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Regional Convergence and Spatial Shift-Share Analysis of Labor Productivity in Indonesia

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ABSTRACT

Research Originality: This study offers a new method to analyze district labor productivity in Indonesia.

Research Objectives: This study examines the convergence of district labor productivity in Indonesia and the role of structural change in this district labor productivity growth.

Research Methods: This study uses spatial convergence and spatial shift-share analysis. This study collected data from BPS-Statistics Indonesia at the district level between 2010 and 2022.

Empirical Results: Labor productivity in Indonesia exhibits convergence. Neighbor districts' characteristics, such as initial labor productivity and unobserved variables, affect this convergence. The intrasectoral component has the most significant effect on labor productivity growth. The intersectoral component, caused by structural change, has almost no effect.

Implications: The Indonesian government can improve intrasectoral productivity growth to accelerate labor productivity development.

Keywords:
labor productivity; spatial β convergence; spatial shift-share analysis; intrasectoral component; structural change

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INTRODUCTION

The latest trend in Indonesia's economic growth indicates diminished optimism. Prior to the COVID-19 epidemic, labor productivity had been diminishing since 2010. The analysis of output per worker uncovers an increasingly concerning tendency. The contribution of human capital to economic growth has consistently diminished during the last twenty years (Ikhsan et al., 2021).

At the same time, Indonesia has entered a new period called a demographic dividend. A demographic bonus occurs when the population of individuals aged 15 to 64 exceeds that of the non-productive population. BPS-Statistics Indonesia (2023) indicates that 69.05 percent of Indonesia's total population in 2024 comprises individuals of productive age. A demographic dividend can be advantageous when the youth have access to quality education and resources that improve their self-worth. Human resource enhancement that does not align with demographic advantages will substantially decline labor productivity growth.

Labor productivity is a key performance indicator at all levels of the economy, from the shop floor through business enterprises to the national economy, because higher labor productivity can stimulate job creation, decrease cost (Abdel-Hamid & Abdelhaleem, 2020), and increase economic growth (Auzina-Emsina, 2014; Bakas et al., 2020). Bendesa et al. (2016) argued that regional inequality is a prevalent characteristic of the Indonesian economy. Compared to the Association of Southeast Asian Nations (ASEAN) countries, Indonesia's labor productivity is also inferior to that of Singapore, Malaysia, and Thailand. To reduce disparities across regions and countries, Indonesia must increase labor productivity.

Given the importance of labor productivity, regional policies prioritize increasing its growth. Structural change can achieve this aim. When poorer regions with relatively more labor in low-productivity sectors, such as agriculture, experience faster productivity growth due to labor reallocation, structural change can have a convergent effect on labor productivity (O'Leary & Webber, 2015).

Structural change's impact on aggregate labor productivity growth is typically measured by classical shift-share analysis. The classical shift-share analysis is popular among planners, geographers, and regional scientists due to its simplicity and affordability, as it is neither data-intensive nor mathematically complex. Nevertheless, classical shift-share analysis focuses on the interdependence of regions concerning national changes, disregarding the interrelationships among these regions. Regional spatial independence is an unrealistic supposition. Regions are interconnected (Mussini, 2019; Montania et al., 2021). Therefore, the shift-share model should include spatial interaction.

There are two ways to examine spatial dependence in a shift-share model. First, the researcher uses spatial shift-share decomposition. Nazara and Hewings incorporate spatial structure within the shift-share analysis to consider interregional interaction in the decomposition analysis (Mussini, 2019). Second, the researcher uses stochastic shift-share analysis and includes spatial dependence in this model. Melchor-Ferrer (2020), for

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instance, uses spatial econometrics to estimate each sector's spatial spillovers, determine each sectoral component's contribution to productivity growth, and identify any potential spatial feedback in this process.

This study aims to show whether structural change affects labor productivity growth in Indonesia. Using the same spatial-shift share analysis method as Melchor-Ferrer (2020), this study identifies the primary sectoral component that drives labor productivity growth and measures the direct, indirect, and total impact of this sectoral component on productivity. Based on these results, policymakers can design regional policies to meet the demographic bonus and improve labor productivity. Furthermore, this study also evaluates the convergence of regional labor productivity, recognizing that a decrease in regional inequality usually follows an increase in labor productivity.

