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Spatial Analysis and Spillover Effects on Economic Growth in Central Java

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Abstract

This study investigates the impact of regional spillover effects on economic growth in Central Java's regencies and cities, focusing on Knowledge Spillover, Industry Spillover, Private Investment Spillover, and Government Expenditure Spillover using a spatial econometrics panel model. The results indicate significant effects on local economic growth; however, direct spillover effects, which are represented by the variable Wx in the Spatial Durbin Model (SDM), were not significant. This may be due to limited resource mobility, varying regional absorption capacities, and temporal dynamics. Direct spillover effects typically involve immediate economic interactions between neighboring regions, but in this study, these effects did not materialize as expected. Conversely, indirect spillover effects, reflected by spatial parameters ρ in the Spatial Autoregressive Model (SAR) and λ in the Spatial Error Model (SEM), highlight the importance of broader spatial dynamics across regions. These effects underscore the significance of interregional linkages rather than direct regional interactions, showing that regional synergies play a crucial role in fostering economic growth. From a policy perspective, the study recommends strengthening interregional cooperation by enhancing mechanisms such as information flow, technology transfer, and investment. Investment in digital infrastructure, the creation of innovation hubs, and cross-regional investment funds can help bridge the development gap and foster sustainable growth. Policies that support labor mobility and skill-building opportunities, especially for marginalized groups and women, are essential to promote equitable and inclusive economic development across regions.

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INTRODUCTION

Economic growth is a multidimensional process that reflects the development and transformation of economic activities over time. It involves increasing productivity, fostering innovation, and enhancing the quality of labor and capital (Todaro & Smith, 2011). However, economic growth is rarely uniform across regions, as spatial disparities often emerge due to differences in resources, infrastructure, and economic interactions. These disparities highlight the importance of spatial analysis, a framework that examines how economic activities are distributed geographically and how they influence neighboring areas. A key component of spatial analysis is the concept of spillover effects, which refer to the positive or negative externalities generated by economic activities in one region on others (Richardson, 1976).

Theories of regional economic growth have extensively explored the nature and impact of spillover effects. Perroux's (1950) growth pole theory posits that economic development originates in specific centers and spreads outward to surrounding areas, eventually fostering regional balance. Similarly, Hirschman (1968) introduces the trickle-down mechanism, which predicts that the benefits of concentrated growth will diffuse to lagging regions. However, other scholars emphasize the risks of polarization and inequality. Myrdal (1957) warns of the backwash effect, where growth in advanced regions exacerbates disparities in less developed ones (Jhingan, 2016). These conflicting views underline the need for empirical analysis to better understand how regional spillover effects operate, particularly in spatially diverse economies.

Indonesia's economic growth, as an integral part of the Association of Southeast Asian Nations (ASEAN), has shown a consistent upward trend in recent years. Data from the Central Statistics Agency (BPS, 2023) indicates that Indonesia's economic growth has remained stable at around 5% from 2019 to 2023. This growth is bolstered by contributions to the Gross Regional Domestic Product (GRDP) from various regions, reflecting the diverse economic potential across the archipelago. Figure 1 illustrates the proportion of GRDP contributions from each region, emphasizing the significance of regional economies in sustaining Indonesia's national development.

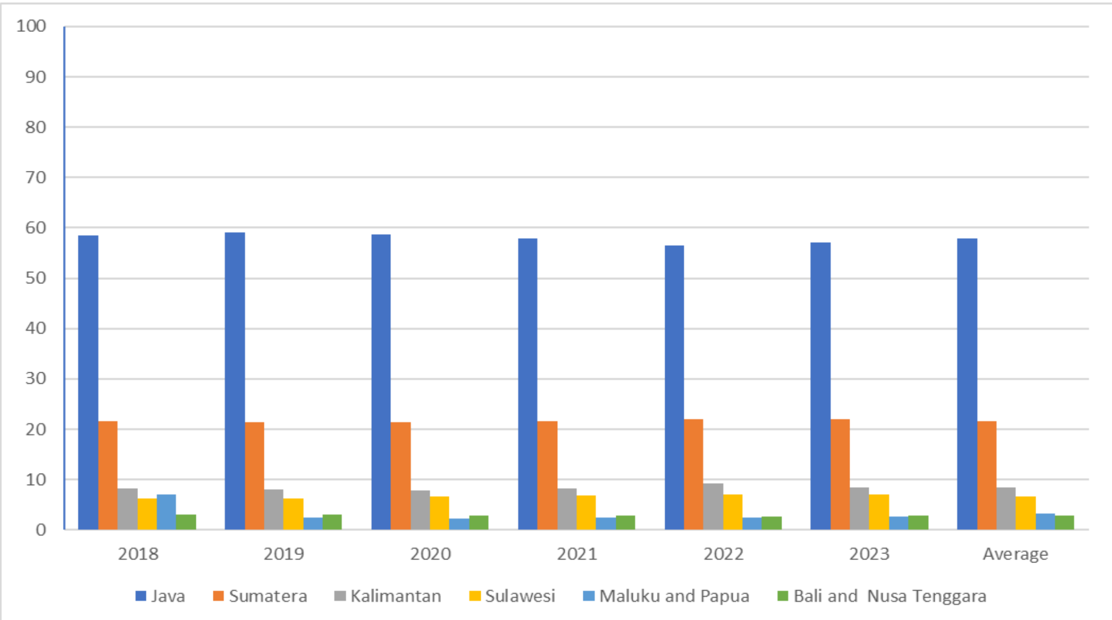

Figure 1. Contribution of GRDP by Region to the Indonesian Economy (Percentage)
Source: BPS Central Java Province, 2023

In Figure 1, Java Island is the most significant contributor to Indonesia's GRDP, accounting for over 50% of the national economy. This positions Java as the country's economic heart, with its strategic role driven by concentrated industrial, trade, and service activities. Following Java, Sumatra is the second-largest contributor, with Kalimantan, Sulawesi, Maluku, Papua, and Bali and Nusa Tenggara playing smaller but vital roles. However, within Java, economic growth is not uniformly distributed among its provinces (BPS, 2023a). Figure 2 highlights the variations in economic growth rates across provinces in Java based on constant 2010 prices.

