value-added but low labor elasticity, as output surges in mining or smelting rely on heavy machinery and specialized labor rather than absorbing the local workforce.

Table 8 presents the findings from our benchmark SDM with spatial regimes (dynamic SDM with lag Y), while the results from the remaining specifications are shown in Appendix J. The findings from our SDM with spatial regimes (Table 8) confirm that the spatial dependencies identified at the district level also operate at the provincial scale. The signs of the regime-specific elasticities remain consistent. Group 1 provinces continue to show significant negative total effects, while Group 2 provinces exhibit a near-zero direct effect but large, significant negative indirect effects (-0.211 in the long run). This implies that growth in Group 2 is largely ”jobless” locally, but its economic expansions significantly reduce unemployment in neighboring provinces through output linkages and labor migration. Group 3 shows the smallest response, consistent with a regime where labor adjustment occurs through hours and informality. In summary, the province-level analysis demonstrates that the heterogeneous and spatially dependent nature of Okun’s law in Indonesia is robust to spatial aggregation. Our findings reflect fundamental structural differences in how regional economies process growth shocks and are not only driven by local idiosyncrasies.

Table 8: Spatial Durbin Model with Spatial Regimes

	Direct Effects	**Indirect Effects**	**Total Effects**
Short Run			
Δ GDP G_1	-0.216***	-0.031	-0.247***
	(0.033)	(0.038)	(0.050)
Δ GDP G_2	-0.061***	-0.296***	-0.357***
	(0.021)	(0.067)	(0.065)
Δ GDP G_3	-0.021**	0.050	0.030
	(0.010)	(0.047)	(0.052)
Long Run			
Δ GDP G_1	-0.171***	-0.007	-0.177***
	(0.026)	(0.028)	(0.037)
Δ GDP G_2	-0.045***	-0.211***	-0.256***
	(0.017)	(0.050)	(0.048)
Δ GDP G_3	-0.017**	0.038	0.021
	(0.008)	(0.034)	(0.037)
Spatial ρ			0.354***
			(0.051)
Observations			340
AIC			822.742
Within R^2			0.420

Notes: The table above presents the marginal effects of our SDM with heterogeneous slopes (Equation 5). The specification includes both the spatial and the time lags of Δ unemployment rate in addition to province and year fixed effects. Reported effects are LeSage-Pace average marginal effects. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

In short, the province-level analysis confirms the structural interpretation of our main results. The heterogeneous and spatially dependent nature of Okun's law in Indonesia persists when the spatial unit is broadened, demonstrating that our findings are robust to alternative spatial aggregation and not driven by local idiosyncrasies or scale effects. The consistency between the district-level and province-level findings strengthens our confidence that the latent regimes reflect genuine structural differences in how regional economies process growth shocks.

4.2 Lasso classification based on a Simple Kaldor-Verdoorn Relationship

Finally, we construct an alternative regime partition based on a Kaldor–Verdoorn (KV)–type relationship between manufacturing employment growth and manufacturing output growth for 2011–2020. We obtain the dataset from the World Bank's Indonesia Database for Policy and Economic Research (World Bank Indo-Dapoer). However, data on the number of people employed in the manufacturing sector are unavailable for 2016. As such, we impute the data using linear interpolation. Moreover, we use data for all 479 districts and merge the newer split districts from after 2012 into their previous/parent districts. We also note that there are abnormal growth rates in the number of people employed in the manufacturing sector for several districts. Therefore, we winsorize the top and bottom one percentiles when running this classification lasso regression.

The classifier-lasso selects three regimes, as shown in Appendix K. We use these regimes to allow Okun's coefficient and spillover effects to differ across groups using the same specification as in Equation 5. The results of our benchmark SDM specification are presented in Table 9, while the results from alternative specifications are presented in Appendix L.

As shown in Table 9, using KV-motivated regimes, the SDM results remain heterogeneous across regimes. The sign pattern and the spatial dependence parameter ρ are similar to our main estimation results in Table 6, indicating that Okun's relationship is spatially dependent across districts even when a different classification criterion is used. Similarly, the heterogeneity in the Okun's law estimates across regimes also holds, although the magnitudes are smaller. The KV-based Groups 1–2 exhibit a negative direct Okun effect, while KV Group 3 shows a positive direct and spillover effect.

5 Conclusion

This study re-examined Okun's law across 514 Indonesian districts using a classification-Lasso (c-lasso) approach that lets district groupings emerge from the data rather than from predetermined geographic divisions. The method uncovered four latent spatial regimes—cutting across traditional West–East and island-based classifications—with markedly different growth–unemployment dynamics. Labor-intensive urban and smallholder-plantation districts (Group 1) displayed a strong negative Okun coefficient, consistent with thick labor markets where growth is rapidly unemployment-reducing. Capital- and resource-intensive districts (Group

Table 9: Robustness Check: SDM with Spatial Regimes

	Direct Effects	**Indirect Effects**	**Total Effects**
Short Run			
Δ GDP G_1	-0.035***	-0.049	-0.084**
	(0.012)	(0.031)	(0.034)
Δ GDP G_2	-0.075**	-0.010	-0.085
	(0.030)	(0.059)	(0.069)
Δ GDP G_3	0.016*	0.065**	0.081***
	(0.009)	(0.026)	(0.029)
Long Run			
Δ GDP G_1	-0.028***	-0.039	-0.067**
	(0.010)	(0.025)	(0.027)
Δ GDP G_2	-0.061**	-0.007	-0.067
	(0.017)	(0.047)	(0.055)
Δ GDP G_3	0.013*	0.052**	0.065***
	(0.007)	(0.021)	(0.023)
Spatial ρ			0.125***
			(0.024)
Observations			4311
AIC			15608.186
Within R^2			0.119

Notes: The table above presents the marginal effects of our SDM with heterogeneous slopes (Equation 5) using classification based on a Kaldor-Verdoorn-type relationship. The specification includes both the spatial and the time lags of Δ unemployment rate in addition to district and year fixed effects. Reported effects are LeSage-Pace average marginal effects. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

2), in contrast, showed positive coefficients, reflecting output expansion that raises measured open unemployment. Transitional and peripheral districts (Groups 3 and 4) exhibited weak or statistically imprecise relationships, suggesting that adjustment in these areas occurs primarily through underemployment and informality rather than formal unemployment—a pattern that may not be fully captured by standard unemployment-based indicators.