The important question is how to quantify the degree of regional interaction. This study can consider two broad classes as spatial weight matrices: geographical variables and economic variables. Some examples of geographical variables are the inverse of the squared distance between regions, the negative exponential function of the distance between territorial units, physical contiguity (Mussini, 2019), k-nearest neighbors (Melchor-Ferrer, 2020), and threshold (arc) distance (Melchor-Ferrer, 2020). Economic variables are the basis for the interrelationship of economic outcomes or potentials, such as migration patterns or trade flows. Previous studies deem two regions closer when they share more excellent economic interactions. Those interactions are shown by income per capita, employment level, commercial relations, or Gross Domestic Product (GDP). This study employs the migration pattern as a spatial weight matrix, as it is suitable for application in Indonesia, an archipelago nation. To the author's knowledge, no previous studies in Indonesia have used this method on similar topics.

METHODS

The concept of convergence refers to the decline in dispersion (disparity) of a development indicator, such as labor productivity distribution, across regions as economic entities. In growth analyses of labor productivity, convergence has a slightly different meaning: it refers to relatively lower growth of a labor productivity, with relatively higher labor productivity. Convergency measurements can use β convergence. The approximation for non-spatial β convergence is:

$$\frac{1}{T} ln\left(\frac{LP_{i,t}}{LP_{i,t-T}}\right) = \alpha + \beta \ ln \ LP_{i,t-T} + u_{i,t} \tag{1}$$

where α is intercept term, β is the coefficient of $ln\ LP_{i,t-T}$ with $-1 < \beta < 0$, $LP_{i,t-T}$ is the labor productivity at district i for the year t-T, T is a year time interval, and $u_{i,t}$ is a disturbance term. The condition $\beta < 0$ implies β convergence because the annual growth rate $\frac{1}{T} ln\left(\frac{LP_{i,t}}{LP_{i,t-T}}\right)$ is the inversely related to the $ln\ LP_{i,t-T}$. A higher coefficient β corresponds to a greater tendency for convergence.

Structural change can affect regional productivity differences and promote growth through labor movement across sectors of an economy (Konte et al., 2022). In the convergence discourse, structural change may yield a convergent impact when poor regions, characterized by a higher proportion of labor in low-productivity sectors like agriculture, demonstrate accelerated productivity increase through labor reallocation. Structural change may result in regional divergence if rich regions expand more rapidly due to the reallocation of labor from lower- to higher-productivity sectors. O'Leary and Webber (2015) identify that structural changes within a sector exert a converging effect. The shift-share method is employed to elucidate regional production discrepancies. O'Leary & Webber (2015) break down the aggregate productivity growth for region i in year t into three components, as outlined in the following expression:

$$\begin{aligned} growth\ LP_{i,t} &= \frac{LP_{i,t} - LP_{i,b}}{LP_{i,b}} \\ &= \left(\frac{\sum_{j=1}^{n} LP_{i,j,t} S_{i,j,b}}{\sum_{j=1}^{n} LP_{i,j,b} S_{i,j,b}} - 1\right) + \left(\frac{\sum_{j=1}^{n} LP_{i,j,b} S_{i,j,t}}{\sum_{j=1}^{n} LP_{i,j,b} S_{i,j,b}} - 1\right) \\ &\qquad + \left(\frac{\sum_{j=1}^{n} \left(LP_{i,j,t} - LP_{i,j,b}\right)\left(S_{i,j,t} - S_{i,j,b}\right)}{\sum_{j=1}^{n} LP_{i,j,b} S_{i,j,b}}\right) \\ &= intra_{i,t} + inter_{i,t} + residual_{i,t} \\ &= intra_{i,t} + combined_{i,t} \end{aligned} \quad (2)$$

where b is the base year; n is the set of sectors; and S_j is the share of sector j in total employment.