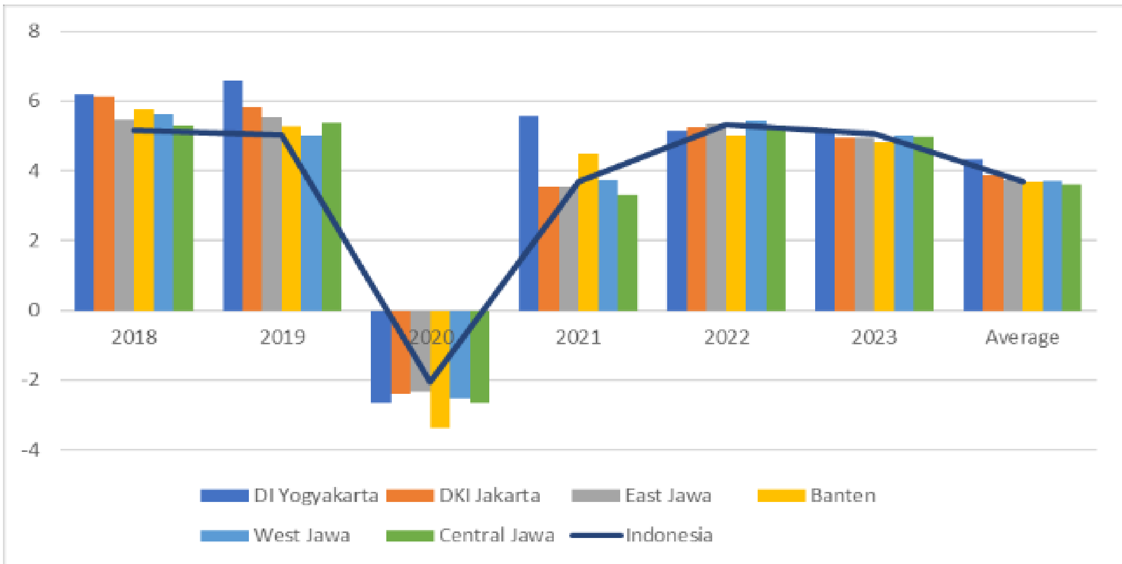

Figure 2. GDP Growth Rate at Constant 2010 Prices for Provinces in Java Island (Percentage)
Source: BPS Central Java Province, 2023

As seen in Figure 2, Central Java records the lowest economic growth rate among the provinces on Java Island, consistently falling below the national average. This highlights regional disparities within Java, despite its dominant economic contribution. These disparities necessitate a more detailed spatial analysis to uncover the potential spillover effects from the economic activities of neighboring regencies and cities within Central Java. Understanding these spillover dynamics is essential for designing policies that promote equitable development across the region, leveraging localized economic potential to address disparities and foster balanced growth.

Spatial analysis offers a powerful tool to examine the interconnectedness of economic activities across regencies and cities, emphasizing the importance of spatial dependence, where economic advancements in one area might stimulate or hinder growth in adjacent regions (Paas et al., 2011). Spillover effects, which highlight the influence of economic activities in one region on its neighbors, underscore the necessity of incorporating geographic dimensions in regional economic analyses (Janikas & Rey, 2008). Furthermore, applying spatial econometric models—such as spatial Durbin, spatial lag, or spatial error models—provides robust insights into the dynamics of regional interdependence, offering a comprehensive understanding of regional disparities and potential policy pathways to achieve balanced growth (Anselin, 1988).

Capello (2009) classified spillover effects into three key types: knowledge spillovers, industry spillovers, and growth spillovers, each crucial in fostering regional economic development. The Marshall-Arrow-Romer theory provides a deeper understanding of knowledge spillovers, describing them as the dissemination of knowledge among workers across firms within a region. A higher concentration of workers in an industry creates greater opportunities for exchanging ideas, leading to innovation and economic growth. This concept is supported by studies such as those by Saputra (2017) and Ding et al. (2022), which highlight knowledge spillovers' positive and significant impact on economic growth, with human capital as a vital contributor to this process.

Additionally, the concept of agglomeration explains how the clustering of industries within a region facilitates positive externalities. As more industries establish themselves in a given area, industry spillovers, which generate added value and enhance the economy, become more prevalent. Research by Atikah et al. (2021) and Laksono et al. (2018) further supports this, showing that industry spillovers significantly impact economic growth, aligning with theories such as the sector of growth, polarization, linkage effect, and industrial effect.

However, despite the established importance of knowledge and industry spillovers, a noticeable gap exists in the literature regarding exploring private investment and government expenditure spillovers, particularly within a spatial framework. While existing studies have primarily focused on knowledge and industry spillovers, the role of private investment and government expenditure in regional economic growth, particularly in Central Java, remains underexplored. These elements are crucial for fostering regional development, especially in areas where public and private investments are pivotal in shaping economic progress. Furthermore, while spatial econometrics offers a powerful tool for capturing regional heterogeneity and interdependence, it remains underutilized in examining spillover effects, particularly in the context of Central Java.

Additionally, most existing studies have analyzed spillover effects generally, without distinguishing between direct and indirect spillovers. While spillovers are often acknowledged in the regional development literature, the differentiation between direct spillovers (immediate and local effects) and indirect spillovers (effects through broader spatial dynamics) has rarely been explored. This gap is especially relevant for understanding regional economies, as the mechanisms driving direct and indirect spillovers can significantly differ. For example, direct spillovers are often tied to immediate neighboring regions, while indirect spillovers are driven by broader, less direct spatial interconnections, such as knowledge exchange, technology transfer, or private investment flows. This research seeks to explicitly address this gap by distinguishing between these two types of spillover effects, offering a more nuanced understanding of how regional economies interact and grow.

