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Trade Spillover-Induced Backwash Effect and Regional Growth Disparities: A System GMM Approach in Central Java

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ABSTRACT

This study investigates the determinants of regional economic growth in Central Java Province, focusing on trade spillovers, total factor productivity (TFP), and labour composition. Using panel data from 35 regencies and cities over 2011–2024, the analysis applies the System Generalized Method of Moments (SYS-GMM). Results reveal persistent growth, as past output strongly influences current performance. Specifically, the coefficient of the lagged GRDP variable remains above 0.96 across specifications, indicating strong path dependence. Investment, measured by Gross Fixed Capital Formation (GFCF), significantly drives short- and long-term growth. Human capital also matters, with educated and less-educated labour contributing, though the latter remains dominant. Elasticity estimates show that the long-run effect of GFCF reaches approximately 0.45, reinforcing its central role in capital-driven expansion. In contrast, TFP shows weak and insignificant effects, reflecting technological adoption, infrastructure, and workforce quality constraints. Notably, trade spillovers exert a negative influence. Having a commercial link or geographical proximity to a main growth centre does not always guarantee positive outcomes and may even lead to a backwash effect. Indicating a conditional spillover pattern whereby only regions with sufficient absorptive capacity benefit, while others experience backwash tendencies. These findings highlight the need for spatial policies that focus on enhanced connectivity, the creation of additional growth hubs, and upgrading workforce skills to ensure a more balanced spread of development benefits.

1. INTRODUCTION

According to the Regional Long-Term Development Plan (RPJPD) for 2025-2045, one central aim for Central Java is to build a regional economy that is both competitive and sustainable. The province is seen as a potential future hub for growth within Java, utilizing its advantageous geographical location, accessible resources, and the backing of Special Economic Zones (KEK). In this model, Semarang is the primary driving force behind economic development throughout the region. A persistent challenge persists in significant economic disparities between different regions. The rapid expansion of cities like Semarang, accompanied by their adjacent industrial zones, is clearly evident, in contrast to other local regions lagging. The impacts of growth centers have not been uniformly spread across the surrounding regions so far.

To better align with Marshall's foundational theory of industrial districts, this study positions spillovers as outcomes of agglomeration forces, namely labor pooling, input–output linkages, and intra-industry knowledge exchange. These forces shape how productivity advantages in core regions diffuse, or fail to diffuse, to surrounding economies.

Semarang's high productivity is expected to be passed on to other regions, with the effects of trade spillovers and the transfer of human capital and technology playing a key role in this process. Moreover, educated workers in Semarang City are instrumental in disseminating knowledge to workers beyond the city. In line with Myrdal's spread–backwash framework, this study explicitly extends the theory by embedding spillover dynamics within a modern econometric system (System GMM), which allows identification of persistence, asymmetric diffusion, and endogenous spatial linkages. This transfer of knowledge can significantly impact enhancing human capital externalities, as the presence of educated workers can make other workers more productive. Marshall [1] posited that social interactions among workers create learning opportunities, which subsequently elevate productivity. Several studies have estimated the magnitude of these worker spillovers based on education levels and wages [2-4].

Rauch's [5] study found a positive correlation between income and an individual's mean years of schooling (MYS). The importance of human capital externalities in economic development has been extensively documented [6]. A strand of growth theory literature assumes that knowledge is mainly shared within a country's borders, suggesting limited international knowledge transfer. This assumption raises an important question: to what extent do knowledge externalities restrict their impact within geographical areas? Krugman stressed the significance of these spillovers, advising researchers to concentrate more on the impact of geographical proximity. Building on the study's early observations about industrial concentration in urban areas [1], Krugman further explored the underlying mechanisms. Marshall attributed the emergence of geographically concentrated industrial districts to three key factors: (i) the availability of large markets for specialised labour, (ii) the development of industries producing specialised intermediate goods, and (iii) the presence of knowledge spillovers among firms within the same industry. This study positions trade spillovers as a key mechanism that reinforces these Marshallian forces, particularly by increasing interregional trade linkages that facilitate economic concentration in growth centers while enabling the diffusion of knowledge to surrounding regions.

Economists contend that human capital, technology transfer, and spillovers can significantly propel economic growth [7-11]. Moretti [3] suggested that companies in cities with high 'college growth' rates quickly increase labour productivity. The estimated disparity in productivity between cities with high and low levels of human capital matches the manufacturing wage differences seen between such cities. According to Moretti [3], manufacturing companies benefit more when human capital is located in a close geographical and economic area. The interactions among workers in different industries are the source of the spillovers identified in this study. Previous studies have examined the spillover effects in relation to foreign direct investment, tourism, the digital economy, finance, and globalisation, as investigated by references [12-15].

