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The Impact of Main Port Accessibility on Structural Transformation in Indonesia

ABSTRACT

Indonesia's structural transformation remains uneven across regions, with persistent gaps in labor productivity between traditional and modern sectors. This study analyzes the effect of geographic accessibility on labor structural transformation in Indonesia, focusing on the role of ports in driving economic sector shifts. The study uses panel data of 289 districts/cities for the period 2017-2022 and the Panel-Corrected Standard Errors (PCSE) method. The results found that regions with better port access experienced an increase in the proportion of labor in the industrial, trade, and service sectors. Meanwhile, remote areas remain dependent on the agricultural sector. This finding confirms that port infrastructure plays an important role in diversifying the employment structure. In addition, education, GRDP per capita, and urbanization variables are proven to significantly accelerate structural transformation. This research provides important policy implications for logistics infrastructure development and human capital strengthening in order to promote inclusive economic growth.

Keywords: *Labor Force; Panel Data; PCSE; Port Accessibility; Structural Transformation*
JEL Classification Codes: R40, O18, O14

INTRODUCTION

As an archipelagic nation with over 17,000 islands, Indonesia faces significant challenges in integrating its national economy. Its strategic geographic location between two continents and two oceans makes Indonesia a crucial international trade route, with maritime transportation serving as the primary backbone for the mobility of goods and services. Ports, as logistics hubs and regional connectivity hubs, play a vital role in streamlining domestic and global distribution flows, reducing logistics costs, and enhancing national economic competitiveness (Ministry of Transportation of the Republic of Indonesia, 2024).

According to the National Port Master Plan (RIPN), updated through Regulation KM 217/2022, Indonesia has 636 active ports, consisting of 28 main ports, 167 gathering ports, and 278 feeder ports. Among the main ports, four-Tanjung Priok, Tanjung Perak, Belawan, and Makassar-play a strategic role as national trade and distribution hubs. These ports not only serve as logistics hubs but also serve as catalysts for regional economic growth, particularly for the hinterland regions to which they are directly connected.

Structural transformation, the shift of labor from low-productivity sectors like agriculture to high-productivity sectors like industry and services, is a key indicator of long-term economic development (Kuznets, 1955). This transformation reflects economic modernization and increased labor productivity. However, in Indonesia, this process has been uneven. Regions with adequate infrastructure and port access have shown rapid progress, while remote areas remain trapped in the primary economic structure (Biomantara and Herdiansyah, 2019). Inequality in port accessibility creates significant differences in economic growth between regions, leading to increasing socioeconomic disparities (Standard Chartered, 2023).

Global literature confirms that transportation infrastructure, including ports, plays a crucial role in accelerating industrialization and structural transformation. Transportation infrastructure lowers logistics costs, increases manufacturing productivity, and expands market access (Krugman and Venables, 1995; Holl, 2016). In the context of developing countries, infrastructure development also triggers the relocation of labor from the agricultural to industrial sectors (Asher and Novosad, 2017; Faber, 2014). Accessibility to major ports in Indonesia has been shown to increase labor productivity and per capita GRDP, as well as reduce poverty, especially in areas closer to the ports (Yudhistira and Sofiyandi, 2018). Thus, ports serve not only as logistics infrastructure but also as a crucial instrument for regional economic transformation.

However, most previous research in Indonesia has focused on macro-indicators such as per capita GDP and poverty. Studies specifically linking port accessibility to changes in the cross-sectoral employment structure at the district/city level are still limited (Hubbansyah et al., 2023). However, micro-regional analysis is more capable of depicting the spatial dynamics of economic transformation between regions. Furthermore, many studies use a cross-sectional approach without considering temporal dynamics and spatial heterogeneity, thus under-capturing long-term relationships between variables (Wan et al., 2018).

In this context, this study highlights the importance of spatial factors and port connectivity in influencing labor distribution across economic sectors. Accessibility to major ports is measured as the shortest geographic distance from the district/city center to the major port using a Geographic Information System (GIS), capturing variations in the connectivity of hinterland regions (Bottasso et al., 2014). This approach allows for analysis of spillover effects from major ports to surrounding regions without ports, providing a deeper understanding of the impact of maritime connectivity on regional economies.