This study aims to bridge these gaps by conducting a comprehensive spatial analysis of spillover effects in Central Java. Specifically, it investigates the influence of knowledge spillover, industry spillover, private investment spillover, and government expenditure spillover on the economic growth of regencies and cities from 2019 to 2023. By employing spatial panel data modeling, the study aims to uncover the extent and nature of these spillover effects, offering a more nuanced understanding of regional economic dynamics. The findings are expected to provide valuable insights for policymakers in crafting targeted strategies to promote equitable growth and address regional disparities in Central Java.

RESEARCH METHODS

This study employs spatial econometrics using a panel data model to evaluate the spatial effects between the investigated variables. Spatial regression models differ significantly from conventional linear regression models, particularly in incorporating predictor variables that capture spatial dependencies. Three types of predictor variables used to assess spatial dependence include spatial lag error variables (Wu), spatial lag independent variables (WX), and spatial lag dependent variables (WY) (Elhorst, 2010). Based on these three types of spatial interactions, the spatial panel data models used in this research are as follows:

The Spatial Durbin Model (SDM) is a spatial regression model that suggests the dependent variable in one region is influenced by both the independent variables within that region and by the changes in the dependent and independent variables in surrounding regions. The panel data Spatial Durbin Model is formulated as follows (1):

$$Y_{it} = \lambda \sum_{j=1}^{n} W_{ij}\, Y_{jt} + \alpha + X_{it}\beta + \sum_{j=1}^{n} W_{ij}\, X_{ijt}\ \theta + \mu_i + \varepsilon_{it}\ \mu_i \quad \text{...(1)}$$

Where Y is Dependent variable; X is Independent variable; Wis Spatial weight matrix; Λ is Coefficient for dependent variables in neighboring regions; A is Vector of fixed parameters in the model; β is the regression measurement coefficients; Θ is coefficient for independent variables in neighboring regions; $\mu_i$is spatial-specific effects; and ε_{it} is error term.

In this equation, WY represents the spatial weight matrix for the dependent variable, while WX refers to the spatial weight matrix for the independent variables. The spatial autoregressive model (SAR), or the spatial lag model, is a spatial regression model that recognizes that local factors and the dependent variables in surrounding areas influence the dependent variable in a given location. The SAR model is expressed as follows:

$$Y_{it} = \lambda \sum_{j=1}^{n} W_{ij}\, Y_{jt} + \alpha + X_{1t}\beta_1 + X_{2t}\beta_2 + X_{3t}\beta_3 + X_{4t}\beta_4 + \mu_i + \varepsilon_{it} \quad \text{..................................(2)}$$

Where Y is Dependent variable; X si Independent variables W is Spatial weight matrix; λ is Coefficient for dependent variables in neighboring regions; A is Vector of fixed parameters in the model; β is Regression measurement coefficients; μ_i is Spatial-specific effects; ε_{it} is measurement error.

In this equation, λ represents the spatial autoregressive coefficient, WY refers to the spatial weight matrix for the dependent variable, and β represents the regression coefficients for the independent variables.

The Spatial Error Model is a regression model that reveals the impact of spatial interactions on residual errors. The model is formulated as follows (3):

$$Y_{it} = \rho \sum_{j=1}^{n} W_{ij}\, u_{jt} + \alpha + X_{1t}\beta_1 + X_{2t}\beta_2 + X_{3t}\beta_3 + X_{4t}\beta_4 + \mu_i + \varepsilon_{it} \quad \text{.................................. (3)}$$

Where Y is Dependent variable; X si Independent variables W is Spatial weight matrix; λ is Coefficient for dependent variables in neighboring regions; ρ is Coefficient for the lag error, measuring spatial effects on residual errors; β is Regression measurement coefficients; μ_i is Spatial-specific effects; ε_{it} is error term.

In this equation, ρ represents the error lag coefficient that measures spatial influence on residual errors, and W is the spatial weight matrix. The β represents the regression coefficients for the independent variables.

The adoption of the Spatial Durbin Model (SDM), Spatial Autoregressive Model (SAR), and Spatial Error Model (SEM) in this study is theoretically grounded and methodologically justified, as each model captures distinct forms of spatial dependence and spillover mechanisms. Recognizing the inherently spatial nature of regional economic phenomena, especially in inter-district and inter-city dynamics, necessitates using robust spatial econometric techniques. These models offer complementary perspectives that, when employed in tandem, provide a more comprehensive analytical framework for understanding how regional interactions shape economic outcomes.

The Spatial Durbin Model (SDM) is chosen because it accounts for spatial dependence in both the dependent and independent variables, providing a comprehensive analysis of both direct and indirect spillover effects across regions (Elhorst, 2010). This model avoids the bias and inconsistency issues that arise when spatial dependence in explanatory variables is ignored, which can occur in simpler models such as SAR and SEM (LeSage, 2008). The Spatial Autoregressive Model (SAR) focuses on spatial autocorrelation in the dependent variable, which is critical for understanding how economic outcomes in one region are influenced by those in neighboring regions (Anselin, 1988). SAR is particularly useful in modeling scenarios where the dependent variable exhibits strong spatial lag effects, such as regional economic growth driven by neighboring areas' performance. The Spatial Error Model (SEM) effectively captures spatial autocorrelation in the error terms, which may result from omitted variables or unobserved spatial heterogeneity (Bivand et al., 2013). SEM ensures that spatial dependencies in the residuals do not bias the estimates, making it suitable for robust analysis of regional spillovers.

The application of SDM, SAR, and SEM reflects a rigorous methodological approach to analyzing spatial dynamics in regional economic growth. While SDM enables the decomposition of spatial effects into direct and indirect impacts, SAR elucidates the endogenous spatial propagation of economic outcomes, and SEM corrects for spatially structured disturbances that could otherwise distort inference. By employing this triad of models, the analysis acknowledges the multifaceted nature of spatial interdependence and ensures empirical validity in the presence of observed and unobserved spatial influences. This comprehensive modeling strategy ultimately strengthens the study's empirical foundation and enhances its findings' relevance for spatially informed policy interventions.