This phenomenon highlights the need for further examination into the factors causing regional economic inequalities. Examining the roles of trade and productivity through the conceptual lenses of trade spillovers and total factor productivity is a pertinent line of inquiry. Trade spillover refers to the indirect benefits that arise from trade and investment activities, including technology transfer, improved production efficiency, and the integration of local businesses into global supply chains [16]. At the same time, TFP measures the efficiency and technological innovation in the use of production inputs and is a key driver of long-term economic growth. Both factors are considered crucial for promoting regional development and reducing inter-regional disparities.

Perroux's [17] growth pole theory, first proposed in 1950, suggested that economic growth begins in areas with high production capabilities and can then spread to nearby regions. The extent of this spillover effect depends on several factors, including local absorptive capacity, the quality of connective infrastructure, and the structure of the regional economy. The dynamics of economic growth in any given area are significantly shaped by its geographical and economic connections with other regions. This aligns with Myrdal's hypothesis of spread and backwash effects, which was proposed in 1958 [18]. According to this hypothesis, resource diffusion and concentration processes simultaneously shape developmental patterns from a spatial perspective**.** Our analysis develops this hypothesis further by demonstrating that the magnitude of backwash and spread effects depends on regional absorptive capacity, institutional quality, and the efficiency of technology transfer as captured by TFP. Through dynamic panel econometric techniques, this study provides stronger empirical evidence for the mechanisms underlying backwash effects in contemporary regional development.

The regional growth of a given area is closely linked to that of other regions through various connections. Notably, the economy of Central Java remains predominantly influenced by a workforce with low levels of educational achievement. Consequently, trade spillovers are expected to facilitate the transfer of technology between regions, thereby improving the quality of human capital and hastening competitive economic growth across the regions of Central Java. This study seeks to examine further the influence of capital stock, human capital, technology, and trade spillovers on economic growth in Central Java, considering the substantial impact of these interregional connections. Research on economic growth in Central Java is notably limited in terms of the effects of trade spillovers and technology transfer. This highlights the compelling reason for conducting research designed to speed up economic growth in order to achieve inclusive development in Central Java.

2. LITERATURE REVIEW

In recent decades, the economic literature has undergone substantial development, exemplified by endogenous growth models based on the Solow framework. The Solow model recognises capital and labour as endogenous factors, whereas technological progress is assumed to be an exogenous factor influencing economic growth [19]. However, classical frameworks alone are insufficient to explain spatially uneven development, necessitating the integration of Marshall's industrial district mechanisms - labour market pooling, specialised input-sharing, and localized knowledge spillovers - into modern regional analyses. This model underscores the significance of capital accumulation and technological progress as primary drivers of economic growth, incorporating the concept of convergence, which refers to the potential for less developed regions to experience more rapid growth through integration and spillover effects from more advanced regions.

To strengthen the theoretical foundation, these classical growth perspectives can be linked to spatial economic models by showing how Marshall's agglomeration economies, Solow's technological progress, and Perroux's growth pole theory evolved into modern frameworks that formalise trade spillovers, spatial dependence, and the diffusion of technology across regions. Such integration highlights that traditional growth mechanisms remain relevant and are now better explained through spatial econometric and new economic geography approaches.

Empirical evidence supporting this theory has become increasingly significant, highlighting the need to analyse trade spillover and total factor productivity (TFP). Perroux's growth pole theory (1950) further emphasises that dominant regions exert propulsive forces through industrial linkages; yet Myrdal's spread–backwash hypothesis warns that such forces may also drain resources from periphery areas, a mechanism still highly relevant in contemporary regional inequality.

Research conducted by Barro and Sala-i-Martin [20] demonstrated the existence of β convergence among regions in the United States, indicating the dissemination of growth. Similar findings by Xu et al. [21] also suggested that growth centers can facilitate progress in surrounding areas through trade, investment, and labour mobility. More recent spatial models, such as New Economic Geography (Krugman, Fujita) and spatial econometric spillover models, formalise these mechanisms through transport costs, agglomeration forces, and interregional dependence. This reinforces the notion that, with appropriate policies, growth centers can serve as catalysts for equitable inter-regional development.

Attaining economic growth is a notable achievement, but it is equally vital to concentrate on boosting productivity to ensure that its advantages endure over the long term. Sustainability of growth depends not only on input accumulation but increasingly on productivity improvements arising from technological diffusion, institutional efficiency, and cross-regional knowledge spillovers. TFP serves as a crucial indicator of this relationship, as it gauges the efficiency with which inputs like labour, capital, and technology are combined to generate output. Within spatial growth theory, TFP is also conceptualised as a mediating variable linking spillovers to long-term competitiveness; regions that absorb external knowledge effectively gain productivity advantages over regions with weaker absorptive capacity. TFP not only reflects the accumulation of inputs but also improvements in efficiency, innovation, and management skills. Over time, TFP becomes a crucial measure of a region's ability to sustain growth without relying solely on increasing inputs. Regions with high TFP generally perform better economically, whereas low TFP suggests innovation, technological adoption, or institutional capacity deficiencies.