The interpretations of the different components in Equation 2 are as follows: The first (intrasectoral component $intra_{i,t}$) is the contribution made to annual aggregate growth by productivity growth within individual sectors (weighted by the share of each one in total employment); the second (intersectoral component $inter_{i,t}$) is the contribution made by changes in the allocation of labor between sectors; this is positive/negative if sectors with high levels of productivity attract more/fewer labor resources and hence increase/decrease their share of total employment; and the third (residual component $residual_{i,t}$) measures the interaction between changes in productivity in individual sectors and changes in the allocation of resources. The fourth component (combined component $combined_{i,t}$) is the difference between productivity growth and the intrasectoral component (Melchor-Ferrer, 2020). The intersectoral component illustrates the impact of structural changes on labor productivity growth. O'Leary & Webber (2015) propose different models for a static shift-share approach that can be expressed as:

$$\begin{aligned} growth\ LP_{i,t} &= \mu_1 + \gamma_1 intra_{i,t} + \upsilon_{1i,t} \\ growth\ LP_{i,t} &= \mu_2 + \gamma_2 inter_{i,t} + \upsilon_{2i,t} \\ growth\ LP_{i,t} &= \mu_3 + \gamma_3 residual_{i,t} + \upsilon_{3i,t} \\ growth\ LP_{i,t} &= \mu_4 + \gamma_4 combined_{i,t} + \upsilon_{4i,t} \end{aligned} \quad (3)$$

where $growth\ LP_{i,t}$ is the annual growth rate of labor productivity for each region.

As explained in the introduction, the aim of the study is twofold. The first objective is to analyze the possibility of labor productivity convergence in Indonesia. The second objective is to examine whether structural change affects labor productivity growth in

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Indonesia. Analysis of the possibility of labor productivity convergence uses spatial β convergence because the economic performance of neighboring regions often has a significant impact, affecting convergence by reducing inequality in certain locations. The equation of spatial β convergence can use the spatial econometric model:

$$\frac{1}{T} ln\left(\frac{LP_{i,t}}{LP_{i,t-T}}\right) = \alpha + \beta\, ln\, LP_{i,t-T} + \delta W \frac{1}{T} ln\left(\frac{LP_{s,t}}{LP_{s,,t-T}}\right) + \theta W ln\, LP_{s,t-T} + u_{i,t} \qquad (4)$$

where $u_{i,t} = \lambda W v_{s,t} + \varepsilon_{i,t}$, $i \neq s$, and W is the spatial weight matrix.

For several reasons, it appears that annual time intervals are insufficient for examining growth convergence. Such shorter durations may indicate substantial short-term disruptions. Consequently, this study selects four-year intervals. For the period 2010-2022, each district has four data points: 2010, 2014, 2018, and 2022. For t = 2014, t - T equals 2010, and the labor productivity growth indicators represent averages from 2010 to 2014 or $\frac{1}{4} ln\left(\frac{LP_{i,2014}}{LP_{i,2010}}\right)$.

The initial step in identifying the most suitable spatial econometric model for the investigation is a general nested spatial model (GNS). The model in Equation 4 can be simplified and expressed in multiple forms based on the estimated values of the parameters δ, θ, and λ. Spatial Error Model (SEM), Spatial Durbin Model (SDM), Spatial Autoregressive Model (SAR), Spatial Lag of X Model (SLX), Spatial Durbin Error Model (SDEM), and Spatial Autoregressive Combined Model (SAC/SARAR). These models incorporate single or combined spatial lags in the dependent variable (SAR, SAC/SARAR, and SDM), the explanatory variables (SDM, SLX, and SDEM), and the error term (SEM, SARAR, and SDEM). SAR, SDM, SDEM, and SAC/SARAR encompass both the direct influence of neighboring predicted outcomes on one's own results and the indirect (spillover) effects on adjacent regions.