RESULTS AND DISCUSSION

The data exploration phase involved categorizing regencies and cities in Central Java into five distinct groups based on their economic growth rates. A color-coding scheme was employed, where darker shades represented higher growth rates, while lighter shades indicated lower growth rates.

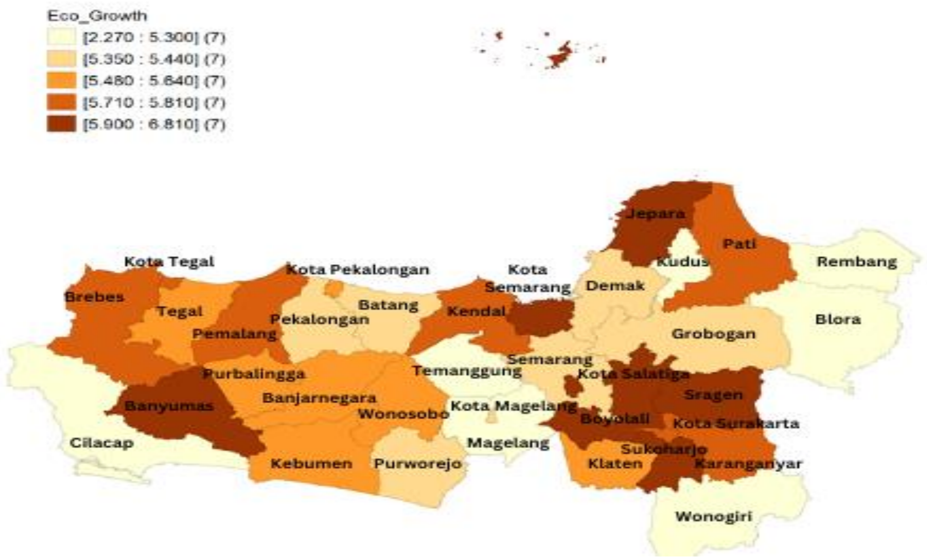

Figure 3. Distribution of Economic Growth in Regencies/Cities in Central Java Province in 2019
Source: Processed secondary data using Geoda, 2025

In 2019, economic growth disparities persisted across the region, as depicted in Figure 4. High-growth areas included Banyumas Regency, Semarang City, Jepara, Salatiga City, Boyolali, Sragen, and Sukoharjo. Meanwhile, Temanggung, Magelang, and Kudus remained among the regions with the lowest growth rates

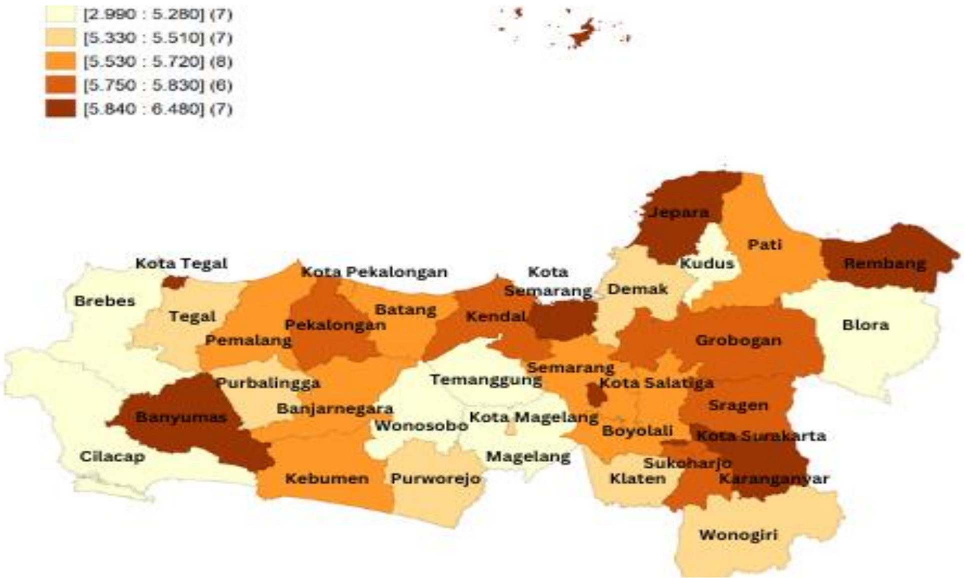

Figure 4. Distribution of Economic Growth in Regencies/Cities in Central Java Province in 2021
Source: Processed secondary data using Geoda, 2025

Figure 5 presents data for 2021, indicating that regencies like Banyumas, Pemalang, Batang, Semarang City, Jepara, and Boyolali experienced high economic growth rates. Conversely, Purbalingga, Semarang City, and Kudus recorded lower growth rates.