To account for spatial interdependence, we embedded these regimes in a dynamic Spatial Durbin Model (SDM) with group-specific slopes. Among the specifications considered, the dynamic SDM with a one-year lag of the dependent variable provided the best fit, as indicated by the lowest AIC, and we treat it as our benchmark. Spatial dependence was significant across all specifications ($\rho = 0.135$, $p < 0.01$), confirming that unemployment changes are spatially linked across districts. The long-run total effects from this benchmark model constitute the most reliable Okun coefficients in our analysis: -0.189 for Group 1, $+0.137$ for Group 2, and small, statistically insignificant values for Groups 3 and 4 (-0.028 and -0.014, respectively). These estimates refine the raw c-lasso coefficients by separating local effects from spillovers. In diversified districts (Group 1), the direct effect (-0.112) and indirect effect (-0.077) are both negative, the latter marginally significant at the 10% level, indicating that growth in neighboring districts matters alongside local growth for reducing unemployment, suggesting that labor-market conditions in these districts may generate employment effects beyond their own borders. In resource-based districts (Group 2), the positive total effect is driven primarily by the local channel (direct effect = 0.071), while spillovers are statistically nonsignificant. Taken together, these findings show that ignoring spatial dependence overstates the local Okun coefficient in diversified areas and obscures the jobless-growth pattern in resource-intensive ones—which underscores the importance of accounting for spatial linkages when designing regionally differentiated employment policies.

These patterns are not confined to the district level. Aggregating to 34 provinces, the c-lasso identified three broad regimes: diversified, demand-rich provinces with a steeply negative Okun coefficient (-0.262); agricultural-commodity provinces with a positive but statistically nonsignificant coefficient, further corroborating the weak growth–employment link in resource-oriented economies; and commodity-frontier and enclave provinces with a small negative coefficient (-0.033). The provincial SDM confirmed the presence of spatial dependence and regime-specific heterogeneity at this broader scale, demonstrating that our findings are robust to changes in the spatial scale of analysis. The district-level benchmark estimates reported above therefore remain the primary reference point for policy design, though the provincial results confirm that regime heterogeneity persists at the governance level where many labor-market programs are coordinated.

Theses results carry policy implications. With benchmark long-run total effects ranging from -0.189 in labor-absorbing districts to $+0.137$ in resource-intensive ones, uniform national employment policies may prove less effective than regionally differentiated approaches. In Group 1 districts—metropolitan areas and labor-intensive plantation regions—growth already translates effectively into employment, and these areas could benefit from policies that sustain growth momentum, such as connectivity infrastructure and skills development. In Group 2 districts, where capital- and resource-intensive production expands output without proportional job creation, policy efforts aimed at economic diversification and strengthening downstream linkages could help convert output gains into broader local employment. For Groups 3 and 4, where adjustment occurs primarily through underemployment and informality, conventional unemployment-targeting programs may be less effective in reaching the most affected workers; complementary measures aimed at improving the quality and stability of existing employment—such as formalization incentives, public works programs, and broader social protection—may warrant consideration. Moreover, since indirect spillover effects constitute a substantial share of total effects in Group 1 districts, concentrating infrastructure and labor-market investments in districts with strong spillover potential could help extend employment benefits to neighboring areas, a consideration that may be relevant to Indonesia's ongoing infrastructure development and fiscal decentralization efforts.

Beyond Indonesia, our integrated framework—combining machine-learning latent classification with heterogeneous-slope spatial econometrics—may offer a useful template for researchers and, potentially, for statistical offices and regional planning bodies studying labor markets in other large, diverse developing economies where conventional geographic groupings may mask important heterogeneity. Future research could apply similar approaches to other macroeconomic relationships—such as regional Phillips curves or fiscal multipliers—where both latent regime structure and spatial interdependence are likely to be empirically consequential.

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- Conflict of interest: This article does not imply any kind of potential conflicts of interest
- Data availability: The data used in this article can be obtained from Indonesia Statistics (https://www.bps.go.id/id)

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Appendix A National Okun's Law

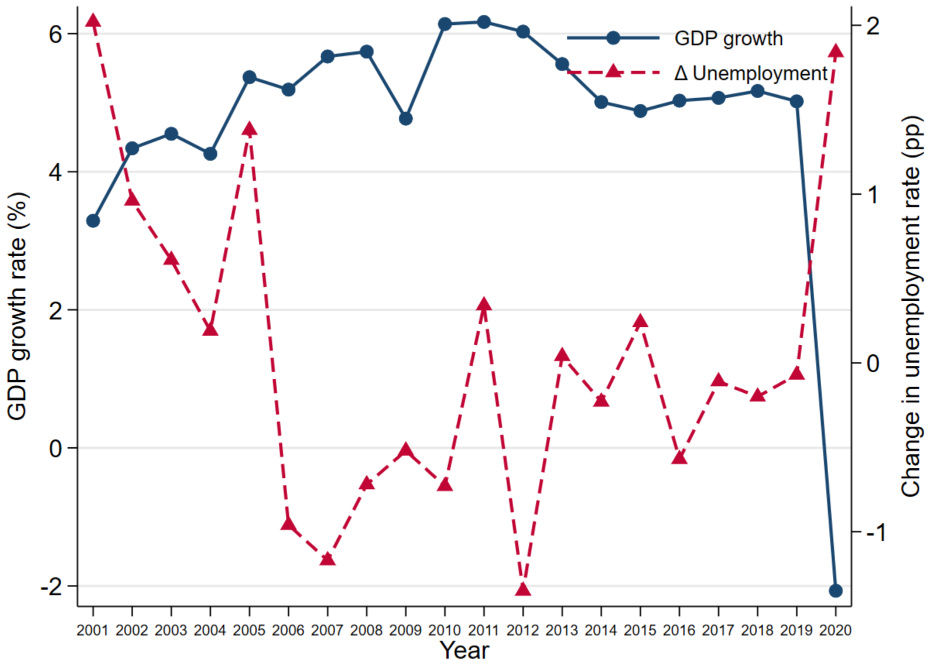


Fig. A1: National GDP growth and unemployment rate change (2001–2020)