TFP is employed to quantify efficiency gains and technological progress that cannot be attributed solely to increases in capital and labour. It effectively measures an economy's ability to adopt and productively transform inputs into outputs. In the context of spillovers, TFP captures whether external advantages translate into internal productivity gains, a crucial mechanism explaining divergence among regions with similar exposure to trade. As a region's TFP increases, its economic growth becomes dependent not only on conventional factor inputs but also on improvements within its production processes. Research by Worku [22] supports Solow's theory, showing a statistically significant positive effect of TFP on the long-term growth rate of real GDP across various Sub-Saharan African countries. Furthermore, a study by Abekah-Koomson et al. [23] found that TFP has been a significant driver of economic growth within the Economic Community of West African States (ECOWAS) region. Previous studies have also examined the relationship between trade openness and economic growth, such as the analysis of Turkey by Çevik et al. [24], and the identification of a long-term relationship among the BRICS nations in a study by Shayanewako [25].

Conversely, researchers such as Ramzan et al. [26] indicated that low-TFP regions may experience negative or limited benefits from trade, reinforcing a conditional spillover hypothesis aligned with Myrdal's backwash effect. However, trade openness can enhance GDP growth once countries reach a minimum threshold level of TFP development. As the level of TFP development increases, so too does trade openness's impact on GDP growth. Another international study by Banerjee and Roy [27] found that domestic technological capabilities and foreign technologies are important forces in determining long-term growth in India, as are human capital and trade, which influence long-term economic growth in India. The findings of Huchet-Bourdon et al. [28] also indicated that countries exporting high-quality products tend to experience faster growth, whereas countries exporting low-quality products incur negative effects on economic growth. Zahonogo [29] recommended that African countries should increase trade with the world while managing their imports effectively to boost their economic growth.

3. METHOD

3.1 Data and source

This study utilizes panel data from 35 regencies and cities in Central Java Province over the period of 2011 to 2024. The data employed comprise the following (Table 1):

Table 1. Research variable description

No.	Variable	Description	Source
1	*Gross Regional Domestic Product* **(GRDP)**	Gross Regional Domestic Product at constant 2010 prices	Central Statistics Agency
2	*Gross Fixed Capital Formation* **(GFCF)**	Gross Fixed Capital Formation at constant 2010 prices	Central Statistics Agency
3	*Educated Worker* **(EW)**	Number of individuals in the labour force whose highest completed education is tertiary level (university)	Central Statistics Agency
4	*Uneducated Worker* **(UW)**	Number of individuals in the labour force whose highest completed education is Senior High School or below	Central Statistics Agency
5	Technology Transfer	Total factor productivity (TFP), calculated using the Growth Accounting Model approach	Processed Data
6	*Trade Spillover* **(TS)**	A composite variable combining trade accessibility, population size, and distance to a benchmark region.	Central Statistics Agency, Google Maps; processed by the author

3.2 Empirical modelling

This study utilizes a modified Cobb-Douglas production function that incorporates spillover and technology effects, as per the approach outlined [30]. The underlying production function model is as follows:

$$\boldsymbol{Y = A_{it}K_{it}^{\beta1}L_{it}^{\beta2}TS_{it}^{\beta3}e_{it}^{\sigma it}} \quad (1)$$

In the model, $\boldsymbol{Y}$ denotes output, $\boldsymbol{L}$ represents labour, K denotes the physical capital stock, $\boldsymbol{TS}$ represents trade spillover, and A is a region-specific multiplicative constant representing location-specific technological capability. Furthermore, β represents the coefficient for each factor input, and σ denotes the spatial efficiency parameter.

$$Y_{it} = \alpha_0 + \beta_1 K_{it} + \beta_2 L_{it} + \beta_3 A_{it} + \beta_4 TS_{it} + \sigma_{it} \tag{2}$$

β_1-β_4 represent the elasticity coefficients of their respective inputs. Solomon and Van Klyton [30] relaxed the assumption of constant returns to scale by introducing a region-specific efficiency parameter, denoted as σ_{it}, which is functionally dependent on the output from the preceding period, Y_{it-1}. This specification enables the modelling of convergence dynamics across countries.

$$\sigma_{it} = a_1 Y_{it-1} + e_{it} \tag{3}$$

The error term in Eq. (3), denoted as e_{it}, comprises three components: the cross-sectional fixed effects, a_1, which account for unobserved variations in output across units; the time-specific effects, λ_t, which capture intangible technical changes over time; and the idiosyncratic error term, u_{it}.

$$e_{it} = a_i + \lambda_t + u_{it} \tag{4}$$

This study adopts the model proposed by Spence [31] and utilizes the dynamic Eqs. (5) and (6).

$$Y_{it} = \alpha_0 + a_1 Y_{it-1} + \beta_1 K_{it} + \beta_2 HC_{it} + \beta_3 A_{it} + \beta_4 TS_{it} + a_i + \lambda_t + u_{it} \tag{5}$$