Various studies in other countries have shown a positive relationship between port access and changes in economic structure. Li and Lu (2024) demonstrated that improvements in port infrastructure in Africa accelerated the shift of labor toward the industrial and service sectors. Similarly, Americo (2022) found that transportation infrastructure in Brazil encouraged labor transfer from the primary to the non-primary sectors. However, similar studies using an empirical approach based on spatial panel data in Indonesia are still rare. Therefore, this study attempts to fill this gap by analyzing data from 289 districts/cities in the hinterland of major ports during the period 2017-2022, using the Panel-Corrected Standard Errors (PCSE) method, which is robust against heteroscedasticity and autocorrelation (Beck and Katz, 1995).

Theoretically, this research enriches the literature on structural transformation by adding the spatial dimension of port infrastructure as a key determinant of shifts in regional economic structure. Practically, the results are expected to provide an evidence-based policy basis for central and regional governments to strengthen investment in maritime connectivity, improve port efficiency, and expand access to the hinterland. These policies are crucial for promoting a more inclusive, equitable, and sustainable economic transformation, particularly in the context of development in eastern Indonesia, which still lags behind in terms of infrastructure.

Thus, this study addresses the central question of the extent to which accessibility to major ports influences the structural transformation of the labor force in Indonesia. This analysis not only provides empirical evidence for Kuznets' classic theory of labor shifts but also emphasizes the importance of geographic dimensions and connectivity in understanding interregional economic inequality. The results are expected to inform the formulation of a national strategy for spatially based infrastructure development that supports economic integration, equitable growth, and improved public welfare across the archipelago.

RESEARCH METHODOLOGY

Research Design and Data Sources

This study uses a quantitative approach with a panel data model to analyze the influence of major port accessibility on structural transformation in Indonesia. The unit of analysis includes regencies/cities located in the hinterland areas of major ports during the 2017-2022 period, selected based on Minister of Transportation Decree No. KP 432 of 2017 in conjunction with KM 217 of 2022 concerning the National Port Master Plan. The data sources include:

a. National Labor Force Survey (SAKERNAS): describes the distribution of the workforce by business sector (agriculture, industry, trade, and services).
b. National Socioeconomic Survey (SUSENAS): provides demographic data, urbanization rates, and average years of schooling.
c. Statistics Indonesia (BPS) publications: used to obtain Gross Regional Domestic Product (GRDP) per capita and other economic indicators.
d. Directorate General of Sea Transportation: Provides the geographic coordinates of major ports, which are then processed using Geographic Information System (GIS) tools to calculate the shortest distance from the district/city to the main port.

The straight-line distance approach was chosen to measure port accessibility because it is computationally efficient and representative in large-scale spatial studies (Gonçalves et al., 2014; X. Chen and Chen, 2021; Tatit et al., 2024). This method allows for precise spatial identification in analyzing the relationship between geographic proximity to major ports and regional economic dynamics.

Research Variables

1) Dependent Variable (*Employment_it* and *ShareGRDP_it*)

Structural transformation is measured through two main proxies: the proportion of sectoral labor in agriculture, industry, trade, and services (*Employment_it*) and the contribution of sectoral GRDP to total district/city GRDP (*ShareGRDP_it*). In this context, the dependent variable indicates the level or status of structural transformation in region *i* at time *t*. These two measures reflect the shift in labor and value added from traditional sectors to modern, high-productivity sectors. The use of this dual proxy aligns with the approaches of Kim et al. (2020), Liu et al.

(2020), and Americo (2022) in analyzing industrialization and structural transformation in developing countries.

2) Independent Variable (*PortAccess_it*)

PortAccess_it is the independent variable in this model. This variable measures the access of region *i*'s access to ports at time *t* which can include the distance to the main port or the quality of available port infrastructure. The hypothesis is that improved access to ports can influence the structural transformation of the region. The independent variable is the area encompassing the hinterland of the main port (*PortAccess_it*) from 2017 to 2022. The hinterland data used in this study represents the actual distance between the district/city center and the main port from the district/city center. The shorter the distance, the higher the accessibility level. This variable refers to the approach of Bottasso et al. (2014) showed that proximity to transportation hubs has a positive effect on regional economic activity.