Here is the edited version:

Figure A1 plots national GDP growth and the change in the unemployment rate over 2001–2020. GDP growth increased steadily from an average of 4.8% during 2001–2009 to 5.4% during 2010–2019, while the unemployment rate declined gradually from 9.3% to 6.1% over the same period. Two exceptions stand out: unemployment rose substantially in 2001 and 2005 despite a rising growth trend, reflecting uneven sectoral and regional recovery following the Asian Financial Crisis, high labour force growth, and the sharp contraction in household purchasing power following the elimination of fuel subsidies in October 2005. The COVID-19 shock in 2020 produced a sharp reversal, with average GDP growth turning negative (-2.07%) for the first time in the sample and the unemployment rate rising by 1.84 percentage points—the largest annual change in the series. The broad mirror-image pattern between the two series provides initial visual evidence of an Okun relationship at the national level.

This figure should nonetheless be interpreted with caution, as the national unemployment series is subject to two structural breaks in the Sakernas survey that affect comparability across the full period. First, BPS expanded the definition of unemployment in 2001 to include discouraged workers—a category outside ILO standards—producing an upward shift in measured unemployment rates unrelated to true labor market conditions Suryadarma et al. (2005). Second, in 2011, Sakernas simultaneously shifted from semi-annual to quarterly enumeration and adopted a new sampling frame based on the 2010 Population Census, replacing the 2007-based frame used through 2010. Both breaks are visible as sharp spikes in the figure. For these reasons, the main analysis uses district-level Sakernas data from 2011 onward, where the survey design and definitions are internally consistent.

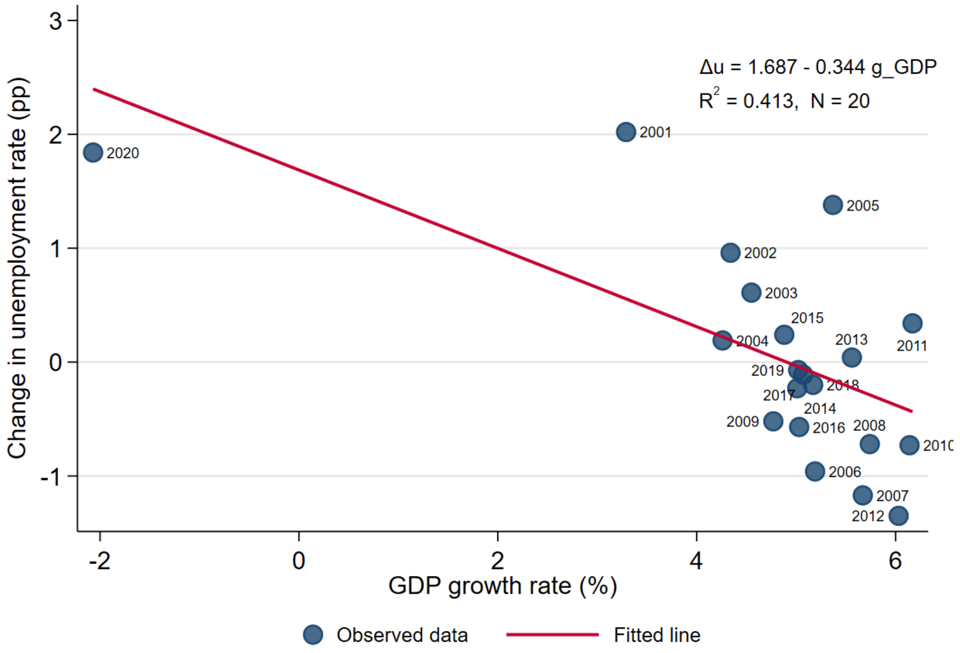
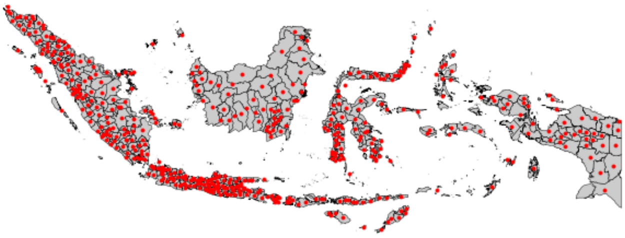


Fig. A2: National Okun's Law: scatter plot with OLS fitted line (2001–2020)

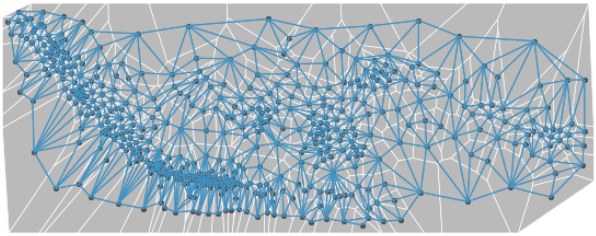
Figure A2 presents the Okun relationship at the national level by plotting the change in the unemployment rate against GDP growth for each year. The OLS fitted line yields an estimated Okun coefficient of -0.344 ($R^2 = 0.413$, $N = 20$), indicating that a one percentage point increase in GDP growth is associated with a 0.34 percentage point decrease in the unemployment rate. While the negative slope is consistent with the theoretical prediction of Okun's law, the relationship is heavily influenced by the 2020 observation, which acts as a leverage point. The remaining years cluster tightly in the 4.5–6% annual GDP growth range with relatively small unemployment changes (on average around -0.044 percentage point), suggesting that the national Okun relationship is weak during normal growth periods and becomes apparent primarily through the large shock of 2020. This pattern motivates the district-level analysis in the main text: the aggregate national relationship may mask substantial heterogeneity across districts with different economic structures and labor market dynamics.