The labour variable is proxied using a Human Capital (HC) approach, which categorises the workforce into two groups: workers with qualifications from Diploma Level 1 to Doctorate (*educated-worker/EW*), and those with qualifications from Primary School to Senior High School or lower (*uneducated-worker/UW*). Then, a technological transfer (*A*) proxied by Total Factor Productivity Growth (TFPG).

$$Y_{it} = \alpha_0 + a_1 Y_{it-1} + \beta_1 K_{it} + \beta_2 UW_{it} + \beta_3 EW_{it} + \beta_4 TFPG_{it} + \beta_5 TS_{it} + a_i + \lambda_t + u_{it} \tag{6}$$

Subsequently, the equations are transformed into a semi-natural logarithmic form, resulting in the following specification.

$$lnY_{it} = \alpha_0 + a_1 lnY_{it-1} + \beta_1 lnK_{it} + \beta_2 UW_{it} + \beta_3 EW_{it} + \beta_4 TFPG_{it} + \beta_5 lnTS_{it} + a_i + \lambda_t + u_{it} \tag{7}$$

A comparison of static panel models (Pooled Least Squares - PLS, Fixed Effects Model - FEM, and Random Effects Model - REM) and dynamic panel models (First-Differenced GMM - FD-GMM, and System GMM - SYS-GMM) was used to choose the most suitable panel data method.

Research by Bond [32] showed that the System GMM estimator outperforms the First-Differenced GMM estimator. Methodologically, the difference in performance between the two estimators is primarily due to the dynamic nature of panel data, which features an N > T ratio and includes persistent and time-invariant variables. In this context, Difference GMM [33] tends to produce downward-biased estimates because the first-difference transformation eliminates all time-invariant variables and further widens the imbalance of data due to the loss of observations in each differencing operation. In addition, the internal instruments in Difference GMM become weak when the dependent variable is highly persistent, as is the case with the economic growth variable used in the model, thereby reducing estimation efficiency [34]. In contrast, System GMM [34, 35] combines level and differenced equations with a more informative stacked instrument matrix, thereby strengthening the moment conditions and producing more consistent estimates. This method maintains time-invariant variables through orthogonal deviation transformations and reduces the risk of instrument proliferation [36] through a controlled instrument structure. In this study, the large N/T ratio, the existence of dependent lag variables, the persistence of the main variables, and the existence of time-invariant dummies make System GMM a more appropriate choice theoretically and empirically than Difference GMM.

The dynamic panel model was chosen due to its ability to incorporate the lag of the dependent variable as a regressor, thereby allowing for the theoretical representation of the persistence effect of the observed phenomenon. However, the inclusion of this lagged dependent variable introduces endogeneity issues, rendering estimations obtained through Ordinary Least Squares (OLS), Fixed Effects (FE), and Random Effects (RE) biased and inconsistent, as noted by Blundell and Bond [34]. To mitigate this problem, the present study employs the Generalised Method of Moments (GMM), specifically the System GMM estimation developed by Blundell, Bond [34] and Arellano and Bover [35].

The System GMM estimation model is utilized because it offers advantages in producing consistent and efficient estimates for panel data where the number of observational units (N) exceeds the time periods (T), and it can accommodate variables that are not strictly exogenous, as discussed by Roodman [36]. This method combines two systems of equations, namely equations in first-difference form and equations in level form, using lags of the variables as instruments. In the estimation process, orthogonal deviations transformation is employed, which enables the optimal processing of unbalanced panel data without eliminating time-invariant variables, as described by Arellano and Bond [33].

Model validity was evaluated using two key methods. Firstly, the Arellano-Bond test for autocorrelation was employed to identify the presence of serial correlation in the residuals. For the instruments to be deemed valid, the null hypothesis of no second-order autocorrelation, AR (2), must not be rejected [33]. Secondly, the Hansen test was used to assess the appropriateness of the overidentifying restrictions, with the null hypothesis stating that all instruments used are exogenous. A high p-value from the Hansen test indicates that the model and its instruments are acceptable [37]. The selection of the System GMM estimation model in this study is based on both methodological and empirical considerations, aiming to produce reliable and accurate estimates within a dynamic panel framework.

3.3 Estimation of spillover calculation

Gravity theory suggests that regions closer to developed areas are likely to experience more favourable spillovers than those located farther away. The spillover equation is as follows:

$$S_{ij} = Z_{it}\left[\frac{1}{d_{max\ \_i}}\left(\frac{y_{max,t} - y_{it}}{y_{it}}\right)\right] \quad (8)$$

where, $\boldsymbol{Z_{it}}$ represents a function of the attractiveness magnitude of city-*i,* for example: its labour force size, or its status as a center for trade and investment, etc., while $\boldsymbol{y_{it}}$ denotes its per capita Gross Regional Domestic Product (GRDP), and $\boldsymbol{d_{max\ \_i}}$ is the distance from city-*i* to the city with the highest per capita GRDP. Should $\boldsymbol{y_{max,i}} = \boldsymbol{y_{it}}$ then the value of the spillover is zero (*spillover term=0*).