3) Control Variables (ControlVarsit)

ControlVarsit includes various other variables that can impact structural transformation, such as:

a) Population: Population size and distribution.
b) Urbanization Rate: Percentage of the population living in urban areas.
c) Average Years of Schooling: Population education level.
d) GRDP per Capita: Gross Regional Domestic Product per capita, which reflects regional economic development.

The selection of control variables refers to the models of Ghani et al. (2014) and Americo (2022) to maintain the validity of the estimation results in infrastructure-based structural transformation studies.

Empirical Model

This study aims to analyze the impact of major port accessibility on structural transformation at the district/city level within the port hinterland. To this end, a panel data regression model was selected through two stages of testing: the Hausman test and the Lagrange Multiplier (LM) test. Based on the test results, the model used consisted of random effects for the agricultural sector and fixed effects for the industrial, trade, and service sectors. Model selection was based on the probability values of each test. Next, a series of classical assumption tests were conducted, including multicollinearity, heteroscedasticity, and autocorrelation.

To address heteroscedasticity (using the Wald test) and autocorrelation (using the Wooldridge test) across all sector models, the subsequent regression analysis used the Panel-Corrected Standard Errors (PCSE) method. This approach is recommended by Beck and Katz (1995) for panel data with a large number of cross-section units (N), a limited time period (T), and the presence of serial correlation and heteroscedasticity.

The PCSE method with PSAR(1) correction was used to address differences in serial autocorrelation between regions (Moundigbaye et al., 2018). For models exhibiting only heteroscedasticity, the heteroscedasticity option was used as a specific adjustment for differences in variance between panel units (STATA, 2022).

The regression model also includes control variables such as population density, urbanization rate, average years of schooling, and the proportion of the agricultural workforce, and applies fixed effects to capture region-specific variations that remain constant over time. This research model is formulated as follows:

$$\begin{aligned} Employment_{it} &= \beta 0 + \beta 1 PortAccess_{it} \\ &+ \beta 2 LnGDRPx_{it} \\ &+ \beta 3 Edu_{it} + \beta 24 LnPopx_{it} \\ &+ \beta 5 Urbanx_{it} + \gamma_i + \delta_t \\ &+ \epsilon_{it} \end{aligned}$$

and

$$\begin{aligned} ShareGDRP_{it} &= \beta 0 + \beta 1 PortAccess_{it} \\ &+ \beta 2 LnGDRPx_{it} \\ &+ \beta 3 Edu_{it} \\ &+ \beta 24 LnPopx_{it} \\ &+ \beta 5 Urbanx_{it} + \gamma_i + \delta_t \\ &+ \epsilon_{it} \end{aligned}$$

$Employment_{it}$ is a proxy variable for structural transformation measured by the proportion of the workforce in a district/city, whether in the agriculture, industry, trade, or services sectors, with data obtained from the National Labor Force Survey (SAKERNAS) database. Meanwhile $ShareGDRP_{it}$ is a proxy variable for structural transformation measured by the share of each sector's

GRDP in agriculture, industry, trade, and services to the total GRDP in a district/city. is a proxy variable for structural transformation measured by the proportion of the workforce in a district/city, whether in the agriculture, industry, trade, or services sectors, with data obtained from the National Labor Force Survey (SAKERNAS) database.

RESULT AND DISCUSSION

Result

Descriptive Analysis

The analysis was conducted on 289 regencies/cities across Indonesia over a six-year period, from 2017 to 2022, creating a panel data structure with a maximum total of 1,734 observations. The descriptive statistics in Table 1 show the main characteristics of the research variables used in the panel data analysis.