Appendix B Thiessen Polygons

(a) Administrative boundaries and centroids



(b) Centroids, Thiessen polygons, and spatial connectivity (based on Queen contiguity)



(c) Administrative boundaries and spatial connectivity (based on Theissen polygons)

Fig. B3: Thiessen Polygons

As shown in panel a, the administrative boundaries of Indonesian districts are not always contiguous due to the presence of islands. Therefore, contiguity, which is the commonly used criterion to determine neighbors, cannot be directly used for Indonesia. To address this limitation, we follow Anselin (2020) in using Thiessen polygons, which is obtained by mapping the original centroids of the district boundaries on the computational geometry approach of Brassel and Reif (1979) and Aurenhammer (1991), as shown in panel b. The resulting connectivity structure is shown in panel c.

Appendix C Diagnostic Tests for Panel Data

Table C1: Diagnostic tests for the baseline TWFE Okun regression (Equation 1)

Test	Statistic	p-value
Wooldridge test for AR(1) in panel residuals	$F(1, 513) = 0.658$	0.418
Modified Wald test for groupwise heteroskedasticity	$\chi^2(514) = 40667.30$	0.000
Pesaran CD test for cross-sectional dependence	$z = 1.777$	0.076

Notes: Tests are based on the baseline TWFE regression of Δu_{it} on district GDP growth and year fixed effects over 2011–2020. Standard errors in the paper are clustered by district, which is robust to heteroskedasticity and within-district correlation.

To test for the effects of the persistence of our variables, we ran the following ARDL(1,1) equation:

$$\Delta U_{it} = \phi\, \Delta U_{i,t-1} + \beta_0\, \Delta \mathrm{GDP}_{it} + \beta_1\, \Delta \mathrm{GDP}_{i,t-1} + \mu_i + \tau_t + \varepsilon_{it}. \tag{C1}$$

and obtained the following results:

Table C2: Dynamic TWFE

Variable	**GDP growth**
Δ U$_{i,t-1}$	-0.294***
	(0.017)
Δ GDP_{it}	-0.005
	(0.009)
Δ $GDP_{i,t-1}$	-0.004
	(0.006)
Constant	-0.004
	(0.052)
Observations	4,626
Within R-sq	0.102

Note: District-level and year fixed effects are included in all models. Robust standard errors in parentheses.

$^{***}p < 0.01$, $^{**}p < 0.05$

The results show that the lagged dependent variable is strongly significant, confirming dynamic adjustment in unemployment changes, but the GDP-growth terms remain statistically indistinguishable from zero, and the implied long-run Okun effect is close to zero. Thus, the weak pooled relationship is not driven by omitted dynamics. Rather, it is consistent with slope heterogeneity that is averaged out in conventional geographic partitions.

Appendix D Exploratory Spatial Data Analysis

In addition to queen contiguity, we also used alternative spatial weights matrices, namely 4 nearest neighbors, inverse distance, and inverse distance with minimum threshold. The results are fairly consistent across different spatial weight matrices. This robustness across alternative neighborhood definitions confirms that the spatial autocorrelation patterns documented in the main text are not an artifact of a particular weight-matrix specification.