4. RESULT AND DISCUSSION

Regional development primarily aims to enhance economic growth, reflected in productive capacity improvements, societal welfare, and structural economic transformation [38]. High economic growth also leads to job creation, increased per capita income, and enhanced regional competitiveness [39]. To develop effective and sustainable development policies, it is essential to understand the factors that influence economic growth. Nevertheless, a major challenge in regional economic development is achieving equitable and just economic growth.

This study uses a panel data approach that covers 35 regencies and cities in Central Java Province from 2011 to 2024. The study focuses on the GRDP as its dependent variable. As shown in Table 2, the average GRDP across these regencies and cities during this period was IDR 25.68 trillion. The GRDP in Magelang City was the lowest at IDR 4.26 trillion, while Semarang City had the highest GRDP at IDR 170.95 trillion. The standard deviation of IDR 24.24 trillion indicates significant variation in GRDP across different regions or over time.

Table 2. Statistical description

Variable	Obs	Unit	Mean	Std. Dev.	Min	Max
GRDP	490	Billion IDR	25,677	24,241	4,255	170,948
GFCF	490	Billion IDR	7,640	13,240	1,022	97,905
UW	490	Worker	416,162	185,663	44,138	1,089,080
EW	490	Worker	43,283	34,324	8,696	278,620
TFPG	490	Index	-0.008	0.103	-1.216	0.552
TS	490	Index	0.001	0.001	-0.0001	0.004

Source: Data processed, 2025.

Table 3. Comparison of dependent lag parameters

	FE	PLS	Diff-GMM	Sys-GMM
Lag Ln GRDP	0.681	0.987	0.843	0.972

Source: Data processed, 2025.

Table 4. Correlation matrix of variables

	GRDP	GFCF	UW	EW	TFPG	TS
GRDP	1.0000					
GFCF	0.8469	1.0000				
UW	0.4797	0.2788	1.0000			
EW	0.8022	0.8810	0.4731	1.0000		
TFPG	0.0534	0.0276	0.0357	0.0588	1.0000	
TS	-0.2058	-0.2075	0.4080	-0.0680	-0.0205	1.0000

Source: Data processed, 2025.

The independent variables used in this analysis include Gross Fixed Capital Formation (GFCF), Uneducated Worker (UW), Educated Worker (EW), Total Factor Productivity Growth (TFPG), and Trade Spillover (TS). The average value of GFCF is IDR 7.64 trillion, with a standard deviation of IDR 13.24 trillion. The minimum recorded GFCF was IDR 1.02 trillion, while the maximum was IDR 97.91 trillion, indicating a significant disparity in GFCF across the observations. The average number of uneducated workers in Central Java Province was 416,162, significantly exceeding the average number of educated workers, which stood at 43,283. This disparity indicates that the workforce in the province is predominantly composed of uneducated workers, who generally possess lower levels of education, skills, and productivity. Many of these workers are employed in the informal sector, which does not necessitate the advanced skill sets characteristic of educated workers. Furthermore, the standard deviation for uneducated workers is wider compared to that of educated workers.

The economic contribution of Total Factor Productivity Growth (TFPG) in Central Java was found to be relatively low. The mean TFPG value of -0.008 indicates a general decline in TFP across observed periods or regions. Notably, the highest recorded TFPG value was 0.552, while the lowest was -1.216. In contrast, the trade spillover variable, which accounts for the interplay between trade mobility, distance, and income of each regency or city in Central Java, exhibits a mean value of 0.001 and a very small standard deviation of 0.001. This suggests that the level of trade spillover tends to be low and relatively stable across observations.

The System GMM model is chosen because the parameter value for the dependent variable's lag (Lag Ln GRDP) in Table 3 falls between the parameter value from the Fixed Effects (FE) model and that from the Pooled Least Squares (PLS) model. Specifically, the parameter value for Lag Ln GRDP (0.972) lies between the FE model's value (0.681) and the PLS model's value (0.987). As a result, this study uses the System GMM estimation model, as all lag parameters for the dependent variable fall within the FE and PLS bounds. The Difference GMM (Diff-GMM) model was not employed to avoid a potential downward bias, which can occur when the lag parameter of the dependent variable is close to or smaller than the value estimated by the FE model [32].

The correlation results in Table 4 show that GRDP has a strong positive relationship with GFCF (0.8469) and EW (0.8022). The moderate correlation between GRDP and UW (0.4797) also shows that economic growth contributes to an increase in uneducated workers, although the relationship is not as strong as with other variables. GFCF itself has a high correlation with EW (0.8810), indicating that increases in fixed capital formation tend to be followed by an increase in educated workers. Meanwhile, TFPG shows a very low correlation with all variables, while the TS variable even has a small negative correlation with some variables, especially GRDP (-0.2058). Overall, the correlation pattern is dominated by a strong relationship between GFCF, educated workers (EW), and GRDP, while TFPG and TS appear less directly related to the dynamics of other variables.