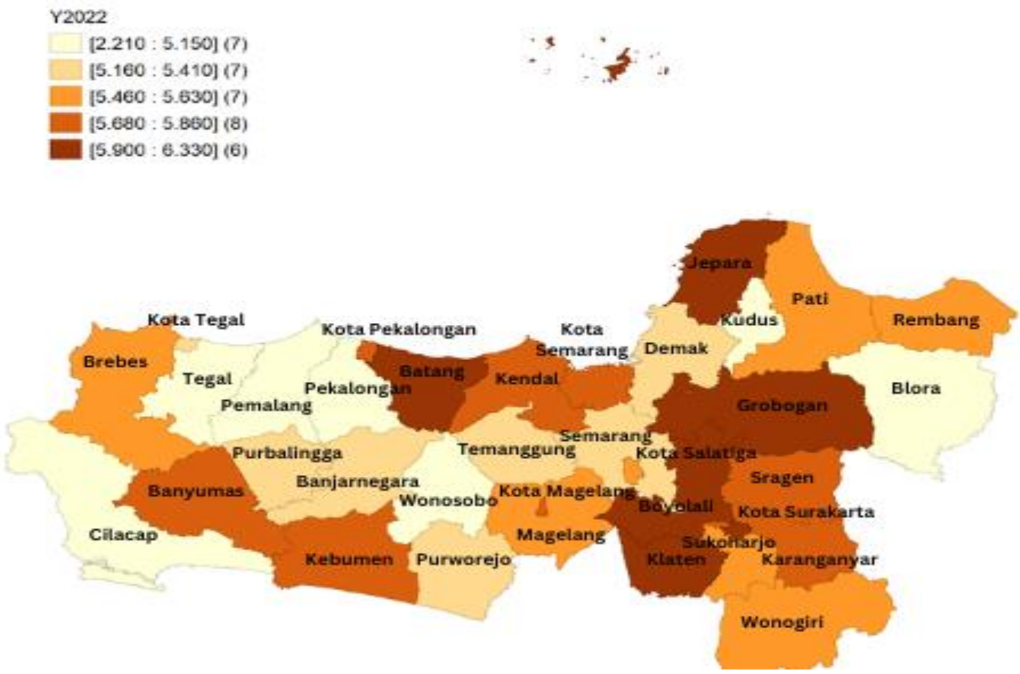

Figure 5. Distribution of Economic Growth in Regencies/Cities in Central Java Province in 2022
Source: Processed secondary data using Geoda, 2025

In 2022, Figure 6 reveals that regencies such as Batang, Klaten, Boyolali, Jepara, and Grobogan stood out for their significant economic growth. On the other hand, Tegal, Pemalang, Pekalongan, Wonosobo, Semarang City, and Kudus regencies exhibited lower growth rates.

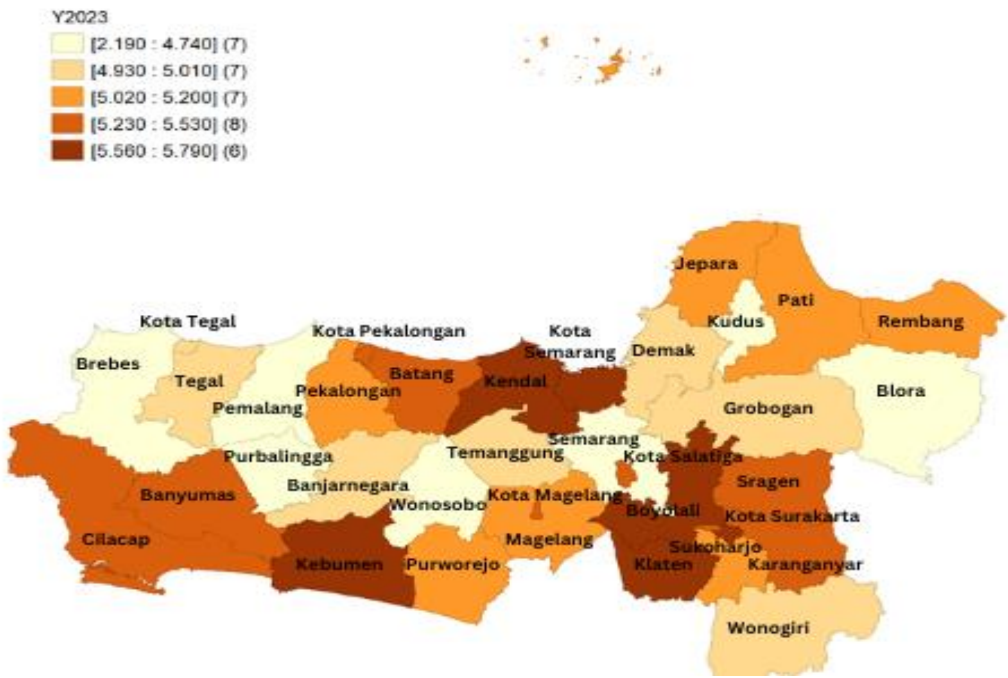

Figure 6. Distribution of Economic Growth in Regencies/Cities in Central Java Province in 2023
Source: Processed secondary data using Geoda

By 2023, economic growth remained varied, as shown in Figure 7. High-growth areas included Kebumen, Kendal, Semarang City, Boyolali, and Klaten regencies. Meanwhile, Brebes, Purbalingga, Pemalang, Wonosobo, Semarang City, and Kudus exhibited slower economic growth.

To analyze spatial relationships among regions in Central Java, this study utilized the queen contiguity matrix, a widely adopted spatial weights matrix in spatial econometrics. The queen contiguity approach defines spatial relationships based on shared borders or vertices, meaning that two regions are considered neighbors if they touch at any point, whether along an edge or a corner. This method provides a more inclusive measure of spatial adjacency compared to the rook contiguity approach, which considers only shared boundaries. Consequently, the queen contiguity matrix allows for a broader identification of spatial interactions, capturing direct and indirect geographical proximity among administrative units.

Table 1. Queen Contiguity Matrix

	Matrix	Description
	Dimension	35 x 35
Link		
	Total	149
	Min	1
	Average	4.257143
	Max	8
	Observation with 1 Connectivity	30, 32
	Observation with 8 Connectivity	9, 22

Source: Data Processed, 2025

The matrix employed in this study is a 35 x 35 matrix, reflecting the total number of regencies and cities in Central Java. As presented in Table 1, the matrix reveals 149 total links or spatial connections among the regions, suggesting a moderately interconnected regional structure. The number of neighbors per observation varies significantly, ranging from a minimum of 1 connection to a maximum of 8. Specifically, observations such as Regions 30 and 32 demonstrate the lowest degree of connectivity, indicating a relatively isolated spatial position, while others, such as Regions 9 and 22, exhibit the highest level of connectivity, potentially serving as spatial hubs within the province. The average number of neighbors per region is approximately 4.26, which suggests that each region is, on average, spatially linked to four other regions.

This distribution of spatial connections is essential for accurately modeling spatial spillover effects, as it directly influences how shocks or policy interventions in one region may propagate across its neighbors. Row normalization was applied to ensure the matrix could be effectively integrated into spatial econometric models. This step transforms the raw connectivity values into standardized spatial weights, ensuring that each row sums to one. The row-normalized queen contiguity matrix thus serves as a foundational tool for estimating spatial lag and error components in the subsequent econometric analysis, enabling the assessment of direct and indirect regional interactions. Applying the queen contiguity matrix enhances the precision of spatial dependency estimation and strengthens the empirical robustness of the study's findings on regional spillover dynamics.