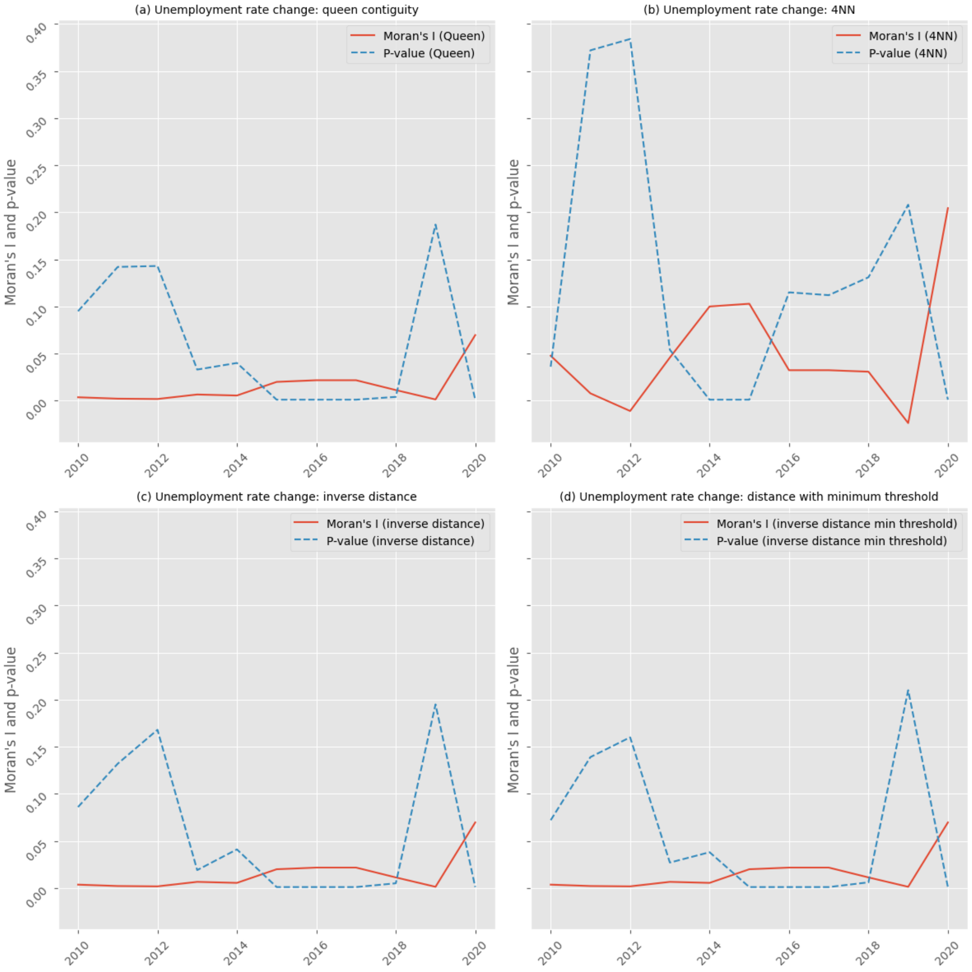


Fig. D4: Moran's I dynamics and Alternative W: Unemployment Rate

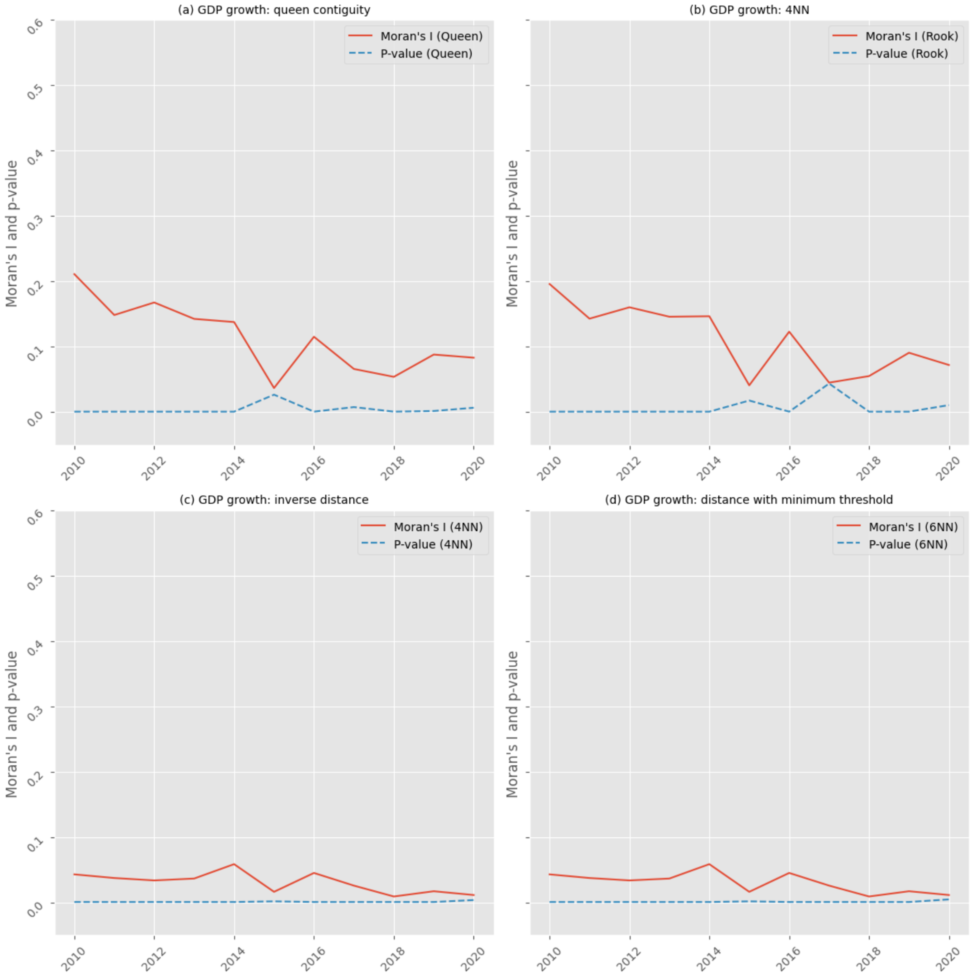


Fig. D5: Moran's I dynamics and Alternative W: GDP growth

Appendix E Model Selection

Table E3: Specification tests for spatial model selection (district-level SDM)

Null hypothesis (restriction)	**Model tested**	**Test statistic (χ^2)**	**p-value**
H_0: $\theta_k = 0$ for all k	SAR (no WX)	62.96	0.000
H_0: $\theta_k = -\rho\beta_k$ for all k	SEM (spatial error only)	78.18	0.000
H_0: $\rho = 0$	SLX (no Wy)	80.57	0.000

All tests are Wald tests based on the heterogeneous-slope Spatial Durbin Model (SDM) with two-way fixed effects. The SAR restriction tests whether the model reduces to a pure spatial lag model ($\theta = 0$); the SEM restriction tests whether spatial dependence occurs only in the error process ($\theta = -\rho\beta$); and the SLX restriction tests whether spatial dependence through ρ is unnecessary ($\rho = 0$). Rejection of all three restrictions (p¡0.01) confirms that the SDM with spatial regimes is the preferred specification.