This study employs a dynamic estimation model approach to investigate the dynamics of regional economic growth; the Difference Generalized Method of Moments (Difference GMM) and the System Generalized Method of Moments (System GMM). The objective of this multi-faceted approach is to compare the consistency and efficiency of the estimation results, taking into account potential bias and endogeneity issues that are commonly present in dynamic panel data. The results from all three models indicate that the majority of the key variables exert a consistent and significant influence on GRDP, with the System GMM producing the most efficient and statistically valid estimates.

The value of the coefficient for the lagged GRDP in Table 5 is significant in the Difference GMM model, with a value of 0.8427, and reaches its highest point in the System GMM model, with a value of 0.9715. Meanwhile, robust estimation of the same variable yields a coefficient of 0.9618, which indicates that GRDP persistence remains consistently strong. This finding is consistent with endogenous growth theory. The theory suggests that past output can create a positive feedback loop on current economic performance. This loop is achieved through mechanisms such as capital accumulation, technological advancement, and learning [33].

The investment variable, represented by GFCF in Table 5, has a positive and statistically significant impact on GRDP in both the short and long term across all models. Within the System GMM estimation, the short-run coefficient for GFCF is 0.0102, and the long-run coefficient is 0.0457, both of which are significant at the 1 percent level. In the short term, the log-transformed GFCF variable indicates that a 1 percent increase in fixed capital formation is associated with a 0.0215 percent rise in GRDP. In the long term, however, the effect becomes substantially stronger, suggesting that sustained improvements in capital accumulation contribute almost 0.44 percent to regional economic output for every 1 percent increase in GFCF. This explicit distinction highlights the fact that, while capital accumulation generates modest immediate gains in production capacity, its long-term effects are far more pronounced, as infrastructure, machinery, and technological assets become fully integrated into the regional economy.

The data indicate that an increase in fixed capital formation, which encompasses infrastructure and productive assets, is essential for promoting sustainable regional economic growth. Investment has a dual impact on economic output. Firstly, it provides an initial boost to current production levels. Secondly, it contributes to an increase in long-term production capacity. This is supported by the theoretical arguments of the Solow growth model and the concept of capital accumulation within the growth accounting framework.

The impact of labour on economic growth is consistently demonstrated across different estimation approaches. Both educated and uneducated workers have a positive and statistically significant influence on GRDP. In the short term, the coefficient for log-transformed educated workers is 0.0091, indicating that a 1 percent increase in educated labour contributes to a 0.0091 percent rise in GRDP. In the long term, the impact strengthens markedly to 0.1852, implying a 0.1852 percent increase in GRDP for the same proportional change.

Similarly, the short-run coefficient for log-transformed uneducated workers is 0.0231, suggesting that a 1 percent increase in this labour group raises GRDP by 0.0231 percent, and this rises substantially to 0.4723 in the long run, reflecting a stronger and more sustained contribution to regional output. These results suggest that regional economic growth is influenced by both the quantity and quality of labour input. Highly educated workers tend to participate in high-technology or high-value-added sectors, whereas less educated workers remain central to labour-intensive industries such as agriculture and light manufacturing. Consequently, both groups play a complementary role within the regional economic structure.

Interestingly, the estimation results from the difference GMM model show that the Total Factor Productivity Growth (TFPG) variable, which represents technology transfer, has a positive and statistically significant effect on GRDP, with a coefficient of 0.0385. This implies that a 1 percent increase in TFPG is associated with a 0.0385 percent rise in regional economic output. This indicates that productivity-enhancing technological improvements still contribute positively to short-term growth dynamics.

However, in the System GMM estimation and its robust specification, the TFPG variable becomes statistically insignificant. This discrepancy may suggest that the effects of technological productivity are more apparent when endogeneity is only partially corrected, but less so when the model more rigorously accounts for the error structure and instrument validity. This further suggests that the regional technology adoption process may be progressing slowly, or be constrained by institutional barriers, infrastructure limitations or inadequate human resource readiness.

A key outcome of this research is the statistically significant negative relationship between the trade spillover (TS) variable, measured in its log-natural form, and GRDP in the difference GMM model, where TS has a coefficient of –0.0664. This implies that a 1 percent increase in log-natural TS is associated with a 0.0664 percent decline in regional economic output. This indicates that exposure to neighbouring economic activity may have a negative short-term impact on GRDP.

However, the System GMM estimation shows that log-natural TS is not statistically significant. This result remains consistent when using the robust model, which uses the lag of log-natural TS as an additional correction for endogeneity and serial correlation. The absence of significance in the System GMM and robust specifications, which are more stringent, indicates that the true effect of trade spillover on GRDP may be weaker or more context-dependent than suggested by the Difference GMM estimation.