Building upon the established spatial structure derived from the queen contiguity matrix, the next analytical step involved testing for the existence of spatial dependence among the 35 regencies and cities in Central Java. Understanding whether spatial interdependence exists is a critical prerequisite for applying spatial econometric models, as it validates the inclusion of spatial lag or spatial error components. While Moran's I index is traditionally employed to detect spatial autocorrelation in cross-sectional data, it cannot account for temporal dynamics. Therefore, given the panel nature of the dataset used in this study, Pesaran's cross-sectional dependence test was deemed more appropriate for evaluating spatial relationships over time.

Table 2. Results of Pesaran's Test

Pesaran's test of cross-sectional independence	0.0000
Average absolute value of the off-diagonal elements	0.540

Source: Data Processed, 2025

As shown in Table 2, Pesaran's test yielded a probabilistic value of 0.0000. This value is well below the conventional significance threshold of 0.05, leading to the rejection of H_0 and acceptance of H_1, which posits the existence of spatial correlation among units, is accepted. This finding confirms that spatial dependence is indeed present within the dataset, validating the application of spatial econometric techniques in the subsequent stages of analysis.

The average absolute value of the off-diagonal elements in the residual correlation matrix was 0.540. This relatively high value provides further evidence of substantial interconnectivity among regions. It indicates that the economic behaviors or outcomes in one region or city are statistically related to those in others, reinforcing the need for models to capture these spatial spillover effects. The detection of such interdependence not only enhances the empirical rigor of the analysis but also provides theoretical justification for exploring how spatial proximity influences regional development trajectories in Central Java.

Before conducting the spatial regression analysis, a series of diagnostic tests were performed to ensure the robustness and validity of the model specification. One of the fundamental diagnostics conducted was the multicollinearity test, which evaluates the extent to which independent variables in the regression model are linearly correlated. According to (Gujarati & Porter, 2009), high multicollinearity can inflate standard errors, obscure the proper relationship between variables, and ultimately undermine the reliability of the model's coefficient estimates.

Table 3. Results of Multicollinearity Test

Variable	VIF	1/VIF
KSP	1.46	0.687275
ISP	1.25	0.797656
PISP	1.24	0.804028
GESP	1.05	0.949133

Source: Data Processed, 2025

Table 3 presents the results of the Variance Inflation Factor (VIF) test for each explanatory variable used in the model: Knowledge Spillover (KSP), Industrial Spillover

(ISP), Private Investment Spillover (PISP), and Government Expenditure Spillover (GESP). The VIF values range from 1.05 to 1.46, all falling well below the commonly accepted threshold of 10. This indicates that multicollinearity is not a concern in the dataset, as no independent variable shows a problematic degree of linear association with the others. Furthermore, the inverse of the VIF (1/VIF) values, which serve as a measure of tolerance, are also comfortably above the critical level of 0.1, providing additional assurance of the model's stability.

The acceptance of H_0This, which states that there is no multicollinearity among the independent variables, confirms that the model is statistically sound. As a result, the estimated coefficients in the subsequent regression analysis can be interpreted with confidence, knowing that inter-variable dependencies do not distort them. This diagnostic outcome strengthens the analytical framework's overall credibility and supports using the selected independent variables to investigate spatial spillover effects on regional economic growth in Central Java.

In addition to examining multicollinearity, the study also addressed the issue of heteroskedasticity, a condition in which the variance of the error terms varies across observations. Heteroskedasticity, if present, can lead to inefficient parameter estimates and invalid inference due to biased standard errors (Wooldridge, 2016). To formally test for this condition, the Breusch-Pagan test was employed, which assesses whether the variance of the residuals from a regression is dependent on the values of the independent variables.

Table 4. Results of Heteroskedasticity Test

chi2(1)	90.17
Prob > chi2	0.0000

Source: Data Processed, 2025

As reported in Table 4, the Breusch-Pagan test yields a chi-square statistic 90.17 with an associated p-value of 0.0000. This p-value falls well below the conventional significance level of 0.05, leading to the rejection of the null hypothesis (H_0) that assumes homoskedasticity. The result therefore confirms the presence of heteroskedasticity in the residuals of the initial regression model, suggesting that the assumption of constant variance is violated.

Nonetheless, it is important to note that the primary analytical approach employed in this study involves spatial panel regression models—namely, the Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), and Spatial Durbin Model (SDM). These spatial econometric frameworks are designed to accommodate various forms of spatial dependence, including spatial heterogeneity and spatially correlated disturbances (Anselin, 1988; Elhorst et al., 2014; LeSage, 2008). As such, these models adjust for heteroskedasticity and spatial autocorrelation within the data structure. Consequently, it is unnecessary to apply additional corrective measures, such as heteroskedasticity-robust standard errors, since the spatial models offer a more comprehensive and efficient approach for handling these econometric challenges.

The subsequent analysis focuses on the spatial panel regression results using the Spatial Durbin Model (SDM), Spatial Autoregressive Model (SAR), and Spatial Error Model (SEM). These models estimate the relationships between economic growth and selected explanatory variables while considering spatial dependence across regions.

Table 5. Results of Spatial Panel Model Estimation

Variable	SDM	SAR	SEM
KSP	22,944***	26,950***	28,849***
ISP	-5,126	7,467	9,950
PISP	0,322**	0,341**	0,364***
GESP	0,001***	0,001**	0,001**
_cons	2,000***	2,000***	
θ KSP	14,320		
θ ISP	123,194		
θ PISP	-0,059		
θ GESP	0,000		
ρ	0,145	0,316***	
λ			0,312*

Legend: * p<0.05; ** p<0.01; *** p<0.001

Source: Data Processed, 2025

Table 5 displays the estimation results across the three models. Across all specifications, Knowledge Spillover (KSP) emerged as a consistently significant and positive contributor to regional economic growth, with coefficients ranging from 22.944 to 28.849 and significance at the 1% level. This finding reinforces the hypothesis that knowledge externalities—such as innovation diffusion or information exchange—are key drivers of regional economic performance. These results align with the Marshall-Arrow-Romer (MAR) theory, which emphasizes the role of localized knowledge exchange in fostering innovation and productivity. Moreover, they are consistent with empirical findings by Firmansyah (2019) and Saputra (2017), both of whom confirmed the positive influence of knowledge spillover on regional growth dynamics.