Appendix F C-lasso groupings versus West/East and main islands division

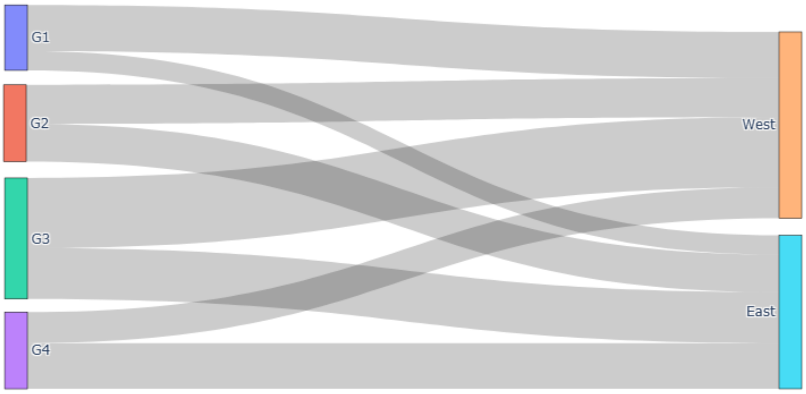


Fig. F6: C-lasso groupings versus West/East division

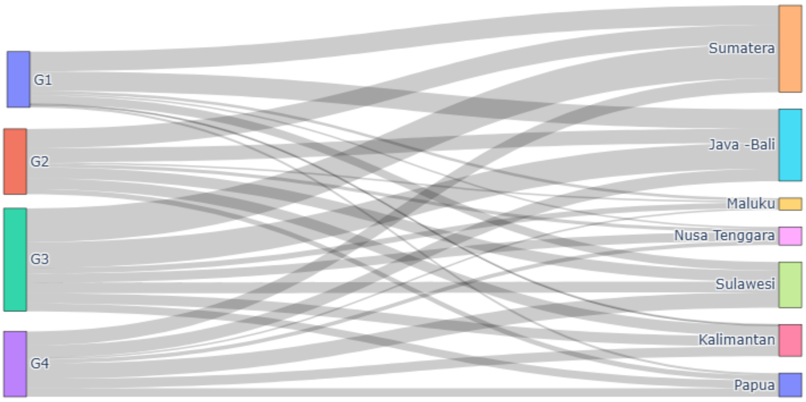


Fig. F7: C-lasso groupings versus main islands division

Appendix G SDM results: Coefficients

Table G4: SDM with Spatial Regimes

Variable	**Static SDM**	**Lag Y**	**Lag WY**	**Lag Y and WY**
Main				
Δ GDP$_{it}$ Group 1	-0.178***	-0.157***	-0.154***	-0.157***
	(-0.0241)	(-0.0259)	(-0.0247)	(-0.026)
Δ GDP$_{it}$ Group 2	0.0905***	0.0614**	0.0654***	0.0615**
	(-0.0177)	(-0.0198)	(-0.0188)	(-0.0199)
Δ GDP$_{it}$ Group 3	-0.0438*	-0.0355*	-0.0321*	-0.0354*
	(-0.0176)	(-0.0169)	(-0.0138)	(-0.0168)
Δ GDP$_{it}$ Group 4	0.0268***	0.0109	0.00938	0.0108
	(-0.0058)	(-0.00921)	(-0.00914)	(-0.0091)
$Time\ lag\ of\ Y$		-0.221***		-0.226***
		(-0.0167)		(-0.017)
$Time\ lag\ of\ WY$			-0.00562	0.0700*
			(-0.0347)	(-0.0336)
$W\Delta$ GDP$_{it}$ Group 1	-0.205***	-0.199***	-0.188***	-0.190***
	(-0.0395)	(-0.0396)	(-0.0368)	(-0.0396)
$W\Delta$ GDP$_{it}$ Group 2	-0.140***	-0.100**	-0.0963**	-0.0973**
	(-0.0381)	(-0.036)	(-0.0348)	(-0.0361)
$W\Delta$ GDP$_{it}$ Group 3	-0.0526*	-0.0687**	-0.0653*	-0.0642*
	(-0.022)	(-0.0254)	(-0.0255)	(-0.0252)
$W\Delta$ GDP$_{it}$ Group 4	-0.0695**	-0.0669**	-0.0712**	-0.0684**
	(-0.0229)	(-0.0241)	(-0.0228)	(-0.0241)
Observations	5140	5140	5140	5140
AIC	19936	16938.6	17415	16932.5
R-sq within	0.0699	0.157	0.0683	0.159

Appendix H SDM results: Marginal Effects of Alternative Specifications

Table H5: Static SDM

	Direct Effects	Indirect Effects	Total Effects
Long Run			
Δ GDP G_1	-0.157***	-0.127***	-0.284***
	(0.028)	(0.049)	(0.057)
Δ GDP G_2	0.112***	0.029	0.142**
	(0.019)	(0.056)	(0.063)
Δ GDP G_3	-0.038**	-0.007	-0.045
	(0.015)	(0.026)	(0.033)
Δ GDP G_4	0.030***	-0.043	-0.013
	(0.008)	(0.030)	(0.030)
Spatial ρ			0.131***
			(0.024)
Observations			5140
AIC			19812.012
Within R^2			0.042

Notes: The table above presents the marginal effects of our SDM with heterogeneous slopes (Equation 5). The specification includes district and year fixed effects. Reported effects are LeSage-Pace average marginal effects. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table H6: SDM with Time lag of WY

	Direct Effects	**Indirect Effects**	**Total Effects**
Short Run			
Δ GDP G_1	-0.138***	-0.101**	-0.239***
	(0.027)	(0.049)	(0.054)
Δ GDP G_2	0.088***	0.077	0.165***
	(0.020)	(0.053)	(0.061)
Δ GDP G_3	-0.027**	-0.008	-0.035
	(0.012)	(0.029)	(0.030)
Δ GDP G_4	0.014***	-0.041	-0.027
	(0.005)	(0.031)	(0.032)
Long Run			
Δ GDP G_1	-0.138***	-0.095**	-0.233***
	(0.027)	(0.048)	(0.053)
Δ GDP G_2	0.088***	0.073	0.161***
	(0.020)	(0.052)	(0.059)
Δ GDP G_3	-0.027**	-0.008	-0.034
	(0.012)	(0.028)	(0.029)
Δ GDP G_4	0.014***	-0.040	-0.026
	(0.005)	(0.031)	(0.031)
Spatial ρ			0.136***
			(0.024)
Observations			4626
AIC			17316.260
Within R^2			0.032