This pattern reinforces the idea that proximity to growth centers or increased access to interregional trade does not necessarily lead to higher regional growth. The negative association observed may be driven by economic leakage, whereby economic activity is concentrated within the dominant growth hub, with surrounding regions largely acting as passive supporters. Furthermore, peripheral regions may have limited connective infrastructure, labour competitiveness, and institutional quality, which restricts their ability to capitalise fully on trade-induced growth opportunities.

Table 5. The result estimation (Robust)

	Diff GMM	Sys GMM	Sys GMM Robust
L.Ln_GRDP_ct	0.8085*** (0.0158)	0.9511*** (0.0151)	0.9618*** (0.0220)
ln_TS	-0.0664*** (0.0083)	-0.0038 (0.0046)	
lag_ln_TS			-0.0018 (0.0048)
Ln_GFCF (short run)	0.0766*** (0.0086)	0.0215*** (0.0055)	0.0173* (0.0086)
Ln_GFCF (long run)		0.4398*** (0.0653)	0.4524*** (0.0773)
ln_UW (short run)	0.1069*** (0.0108)	0.0231* (0.0114)	0.0160 (0.0146)
ln_UW (long run)		0.4723*** (0.0949)	
ln_EW (short run)	0.0277*** (0.0066)	0.0091** (0.0035)	0.0079** (0.0037)
ln_EW (long run)		0.1852*** (0.0531)	0.2066*** (0.0743)
TFPG	0.0385*** (0.0102)	0.0104 (0.0087)	0.0054 (0.0099)
constant	-0.8842 (0.1578)	-0.0735 (0.1004)	-0.0238 (0.1097)
N	399	433	432
F-Statistics		68387.88	65465.31
Arellano-Bond test for AR (1) in first differences:	z = -3.21 Prob > z = 0.001	z = -1.39 Prob > z = 0.163	z = -1.39 Prob > z = 0.164
Arellano-Bond test for AR (2) in first differences:	z = -4.07 Prob > z = 0.000	z = -1.23 Prob > z = 0.217	z = -1.25 Prob > z = 0.210
Sargan test of overidentifying restrictions:	$Chi^2(78) = 452.62$ Prob > $chi^2 = 0.000$	$Chi^2(1) = 2.57$ Prob > $chi^2 = 0.109$	$Chi^2(1) = 5.09$ Prob > $chi^2 = 0.024$
Hansen test of overidentifying restrictions:		chi2(1) = 1.24 Prob > $chi^2 = 0.265$	$chi^2(1) = 2.77$ Prob > $chi^2 = 0.096$

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Source: Data processed, 2025.

The negative TS coefficient in the Difference GMM specification may partly reflect reverse causality. Regions with structurally lower GRDP tend to exhibit weaker trade linkages and receive less trade from neighbouring growth centres, which generates lower or negative trade spillover values. This suggests that GRDP may also influence TS. The System GMM estimator's internal instrumentation strategy relies on deeper lags of the endogenous variables, thereby mitigating potential reverse causality and simultaneity bias. The fact that the TS becomes statistically insignificant in the more robust System GMM and two-step robust models indicates that the initially observed negative relationship in the Difference GMM estimator is likely affected by endogeneity rather than capturing a stable causal link.

Based on the diagnostic statistics presented in the table, the System GMM model is the most reliable and methodologically robust of the three assessed approaches. Unlike the Difference GMM model, which has a rejected Sargan test (p = 0.000), indicating invalid over-identifying restrictions, System GMM estimation produces satisfactory results for both the Hansen (p = 0.265) and Sargan (p = 0.109) tests, confirming the joint validity of the instrument set.

The Arellano–Bond AR (2) test also supports this conclusion, with a p-value of 0.217 indicating the absence of second-order serial correlation, which reinforces the internal consistency of the estimator. While the robust specification yields a borderline Sargan value (p = 0.024), the Hansen statistic remains acceptable (p = 0.096) and the AR (2) test continues to show no indication of autocorrelation. This demonstrates that the model remains stable under alternative estimation settings. Furthermore, the total number of instruments used (only five) remains substantially below the number of cross-sectional units (N = 35), aligning with Arellano and Bover [35]'s recommendation that the number of instruments should not exceed the number of observations in order to avoid overfitting and artificially inflated Hansen test statistics. Taken together, these results confirm that the System GMM framework adheres most strongly to the key econometric assumptions of instrument exogeneity, the absence of higher-order autocorrelation, and an appropriate instrument count. This makes it the most valid and credible model for drawing causal inferences regarding the relationships between the analysed variables [35, 36].