Conversely, Industry Spillover (ISP) did not show a statistically significant effect in any of the models, suggesting that industrial clustering alone may not generate measurable regional growth spillovers within the current sample and period. This result appears to contradict the agglomeration theory, which posits that spatial concentration of industries can foster productivity gains through shared resources, knowledge, and infrastructure. However, recent empirical findings provide support for these results. For example, Imantria (2024) reported that the manufacturing industry agglomeration in Central Java had an insignificant effect on regional economic growth. Furthermore, studies by Tulus et al. (2020)and Karim et al. (2017) emphasized that although the manufacturing sector and infrastructure investments have expanded, their spillover effects across neighboring regions remain limited. These findings suggest that within Central Java, manufacturing industries may still operate in isolated clusters without generating substantial interregional externalities, possibly due to fragmented supply chains, limited labor mobility, or infrastructural disparities.

Private Investment Spillover (PISP) demonstrated a statistically significant but modest positive effect, with coefficients ranging from 0.322 to 0.364. This suggests increased private sector investment in one region can generate beneficial impacts beyond its immediate boundaries. This finding aligns with the principles of the growth center theory and the growth pole theory, which offer deeper insights into the role of private investment in regional economic development. The growth center theory emphasizes the importance of economic hubs as key drivers of regional progress, while the growth pole theory explains how private investment can catalyze economic growth in these central areas. Both theories underscore the significant role of private investment in stimulating regional economic growth, with higher levels of private investment increasing the potential for economic advancement and creating positive spillover effects to neighboring regions.

Similarly, Government Expenditure Spillover (GESP) exhibited consistently significant and positive effects, albeit with smaller coefficients, indicating that public spending contributes to regional economic improvement and may facilitate spatial spillover through infrastructure development and service delivery. These results are consistent with polarization theory, linkage effect theory, and industrial effect theory, all of which provide a foundation for understanding the impact of government spending policies on regional economic growth. Polarization theory highlights how government expenditure can influence economic polarization in a region, while the linkage and industrial effect theories emphasize the relationships between economic sectors and the effects of their interactions on overall regional growth. As government expenditure increases, so does the potential for economic ripple effects, influencing both the economy and interregional interactions.

Spillover effects in this study describe how changes in one region can influence neighboring regions through spatial interactions, either directly or indirectly. According to Ojede et al. (2018), direct spillovers refer to immediate impacts on adjacent areas due to geographic proximity, such as knowledge transfer or labor mobility. Indirect spillovers reflect broader effects transmitted through economic networks or policy channels that extend beyond immediate neighbors. This study assessed direct effects using the Spatial Durbin Model (SDM), with the spillover coefficients (θ) capturing the magnitude of influence from one region to its neighbors. Meanwhile, indirect effects were evaluated through the Spatial Autoregressive Model (SAR) and the Spatial Error Model (SEM), which account for spatial dependence in the outcome variable or the error term. However, the direct spillover effects, represented by the θ for these indicators, were generally insignificant. This indicates that the interregional influence of these variables was weak within the data used.

One key reason for the lack of significance in the direct spillover effects could be the limited mobility of resources across regions, such as labor and capital. In many cases, the economic integration of neighboring areas is constrained by several factors. For instance, labor mobility may be restricted due to skill mismatches between regions, geographic barriers, or cultural differences. Similarly, capital may not flow freely between regions due to risk perception, local regulations, or the uneven development of financial markets. According to Hanson & Rohlin (2013), competition among neighboring regions for scarce resources, such as skilled labor or private investment, can further limit the capacity of direct spillovers. As regions compete for the same pool of investments and workforce, the potential for immediate and substantial economic interdependence is diminished, leading to weak or negligible direct spillover effects.

Another significant factor contributing to the insignificance of direct spillover effects is the varying capacity of regions to absorb and utilize the incoming investments, knowledge, and resources. Regions differ greatly in infrastructure, institutional frameworks, and overall economic development, influencing their ability to exploit spillover opportunities. Regions with more robust infrastructure, better access to technology, and stronger institutions are better positioned to absorb and leverage knowledge and investment from neighboring areas. On the other hand, areas with weaker institutional frameworks or underdeveloped infrastructure may face challenges in capitalizing on such opportunities. Couture et al. (2021) highlighted that regions with inadequate infrastructure—such as poor transportation networks, limited access to digital resources, or inadequate public services—are less likely to benefit from external investments or knowledge transfer. As a result, the spillover effects in these regions are muted or delayed, contributing to the lack of significant direct spillover effects observed in this study.

The temporal aspect of spillover effects also plays a crucial role in their manifestation. Spillover effects, especially those related to investments or knowledge transfer, may take time to materialize, as they are often tied to long-term commitments and gradual shifts in economic behavior. Abadie et al. (2010) suggest that some spillover effects may require extended periods to manifest, particularly those dependent on infrastructure development, education, or industrial transformations. For instance, private investments in new industries or research and development programs may not show immediate results, and the benefits may take years to be felt in neighboring regions. Similarly, shifts in behavior, such as changes in consumer preferences or the adoption of new technologies, can take time to spread from one region to another. Therefore, the lack of immediate significance in direct spillover effects in this study could reflect the longer time horizon required for these effects to materialize fully.