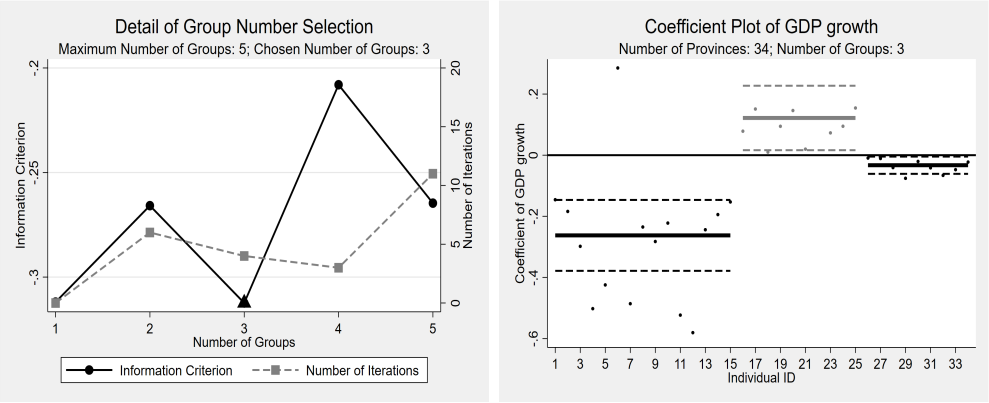
Notes: The table above presents the marginal effects of our SDM with heterogeneous slopes (Equation 5). The specification includes both the contemporaneous spatial Δ unemployment rate (WΔu_t) and its time lag (WΔu_{t-1}) in addition to district and year fixed effects. Reported effects are LeSage-Pace average marginal effects. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table H7: SDM with Time lags of Y and WY

	Direct Effects	**Indirect Effects**	**Total Effects**
Short Run			
Δ GDP G_1	-0.134***	-0.105**	-0.239***
	(0.028)	(0.054)	(0.060)
Δ GDP G_2	0.086***	0.081	0.167***
	(0.021)	(0.053)	(0.059)
Δ GDP G_3	-0.029**	-0.002	-0.031
	(0.014)	(0.027)	(0.031)
Δ GDP G_4	0.016***	-0.037	-0.021
	(0.005)	(0.035)	(0.036)
Long Run			
Δ GDP G_1	-0.109***	-0.085**	-0.194***
	(0.023)	(0.043)	(0.049)
Δ GDP G_2	0.070***	0.066	0.136***
	(0.017)	(0.043)	(0.048)
Δ GDP G_3	-0.023**	-0.002	-0.025
	(0.012)	(0.030)	(0.026)
Δ GDP G_4	0.013***	-0.030	-0.017
	(0.004)	(0.029)	(0.029)
Spatial ρ			0.142***
			(0.024)
Observations			4626
AIC			16810.284
Within R^2			0.117

Notes: The table above presents the marginal effects of our SDM with heterogeneous slopes (Equation 5). The specification includes the time lag of Δ unemployment rate (Δu_{t-1}), WΔu_t, and WΔu_{t-1} in addition to district and year fixed effects. Reported effects are LeSage-Pace average marginal effects. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix I Group number selection: province-level



(a) Detailed group selection (b) Coefficient plot of groups

Fig. I8: Selected number of groups: provinces

Appendix J SDM results, robustness (province-level): Marginal Effects of Alternative Specifications

Table J8: Static SDM

	Direct Effects	**Indirect Effects**	**Total Effects**
Long Run			
Δ GDP G_1	-0.204***	0.002	-0.202***
	(0.031)	(0.037)	(0.047)
Δ GDP G_2	-0.058***	-0.208***	-0.266***
	(0.015)	(0.074)	(0.071)
Δ GDP G_3	-0.032***	0.029	-0.003
	(0.011)	(0.041)	(0.043)
Spatial ρ			0.405***
			(0.052)
Observations			374
AIC			982.998
Within R^2			0.218

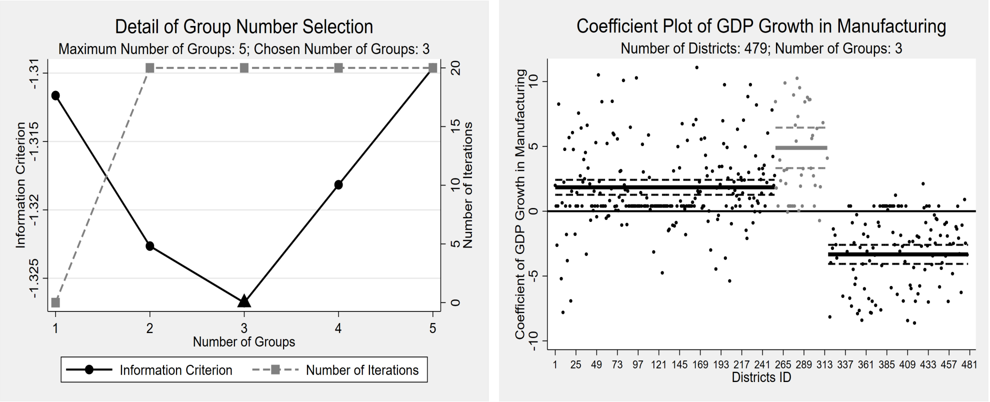
Notes: The table above presents the marginal effects of our SDM with heterogeneous slopes (Equation 5) using province-level data. The specification includes province and year fixed effects. Reported effects are LeSage-Pace average marginal effects. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table J9: SDM with Time lag of WY