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This study offers a more comprehensive econometric analysis of the impact of each component on overall labor productivity growth, as utilized by O'Leary & Webber (2015), through the application of a spatial econometric model. This study use this approach to ascertain the influence of neighboring regions on labor productivity at the district level in Indonesia. By altering Equation 3, the formulas for labor productivity growth are:

$$growth\ LP_{i.t} = \mu_1 + \gamma_1 intra_{i.t} + \varphi_1 W intra_{s.t} + \omega_1 W growth\ LP_{s.t} + \upsilon_{1i.t}$$
$$growth\ LP_{i,t} = \mu_2 + \gamma_2 inter_{i,t} + \varphi_2 W inter_{s,t} + \omega_2 W growth\ LP_{s,t} + \upsilon_{2i,t}$$
$$growth\ LP_{i,t} = \mu_3 + \gamma_3 residual_{i,t} + \varphi_3 W residual_{s,t} + \omega_3 W growth\ LP_{s,t} + \upsilon_{3i,t}$$
$$growth\ LP_{i,t} = \mu_4 + \gamma_4 combined_{i,t} + \varphi_4 W combined_{s,t} + \omega_4 W growth\ LP_{s,t} + \upsilon_{4i,t} \quad (5)$$

Where $\upsilon_{.i,t} = \lambda W \upsilon_{.i,t} + \epsilon_{.i,t}$, $i \neq s$, and W is the spatial weight matrix. This analysis employs panel data from 2010 to 2022, excluding 2016 due to the unavailability of sectoral employment figures at the district level for that year. Labor productivity is defined as gross regional domestic product (GRDP) at constant prices per worker (billion rupiah per worker) or GRDP at constant prices per working hour (million rupiah per working hour). The intrasectoral effect (γ_1) is typically positive, while the contributions of structural change (γ_2, γ_3, γ_4) are approximately zero (O'Leary & Webber, 2015).

The analytical data sources comprise the Inter-censal Population Survey (Supas), the National Labor Force Survey (Sakernas), and GRDP data from BPS-Statistics Indonesia. The purpose of Supas is to assess population size and demographic indicators, encompassing characteristics of the subject population, including births, deaths, migrations, employment, housing, state of residency, and urbanization. Sakernas, a semi-annual household survey, seeks to assess Indonesia's labor force and record structural changes over time. The sample size of Supas exceeds that of Sakernas. This research employs 2015 Supas data to quantify the components of the spatial weight matrix (W) at the district level. Each factor denotes the quantity of recent migrations between two districts for individuals aged 15 years and older.

This study utilizes raw data from Sakernas to estimate the workforce and working hours at the district level across three sectoral categories: (1) primary sector (categories 1-2); (2) secondary sector (categories 3-6); and (3) tertiary sector (categories 7-17), due to sample limitations. This analysis also considers GRDP at constant prices. The calculation integrates the new district data with the current data. This study omits illogical employment numbers at the district level, including cases where the number of sectoral workers is zero, from its analysis. This analysis encompasses 487 districts for each period.

RESULTS AND DISCUSSION

Table 1 indicates that, according to the Hausman test results, the chosen non-spatial model is a fixed effects model (FEM). The coefficient estimate of the natural logarithm of labor productivity signifies reduced labor productivity disparity among Indonesian districts. This result signifies a propensity for convergence in the labor productivity of districts.

Table 1. Estimation of Non-spatial β Convergence in Labor Productivity

Variable	Estimated parameter	t-value
Ln initial labor productivity	-0.038***	-9.95
Constant	-0.155***	-10.18
p-value Hausman test	0.000	

Notes: ***, **, and * statistical significance at the 1%, 5%, and 10%.