Considering the complexity, statistical significance as well as instrument validity of the model, System GMM estimation is the most suitable candidate to represent the dynamic processes of regional economic growth in this research. Its ability to adjust for endogeneity and preserve time-invariant information is very relevant to unbalanced panel data analysis. It is well-established that the trade spillovers tend towards the negative or insignificant; thus, the geographical proximity with the growth center does not lead to a rise of the economy in itself, and in some cases could create backwash effects. This result is consistent with larger structural drivers in Central Java, where urban bias enhances the benefits of core cities while rural labour stickiness inhibits structural change in hinterland districts. Simultaneously, weak institutional quality restricts the peripheral regions' capacity to absorb and exploit external knowledge, capital, and technological flows; which only constrains their potential to reap the benefits of trade linkages. Hence, even strong trade connectivity could confer small benefits in the absence of stronger absorptive capacity. These results confirm that spillovers are conditionally driven and further highlight the importance of regional development policies that can handle both structural constraints and institutional weaknesses. This is so because less dependence on major growth centers of hinterland regions becomes crucial, and this will be achieved through strengthening local processing industries and regional-potential-based SMEs, providing targeted investment incentives in peripheral regions to redirect value creation inward, and stimulating local production networks in the hinterland regions that lead them to gain a proportion of the regional economic activity.

The low and statistically insignificant contribution of TFP in System GMM estimation indicates significant challenges in technology adoption, infrastructure availability, and human resource quality in the regions. This situation necessitates targeted capacity-building programmes, industry-specific vocational training, and technology extension services. Moreover, integrating knowledge hubs with industrial estates is essential to accelerate technology transfer and enhance regional competitiveness. An equally critical issue is the dominance of uneducated workers (UW), whose numbers are ten times greater than those of educated workers (EW). The imbalance in the labour structure requires policies to improve access to vocational education, especially in areas outside major cities. Additionally, it necessitates the development of skill-upgrading schemes for informal workers to help them transition into higher-paying economic sectors.

The findings also reflect underlying structural inequalities across Central Java. The dominance of uneducated labour, nearly ten times the number of educated workers, indicates the presence of rural labor stickiness, where low-skill workers remain concentrated in peripheral regions due to mobility constraints and limited access to high-productivity sectors. This reinforces Myrdal's backwash effect, as growth centers such as Semarang attract capital and skilled labour, while hinterland districts remain locked into low-productivity activities. Moreover, the stronger contribution of uneducated labour to long-run output suggests a persistent urban bias in regional development, where investment, technology diffusion, and skilled employment disproportionately cluster in urban cores rather than rural districts.

Spatial policy strategies must prioritise functional connectivity initiatives that enhance logistics, integrate supply chains, and offer digital market access, extending beyond traditional road and highway infrastructure. Regions struggling with the negative consequences of trade spillovers can benefit from investing in last-mile connectivity and digital infrastructure to mitigate these effects and achieve positive results. Establishing selected cities in the hinterland of Semarang as regional economic distribution nodes, within the framework of a multi-nodal growth model, provides a strategic mechanism to promote a more equitable distribution of development benefits. This approach would be particularly effective if supplemented by allocating local government funds for capital development to establish production facilities, storage facilities, and innovation hubs in these regions.

Implementing investment zoning based on local potential, utilizing trade spillover and TFP data, would aid in determining industrial development priorities. Tax incentives and local levies should be directed towards regions at high risk of experiencing backwash effects. Additionally, policies promoting local content within supply chains should be encouraged. Promoting local content within the supply chain can be achieved by requiring large firms in growth centers to source inputs from surrounding areas through partnership schemes with small and medium-sized enterprises. This approach would help to establish stronger and more sustainable interregional economic connections.

5. CONCLUSIONS

The research indicates that regional economic growth in Central Java is strongly influenced by the persistence of GRDP, capital accumulation (GFCF), and both educated and uneducated labor. The System GMM model proved to be the most reliable based on the Sargan, Hansen, and AR (2) tests, thus serving as the primary basis for drawing conclusions. GFCF has a significant positive effect in both the short and long term, with the long-term effect being much larger because capital accumulation takes time to fully integrate into the economy. Uneducated labor contributes significantly more in the long term than educated labor, reflecting the dominance of labor-intensive sectors and the unequal labor structure. Meanwhile, TFP is insignificant, indicating slow technology diffusion, limited infrastructure, and low human resource quality. The trade spillover variable shows a negative effect in the Difference GMM but is insignificant in the System GMM, indicating that proximity to growth centers has not yet provided stable economic benefits and may reflect backwash effects, economic leakage, and structural inequality between regions.

The policy implications of this study highlight the need for spatially targeted policies to decrease the structural dependence of rural regions on major urban centers. Strengthening small and medium-sized enterprises and local processing industries, investing in surrounding regions, and implementing local content policies for regional supply-chain linkages shall be among the strategies that can be developed. With this in mind, a greater share of provincial capital expenditure should go towards peripheral districts, and there should be increased vocational training, systematic skills upgrading, and improved logistics and digital infrastructure to support growth in productivity. Establishing sub-regional growth hubs around Semarang as secondary nodes within a multi-nodal development framework (and with stronger local procurement requirements) can also redistribute economic opportunities and mitigate backwash effects. Knowledge hubs and industrial zone connectivity, as well as accelerated human-capital development, are equally important in building regional absorptive capacity and transforming trade interactions into more equitable, broad-based growth.

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