Table 1: Descriptive Statistics

Variable	N	*Mean*	*St. Dev*	*Min*	*Max*
Agricultural Workforce (percent)	1,733	40.65	23.19	0.00	100.00
Industrial Sector Workforce (percent)	1,733	11.20	8.25	0.00	52.22
Trade Sector Workforce (percent)	1,733	18.66	8.41	0.00	55.25
Service Sector Workforce (percent)	1,733	29.49	13.44	0.00	72.94
Contribution of the Agricultural Sector (percent)	1,734	23.44	14.89	0.01	62.40
Industrial Sector Contribution (percent)	1,734	13.13	15.17	0.02	79.30
Trade Sector Contribution (percent)	1,734	12.78	5.52	0.37	47.59
Service Sector Contribution (percent)	1,734	31.90	15.03	1.75	75.53
Access to Port (km2)	1,734	147.29	144.45	0.85	1,098.00
Log GRDP per Capita (rupiah)	1,734	10.67	0.71	8.65	13.68
Average Length of Schooling (years)	1,734	8.35	1.78	0.71	13.03
Population Log (people)	1,728	12.74	1.05	9.51	15.60
Urbanization (percent)	1,734	41.61	31.77	0.00	100.00

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Among other sectors, the agricultural sector accounts for the largest proportion of the workforce, with an average of 40.65 percent, indicating that this sector remains the primary source of employment in many regions in Indonesia. However, the distribution varies widely, with a standard deviation of 23.19 percent. Next comes the services sector with an average of 29.49 percent, followed by the trade sector at 18.66 percent, and the industrial sector at 11.20 percent. Meanwhile, the contribution of each business sector's GRDP to total GRDP indicates that the economic structure is dominated by the services sector, followed by the agricultural sector. Industry, services, and agriculture have high standard deviations, indicating significant inequality or diversity.

The trade sector has a much lower standard deviation, reflecting a tendency for the trade sector's contribution to be more uniform across regions than the other three sectors. Meanwhile, the access variable, which measures the distance to major ports, averaged 147.29 km2, with a high standard deviation of 144.45 km2, indicating disparities in logistics access between regions. The furthest distance was recorded at 1,098 km2, while the closest was only 0.85 km2. Furthermore, the GRDP per capita variable, expressed as a natural logarithm (lngdrp), averaged 10.67 with a standard deviation of 0.71. This value indicates that levels of economic well-being across districts/cities tend not to differ significantly. The average length of schooling, at 8.35 years, also shows disparity, with a minimum value of 0.71 years, indicating that there are areas with very low educational attainment.

On the other hand, the population, represented by the logarithm, averaged 12.73, indicating that most districts/cities have populations ranging from 300,000 to 400,000. The urbanization rate shows an average value of 41.61 percent with a deviation of 31.77 percent, which shows that most regions are still in the transition stage towards urbanization, and the level of urbanization varies between regions.

Labor Force Proportion Model Estimation

Regression results using the Panel-Corrected Standard Errors (PCSE) method (Beck and Katz, 1995; Moundigbaye et al., 2018) indicate that port accessibility significantly influences the distribution of labor across sectors. The farther the distance to the port, the higher the proportion of labor in the agricultural sector, while the proportion of labor in the industrial, trade, and service sectors decreases. This finding confirms that port proximity encourages workforce diversification into modern sectors (Rodrigue et al., 2017; Bottasso et al., 2018).

Table 2: PCSE Estimation Results of the Labor Force Proportion Model

	(1) Agricultural Sector	(2) Industrial Sector	(3) Trade Sector	(4) Service Sector
Access to the Port	0.018***	-0.007***	-0.005***	-0.002***
	(0.002)	(0.001)	(0.001)	(0.001)
Log GRDP per Capita	-0.912	-0.485**	-0.046	1.579***
	(0.750)	(0.227)	(0.297)	(0.480)
Average Length of Schooling	-3.031***	-0.578***	0.191	3.002***
	(0.293)	(0.146)	(0.233)	(0.212)
Population Log	-1.033***	2.298***	1.280***	-2.194***
	(0.392)	(0.217)	(0.118)	(0.208)
Urbanization	-0.455***	0.094***	0.161***	0.231***
	(0.026)	(0.009)	(0.025)	(0.020)
Constant	105.453***	-10.661**	-3.740	5.451
	(7.518)	(4.189)	(5.458)	(7.482)
R-squared	0.938	0.669	0.860	0.886
Wald chi^2	1,481.50	1,282.99	451.58	1,064.21
Observations	1,727	1,727	1,727	1,727

Standard errors in parentheses

* *p < 0.1*, ** *p < 0.05*, *** *p < 0.01*

The regression model estimation results (Table 2) show that distance from major ports significantly influences the distribution of labor across economic sectors. A greater distance from a major port is associated with a higher proportion of labor in the agricultural sector, while the proportions of labor in the industrial, trade, and service sectors decrease. This finding indicates that regions located farther from major ports tend to remain more dependent on agriculture, whereas regions with better port access are more likely to experience employment diversification toward non-agricultural sectors.