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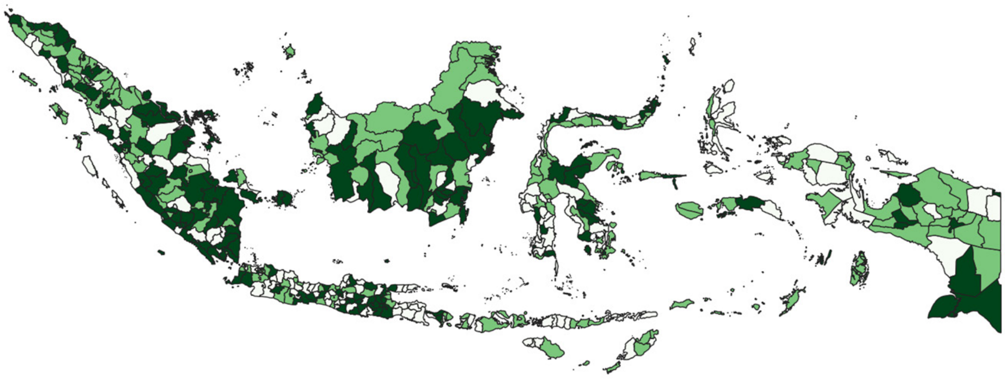
This study uses the spatial analysis method of the equal quantile map (refer to Figure 1) to ascertain the existence of spatial autocorrelation. From 2010 to 2022, districts on the same island had similar yearly labor productivity growth rates. This condition indicates the existence of spatial autocorrelation among Indonesian regions.

Figure 1. Equal Quantile Map of Annual Labor Productivity Growth During 2010-2022



This study employs two robust Lagrange multiplier (LM) tests to assess spatial dependence. The LM-LAG test is a robust LM test designed for a spatially lagged dependent variable. The null hypothesis signifies the lack of significant reliance. The robust LM-ERR test is the LM test designed to detect residual spatial autocorrelation. The null hypothesis posits the lack of residual spatial autocorrelation (Gutiérrez-Portilla et al., 2020). The outcomes of the two assessments indicate the presence of overall spatial autocorrelation. This work utilizes SAR, SDM, SDEM, SLX, SEM, and SAC/SARAR to identify the optimal model. The criterion for model selection is the maximum value of the log-likelihood function during the estimate (Gutiérrez-Portilla et al., 2020). According to the goodness of fit metric presented in Table 2, SDEM can ascertain the convergence of aggregate labor productivity at the district level.

Table 2. The Estimation of Spatial β Convergence in GRDP per Worker

Variable	SAR	SDM	SDEM	SLX	SEM	SAC
Ln initial labor productivity	-0.038*** (-9.95)	-0.048*** (-11.02)	-0.050*** (-11.59)	-0.047*** (-10.86)	-0.040*** (-9.74)	-0.044*** (-10.56)
Spatial ln initial labor productivity		0.085*** (4.58)	0.107*** (4.90)	0.073*** (4.23)		
Spatial autoregressive (lag)	0.008 (0.06)	0.244 (1.74)				-0.818*** (-5.78)
Spatial error			0.445*** (3.49)		0.209 (1.43)	0.835*** (9.07)
Constant	0.066*** (44.14)	0.065*** (44.13)	0.065*** (44.12)	0.066*** (44.14)	0.066*** (44.13)	0.065*** (43.99)
Log-likelihood value	1263.614	1273.984	1277.681	1272.496	1264.629	1274.217

Notes: t-values are given in parentheses. ***, **, and * signify statistical significance at the 1%, 5%, and 10%, respectively.

The SDEM results in Table 2 reinforce that the aspatial panel model was misspecified. The finding suggests that each district's aggregate labor productivity growth is closely related to its neighbors. Variables from other districts can positively affect aggregate labor productivity growth in a district. This indication is seen from coefficient estimation values of $v_{s,t}$ (0.445) and $ln\ LP_{s,t-T}$ (0.107). Components of $v_{s,t}$ are all variables from other districts that influence annual labor productivity growth but are unobserved in the model, such as private capital, public investment in human capital (Álvarez & Barbero, 2016), population growth (Sun et al., 2017), migration (Ganong & Shoag, 2017), and trade-induced technological spillovers (Fadly & Fontes, 2019). These variables can be the channels of the indirect effect. For example, migration contributes to the equalization of factor prices, while trade connections facilitate the dissemination of technologies across and within regions (Vatsa & Pino, 2023). SDEM also allows the convergence of labor productivity in a district, which will affect the local level of initial labor productivity and the other regions through the spatial transmission mechanism.