Finally, measurement issues and model limitations may have affected the observed insignificance of direct spillover effects. Spatial econometrics models, while powerful, rely on the accuracy and granularity of the data used. If the data does not fully capture the nuances of spatial dependencies, such as subtle interactions between neighboring regions, the model may underestimate the significance of direct spillovers. López-Tamayo et al. (2022) discuss how measurement errors, such as inaccuracies in the spatial data or the aggregation of regional-level data, can affect the reliability of model results. In this study, the spatial panel regression models may not have fully captured the complexity of interregional relationships, leading to a potential underestimation of the significance of direct spillover effects. Including additional variables or a more refined model specification might be necessary to capture these interactions better and improve the understanding of how direct spillovers operate across regions.

In contrast, the spatial parameter ρ in the SAR and λ in the SEM exhibited significant results, with values of 0.316 ($p<0.001$) and 0.312 ($p<0.05$), respectively. These results suggest the presence of spatial dependence between regions, where the conditions influence the economic conditions of one region in neighboring regions. This study highlights that spillover effects are more indirect, occurring through global spatial dynamics rather than direct interactions between neighboring regions. This finding is crucial for regional development policies, suggesting that regional synergies should strengthen economic ties across regions, rather than relying on direct effects between neighboring areas.

Given the statistically significant findings for indirect spillover effects, it is evident that interregional economic interactions are predominantly facilitated through broader mechanisms—such as information dissemination, technology transfer, and interregional investment flows—rather than direct physical or geographical proximity. This suggests that economic growth in one region can influence others not through mere adjacency, but through a complex web of social, economic, and technological networks. Consequently, the role of government becomes pivotal in crafting enabling environments where such indirect channels can thrive. Policymakers must proactively design and implement policies that strengthen interregional collaboration, mitigate development disparities, and promote sustainable economic development (Liu et al., 2022; Ma et al., 2023).

One of the most impactful policy measures to enhance indirect spillovers is investment in digital infrastructure. Expanding high-speed internet access and implementing smart city technologies can drastically improve the quality of interregional communication and digital service delivery. These tools enable efficient e-commerce and service provision across regions and empower individuals and firms to access wider markets and knowledge networks. Willem (2006) states that bridging the digital divide between developed and less developed regions fosters a more integrated and inclusive economic landscape. Digital infrastructure is the backbone for knowledge diffusion, financial transactions, and the dissemination of innovation—all critical drivers of regional convergence.

In addition to digital infrastructure, creating interregional innovation hubs presents a strategic approach to encouraging cross-border collaboration. These hubs serve as platforms where local businesses, research institutions, and governmental agencies can jointly work on technology development, knowledge transfer, and skills training. By focusing on emerging sectors such as green energy, digital transformation, or health-tech, these hubs would stimulate localized innovation and foster spillovers that extend beyond regional borders. Abor (2010) highlights that such collaborative ecosystems are essential for long-term, inclusive economic growth, particularly in ensuring that less developed regions are actively included in the innovation cycle.

A further recommendation to strengthen indirect spillovers is establishing a cross-regional investment fund. This fund could provide financial incentives such as tax holidays, subsidized credit, or matching grants to businesses that invest in lagging regions. These targeted supports would attract private capital into underdeveloped areas, stimulate job creation, and reduce economic concentration in metropolitan centers. Such investment strategies have the potential to break the cycle of uneven development and help balance regional growth trajectories. Significantly, the success of such a fund would depend on transparent governance, clear evaluation metrics, and strong partnerships between central and local governments.

Strengthening labor mobility is another essential element in enabling productive spillover effects. Facilitating the movement of skilled workers across regions through relocation grants, housing support, or interregional job matching platforms can help address skill shortages while optimizing the allocation of human capital. According to Hanson & Rohlin (2013), easing barriers to mobility enhances regional productivity and supports smoother economic adjustments. Furthermore, inclusive human capital development programs are critical. Vocational training tailored to high-demand sectors, such as information technology, renewable energy, or logistics, can equip workers from marginalized areas with the skills needed to participate in and benefit from regional economic integration.

To ensure long-term impact, fostering equitable regional development requires ensuring all societal groups can access the opportunities created by spillover effects. Special attention must be given to marginalized populations, including women, rural communities, and minority groups, through targeted upskilling programs and inclusive entrepreneurship support. By prioritizing equity within the development agenda, policymakers promote social justice and unlock untapped economic potential that can further amplify spillover benefits. Equitable access to resources, training, and employment opportunities ensures that the benefits of regional growth are shared widely, supporting social cohesion and long-term national prosperity

CONCLUSION

This study reveals that regional spillover effects, including Knowledge Spillover (KSP), Private Investment Spillover (PISP), and Government Expenditure Spillover (GESP), significantly influence economic growth in Central Java's regencies and cities. At the same time, Industry Spillover (ISP) did not show a statistically significant effect across all model specifications. Despite these significant findings, their direct spillover effects were not statistically significant. Instead, the presence of spatial dependencies, as indicated by the significant spatial parameters in SAR and SEM models, suggests that economic interactions occur more through indirect mechanisms rather than direct influences between neighboring regions. Among the tested models, the SEM model demonstrated the highest explanatory power, reinforcing that spillover effects primarily operate through broader spatial dynamics.

Despite these insights, this study has several limitations. The insignificance of direct spillover effects suggests that additional factors, such as institutional quality and labor mobility, may shape regional economic interactions. One key limitation of this research is its broad focus on Central Java, which may overlook the specific dynamics within particular regions or clusters. Future research should narrow its scope to focus on specific regions or economic zones, such as industrial hubs or rural-urban interfaces, to explore how spillover effects manifest differently across various local contexts. This more localized approach could help identify region-specific factors, such as infrastructure quality, policy interventions, and sectoral differences, which are crucial in shaping economic interactions. Additionally, further studies could refine the methodological approach by focusing on time-series analysis to capture better the evolving nature of spillover effects and their implications for long-term development.

By addressing these limitations and incorporating these recommendations, future research can provide a deeper understanding of the spatial interdependencies that drive sustainable economic growth across Central Java, potentially offering actionable insights for policymakers to design more tailored and effective regional development strategies.

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