The GRDP per capita (GRDP per capita) variable has no significant effect on the agricultural or trade sectors, but has a negative effect on the industrial sector and a positive effect on the service sector. This finding indicates that economic growth creates more jobs in the service sector than in the industrial sector, in line with the tertiaryization trend in modern economies.

Educational attainment, as measured by average years of schooling, has a significant negative effect on the agricultural and industrial sectors, but a positive effect on the service sector. This means that increased education encourages educated workers to shift to sectors that require more complex cognitive skills, such as financial services, education, and technology.

Meanwhile, population (lnpop) has a positive effect on the industrial and trade sectors, but a negative effect on the agricultural and service sectors. This indicates that regions with large populations tend to develop labor-intensive industrial and trade bases, while the service sector thrives in regions with smaller populations and high urbanization.

Furthermore, urbanization has a negative effect on the agricultural sector and a positive effect on the industrial, trade, and service sectors, confirming a structural shift in the workforce from rural to urban areas.

In terms of model accuracy, the coefficient of determination (R^2) value demonstrates strong explanatory power. The agricultural sector has the highest R^2 value (93.8%), followed by the industrial sector (88.6%) and the trade sector (86%), indicating that most of the variation in these sectors is well explained by the independent variables. Conversely, the service sector has a lower R^2 (66.9%), indicating that the dynamics of this sector are influenced by other external factors such as digitalization, technological innovation, and changes in consumption patterns.

Overall, these results reinforce the finding that port accessibility, urbanization, education, and demographic characteristics are key determinants of employment transformation across sectors in

Indonesia. Proximity to major ports has been shown to encourage a shift in the workforce towards more productive and competitive modern sectors.

Sectoral GRDP Contribution Model Estimation

The second model analysis uses sectoral GRDP proportions as the dependent variable to obtain a more comprehensive picture of the dynamics of structural transformation in Indonesia. Estimates were performed using the Panel-Corrected Standard Errors (PCSE) method because test results indicated heteroscedasticity and autocorrelation in most models.

Table 3: PCSE Estimation Results for Sectoral GRDP Contribution Models

	(1) Agricultural Sector	(2) Industrial Sector	(3) Trade Sector	(4) Service Sector
Access to the Port	0.002*	-0.016***	-0.002**	0.004
	(0.001)	(0.004)	(0.001)	(0.003)
Log GRDP per Capita	-4.302***	7.397***	-3.362***	-9.306***
	(0.443)	(0.750)	(0.183)	(1.091)
Average Length of Schooling	1.837***	-1.026***	0.712***	0.018
	(0.336)	(0.253)	(0.083)	(0.221)
Population Log	0.261	4.225***	0.307**	-3.234***
	(0.427)	(0.453)	(0.142)	(0.837)
Urbanization	-0.349***	0.018	0.074***	0.293***
	(0.024)	(0.012)	(0.006)	(0.027)
Constant	63.977***	-108.899***	35.992***	158.223***
	(5.332)	(10.881)	(2.729)	(19.513)
R-squared	0.907	0.825	0.316	0.932
Wald chi2	11,260.57	358.35	775.34	326.32
Observations	1,728	1,728	1,728	1,728

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The estimation results (Table 3) show that distance from major ports significantly affects the contribution of the agricultural, industrial, and trade sectors, while no statistically significant effect is found for the services sector. Regions located farther from major ports tend to exhibit higher agricultural sector contribution but lower industrial and trade sector contribution. This finding suggests that limited accessibility may maintain dependence on primary activities, whereas better port connectivity supports structural transformation toward more productive economic sectors.

The GRDP per capita variable exhibits heterogeneous effects across sectors. Higher regional income is associated with lower contributions from the agricultural, trade, and service sectors, while positively affecting industrial sector contribution. These findings indicate that economic development may encourage structural transformation toward industrial activities and reduce dependence on traditional sectors.