The results of SDEM can decompose into direct and indirect effects. The direct effect refers to the impact of altering a specific explanatory variable in district i on the dependent variable within the same district. In this study, an increase in initial labor productivity values can reduce annual labor productivity growth in the same district. Then, the indirect effect captures the cumulative effect of the changes in variables in districts other than i on the annual labor productivity growth of any district i. In this study, an increase of initial labor productivity and unobserved variables in other districts can improve annual labor productivity growth. The sum of both direct and indirect effects is called the total effect.

The total effect of the initial aggregate labor productivity value is negative. An increase of 1 percent in initial aggregate labor productivity reduces any particular Indonesian district's annual labor productivity growth by 0.023 percent: an increase of 0.027 percent is due to the indirect effect, and a decrease of 0.050 percent comes from the direct one. The coefficient of initial labor productivity ($\hat{\beta}$) is negative and statistically significant at the 1 percent level of significance. This sign is similar to the result in Table 1. The condition $\hat{\beta} < 0$ implies β convergence.

The next step explains the effect of each component on aggregate labor productivity growth using Equation 5. By knowing the contribution of each component, poorer districts can catch up and improve their aggregate labor productivity. Table 3 presents the results. Model 1 is the intrasectoral component model, model 2 is the intersectoral component model, model 3 is the residual component model, and model 4 is the combined component model. Based on model selection criteria, models 1, 3, and 4 use SDEM, while model 2 uses ordinary least squares (OLS).

The result indicates that intrasectoral change has a statistically significant and enhancing effect on aggregate labor productivity growth. The coefficient of the intrasectoral component is the highest. Furthermore, the results indicate that intersectoral and residual changes do not significantly contribute to labor productivity growth, as evidenced by the tiny and insignificant coefficient values. Those results are similar to the findings of O'Leary & Webber (2015).

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Table 3. The Spatial Shift-share Regression Results of Growth of GRDP per Worker

Variable	Model 1 SDEM	Model 2 OLS	Model 3 SDEM	Model 4 SDEM
Intrasectoral component	0.013** (2.49)			
Spatial intrasectoral component	-0.948*** (-4.68)			
Intersectoral component		0.006 (0.10)		
Spatial intersectoral component				
Residual component			0.001 (0.14)	
Spatial residual component			2.861*** (4.02)	
Combined component				0.013** (2.49)
Spatial combined component				-0.985*** (-4.53)
Spatial error	0.596*** (2.62)		0.441* (1.71)	0.567** (2.43)
Constant	-0.009 (-1.24)	-0.011 (-1.65)	-0.0003 (-0.04)	-0.009 (-1.31)

Notes: t-values are given in parentheses. ***, **, and * signify statistical significance at the 1%, 5%, and 10%, respectively.

Table 3 demonstrates that an enhancement in labor productivity within a particular sector, excluding intersectoral labor mobility, substantially aids the overall rise of labor productivity. This scenario may arise from enhanced efficiency, new technologies, or elevated capabilities among the workforce across several sectors. The reallocation of labor between sectors, specifically the transition from low-productivity to high-productivity sectors or the reverse, does not substantially enhance labor productivity in Indonesia. Therefore, structural change does not significantly affect labor productivity growth in Indonesia.

The government can enhance intrasectoral productivity growth by enacting trade, product, and financial market reforms (Konte et al., 2022). Trade reforms can eradicate frictions and costs that hinder the unrestricted movement of products and services between nations, promote the reallocation of resources to more efficient enterprises within the same sector, and enhance sectoral value added. McCaig and Pavcnik (2018) identify a substantial reallocation of labor from informal microenterprises to the formal manufacturing sector due to export prospects stemming from U.S. tariff reductions. Downstreaming mineral policy in Indonesia is a governmental policy aimed at diminishing the export of raw materials and promoting domestic companies to utilize these materials, enhancing domestic added value and generating employment opportunities. If exports are required, processing these raw materials yields the exported items (Ika, 2017).