	Direct Effects	Indirect Effects	Total Effects
Short Run			
Δ GDP G_1	-0.204***	-0.048	-0.252***
	(0.029)	(0.034)	(0.043)
Δ GDP G_2	-0.060***	-0.300***	-0.360***
	(0.019)	(0.062)	(0.058)
Δ GDP G_3	-0.023**	0.072	0.049
	(0.011)	(0.044)	(0.051)
Long Run			
Δ GDP G_1	-0.201***	0.014	-0.187***
	(0.029)	(0.028)	(0.033)
Δ GDP G_2	-0.046**	-0.221***	-0.267***
	(0.020)	(0.050)	(0.043)
Δ GDP G_3	-0.026**	0.063*	0.036
	(0.011)	(0.033)	(0.038)
Spatial ρ			0.325***
			(0.053)
Observations			340
AIC			861.284
Within R^2			0.365

Notes: The table above presents the marginal effects of our SDM with heterogeneous slopes (Equation 5) using province-level data. The specification includes both the contemporaneous spatial Δ unemployment rate (WΔu_t) and its time lag (WΔu_{t-1}) in addition to province and year fixed effects. Reported effects are LeSage-Pace average marginal effects. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix K Group number selection: Kaldor-Verdoorn classification



(a) Detailed group selection

(b) Coefficient plot of groups

Fig. K9: Selected number of groups: Kaldor-Verdoorn classification

Table J10: SDM with Time lags of Y and WY

	Direct Effects	**Indirect Effects**	**Total Effects**
Short Run			
Δ GDP G_1	-0.211***	-0.040	-0.251***
	(0.032)	(0.037)	(0.047)
Δ GDP G_2	-0.064***	-0.300***	-0.365***
	(0.022)	(0.067)	(0.064)
Δ GDP G_3	-0.020**	0.056	0.036
	(0.010)	(0.042)	(0.046)
Long Run			
Δ GDP G_1	-0.169***	-0.004	-0.173***
	(0.026)	(0.027)	(0.033)
Δ GDP G_2	-0.046**	-0.205***	-0.251***
	(0.018)	(0.048)	(0.044)
Δ GDP G_3	-0.017**	0.042	0.025
	(0.007)	(0.029)	(0.031)
Spatial ρ			0.328***
			(0.053)
Observations			340
AIC			824.468
Within R^2			0.421

Notes: The table above presents the marginal effects of our SDM with heterogeneous slopes (Equation 5) using province-level data. The specification includes the time lag of Δ unemployment rate (Δu_{t-1}), $W\Delta u_t$, and $W\Delta u_{t-1}$ in addition to province and year fixed effects. Reported effects are LeSage-Pace average marginal effects. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix L SDM results, robustness (KV): Marginal Effects of Alternative Specifications

Table L11: Static SDM

	Direct Effects	Indirect Effects	Total Effects
Long Run			
Δ GDP G_1	-0.035***	-0.079**	-0.114***
	(0.010)	(0.033)	(0.035)
Δ GDP G_2	-0.071***	-0.023	-0.094
	(0.026)	(0.058)	(0.066)
Δ GDP G_3	0.028***	0.077***	0.105***
	(0.007)	(0.029)	0.105***
Spatial ρ			0.131***
			(0.023)
Observations			4790
AIC			18401.969
Within R^2			0.043

Notes: The table above presents the marginal effects of our SDM with heterogeneous slopes (Equation 5) using classification based on a Kaldor-Verdoorn-type relationship. The specification includes district and year fixed effects. Reported effects are LeSage-Pace average marginal effects. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table L12: SDM with Time lag of WY

	Direct Effects	Indirect Effects	Total Effects
Short Run			
Δ GDP G_1	-0.032***	-0.043	-0.076**
	(0.012)	(0.030)	(0.033)
Δ GDP G_2	-0.072**	0.001	-0.072
	(0.029)	(0.057)	(0.066)
Δ GDP G_3	0.017**	0.061***	0.078***
	(0.007)	(0.022)	(0.025)
Long Run			
Δ GDP G_1	-0.032***	-0.039	-0.071**
	(0.012)	(0.028)	(0.031)
Δ GDP G_2	-0.072**	0.005	-0.067
	(0.029)	(0.054)	(0.063)
Δ GDP G_3	0.016**	0.057***	0.073***
	(0.007)	(0.021)	(0.023)
Spatial ρ			0.122***
			(0.024)
Observations			4311
AIC			16064.361
Within R^2			0.037

Notes: The table above presents the marginal effects of our SDM with heterogeneous slopes (Equation 5) using classification based on a Kaldor-Verdoorn-type relationship. The specification includes both the contemporaneous spatial Δ unemployment rate ($W\Delta u_t$) and its time lag ($W\Delta u_{t-1}$) in addition to district and year fixed effects. Reported effects are LeSage-Pace average marginal effects. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table L13: SDM with Time lags of Y and WY

	Direct Effects	**Indirect Effects**	**Total Effects**
Short Run			
Δ GDP G_1	-0.033***	-0.048	-0.081**
	(0.012)	(0.031)	(0.034)
Δ GDP G_2	-0.077**	-0.012	-0.089
	(0.031)	(0.062)	(0.070)
Δ GDP G_3	0.017*	0.064**	0.081***
	(0.009)	(0.025)	(0.028)
Long Run			
Δ GDP G_1	-0.027***	-0.038	-0.065**
	(0.010)	(0.025)	(0.027)
Δ GDP G_2	-0.063**	-0.008	-0.065**
	(0.025)	(0.050)	(0.056)
Δ GDP G_3	0.013*	0.051**	0.064***
	(0.007)	(0.020)	(0.022)
Spatial ρ			0.125***
			(0.024)
Observations			4311
AIC			15610.118
Within R^2			0.119

Notes: The table above presents the marginal effects of our SDM with heterogeneous slopes (Equation 5) using classification based on a Kaldor-Verdoorn-type relationship. The specification includes the time lag of Δ unemployment rate (Δu_{t-1}), WΔu_t, and WΔu_{t-1} in addition to district and year fixed effects. Reported effects are LeSage-Pace average marginal effects. Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.