Product market reforms eliminate barriers to the effective operation of markets by enhancing competition among providers of products and services. Product market reforms, such as the deregulation of agricultural markets and the liberalization of the telecommunications sector, remove superfluous government interventions and entry obstacles, thereby facilitating market access. This condition heightens market competitiveness and diminishes economic rents, including markups. Nonetheless, the apprehension of forfeiting economic rents motivates enterprises to innovate substantially. Finally, financial reforms reduce credit costs, enabling financially constrained enterprises to get capital and enhance production efficiency. Hence, they contribute to intrasectoral productivity growth (see, for instance, Larrain and Stumpner 2017).

Table 4. The Spatial Shift-share Regression Results of Growth of GRDP per Working Hour

Variable	Model 1 SDM	Model 2 OLS	Model 3 SDEM	Model 4 SDM
Intrasectoral component	0.015** (2.63)			
Spatial intrasectoral component	-0.293* (-1.77)			
Intersectoral component		-0.008 (-0.12)		
Spatial intersectoral component				
Residual component			0.002 (0.27)	
Spatial residual component			2.408*** (5.31)	
Combined component				0.015*** (2.58)
Spatial combined component				-0.392*** (-2.12)
Spatial autoregressive (lag)	0.469*** (3.69)			0.538*** (5.00)
Spatial error			0.624*** (3.00)	
Constant	-0.045*** (-6.46)	-0.048*** (-7.41)	-0.038*** (-5.11)	-0.044*** (-6.40)

Notes: t-values are given in parentheses. ***, **, and * signify statistical significance at the 1%, 5%, and 10%, respectively.

This study employs an alternative measure of labor productivity, specifically GRDP per working hour, for a robustness check. Table 4 shows the results. The optimal models for models 1, 2, 3, and 4 are SDM, OLS, SDEM, and SDM, respectively. The significant coefficient estimation exhibits the same sign, with the intrasectoral component possessing the most significant coefficient value. Tables 3 and 4 show that the intrasectoral component plays the most significant role in aggregate labor productivity growth. The following analysis aims to identify the most relevant intrasectoral component within the sectoral group to enhance the overall labor productivity growth. Using different measurements of labor productivity, Table 5 shows that the OLS model is the best.

Across all sectors, the primary sector has a significant and positive impact on aggregate labor productivity growth. It means that when the primary sector's labor productivity

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increases, aggregate labor productivity grows faster. This result validates the significant contribution of the primary sector in Indonesia. It also suggests that adopting policy measures to increase primary productivity will notably impact aggregate productivity growth.

Table 5. The Effect of Intrasectoral Component on Growth of Labor Productivity by Sectoral Groups

Variable	GRDP per worker		GRDP per working hour	
	Estimated parameter	t-value	Estimated parameter	t-value
Primary sector	0.122***	3.51	0.192***	2.94
Secondary sector	0.145	1.59	0.147*	1.85
Tertiary sector	0.001	0.11	0.002	0.17
Constant	-0.056***	-3.14	-0.103***	-4.60

Notes: ***, **, and * signify statistical significance at the 1%, 5%, and 10%, respectively.

CONCLUSION

Labor productivity in Indonesia exhibited convergence during the period from 2010 to 2022. Neighbor districts' characteristics, such as initial labor productivity and unobserved variables, affect this convergence. This study uses a spatial shift-share analysis method to break down labor productivity growth into four parts: intrasectoral, intersectoral, residual, and combined. The primary influence on aggregate labor productivity growth originates from factors inside the same sector (intrasectoral component). The significant disparities in aggregate labor productivity growth in Indonesia may be attributed to the pronounced variations in production per worker across various sectors. Additional results indicate that the impact of structural change (intersectoral component) on labor productivity is negligible.

Variations in the rise of GRDP per worker among regions may primarily result from district sectoral disparities. Districts characterized by high-growth sectors typically exhibit superior performance regarding GRDP per worker. The different leading sectors in each district may result from resource advantages, such as the mining sector on Sumatra/Kalimantan Island, or geographical advantages, such as the industry/service sector on Java Island. Therefore, we can mitigate regional disparities in labor productivity by enhancing intersectoral productivity growth, particularly in labor-intensive sectors such as the primary sector.

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