These findings may indicate differences in labor absorption patterns across sectors. The insignificant effect in the services sector suggests that educational attainment alone may not be sufficient to explain variations in service sector contribution across regions.

The population variable (lnpop) has a strong and positive effect on the industrial sector, indicating that regions with large populations tend to develop a stronger industrial base. However, the services sector exhibits a negative relationship with population, indicating that service growth is more concentrated in urban areas with medium populations.

Furthermore, urbanization has a negative effect on the agricultural sector and a positive effect on the trade and services sectors, while it is insignificant for industry. This indicates that urbanization drives a shift in economic activity from agriculture to the services and trade sectors, but is not always accompanied by significant industrial expansion.

In general, the coefficient of determination (R^2) values indicate high explanatory power of the model for the services sector (0.932), agriculture (0.907), and industry (0.825), while the trade sector has a lower value (0.316). This value confirms that most of the variation in GRDP in the three main sectors can be explained by the variables of port accessibility, income, education, population, and urbanization. Conversely, the low R^2 in the trade sector indicates the presence of other external factors, such as domestic and global market dynamics, that also influence economic activity in that sector.

Overall, these results confirm that accessibility to major ports and sociodemographic factors play a significant role in determining sectoral contributions to regional GRDP. Proximity to ports accelerates the economic shift toward industry and services, while strengthening the direction of structural transformation toward a more diversified and competitive economy.

Comparison of the Two Models

A comparison between the labor force proportion model (Table 2) and the sectoral GRDP contribution model (Table 3) shows that the labor force-based approach is more representative in explaining the dynamics of structural transformation in Indonesia. The labor force model provides a clearer picture of the shift in economic activity from the traditional to the modern sector through the allocation of labor between sectors.

Variables such as access to major ports, education level, population, and urbanization demonstrate a consistent and significant influence on the decline in the labor force proportion in the agricultural sector and an increase in the service and industrial sectors. Furthermore, the positive influence of GRDP per capita on the service sector confirms that increasing prosperity drives an economic shift toward dominance of the tertiary sector, consistent with tertiarization theory and the Kuznets (1973) development model.

In contrast, the sectoral GRDP contribution model (Table 3) places greater emphasis on the productivity dimension of the economy. The estimation results indicate that per capita income and population play a significant role in increasing the industrial sector's contribution to total GRDP. However, findings such as the positive relationship between education and the contribution of the agricultural sector, as well as the declining contribution of the service sector with increasing prosperity, indicate structural complexity that does not fully align with the theoretical model of classical economic transformation (Lewis, 1954; Chenery and Syrquin, 1975).

Overall, these results suggest that a model based on labor force proportions is more appropriate for capturing the core dynamics of structural transformation, namely labor shifts between sectors, while a model based on GRDP contributions serves as a complement to assess sectoral productivity variations. Therefore, the main discussion of this study focuses on the estimation results of the labor force model (Table 2) because it better illustrates the process of structural economic change substantively and empirically.

Discussion

Port accessibility has been shown to be a key determinant in the structural transformation of regional economies. Regions with high proximity to major ports tend to experience faster workforce diversification and increased contributions of the industrial and service sectors to the regional economy. This finding is consistent with research by Rodrigue, Comtois, and Slack (2017) and Bottasso et al. (2018), which emphasized that ports function as strategic logistics hubs and catalysts for interregional economic integration.

Previous research also supports these findings. Yudhistira and Sofiyandi (2018) found a positive relationship between port proximity and increased labor productivity, while Caballé Valls et al. (2020) emphasized the importance of hinterland connectivity in strengthening regional competitiveness and accelerating the spread of modern economic activity. Thus, port access is not only a logistical aspect but also a transformational factor that plays a crucial role in driving industrialization, regional growth, and national economic integration.

In addition to spatial factors, the results of this study also reinforce the classic theory of Kuznets (1955), which states that increasing per capita income reduces dependence on the agricultural sector and encourages the expansion of the service sector. This finding aligns with the study by Chen and Partridge (2013), which showed that growing social welfare implies a shift in the workforce towards the more productive and high-value-added service sector.

Furthermore, education has been shown to be a crucial component in accelerating structural transformation. Increasing average years of schooling contributes to the shift of the workforce from traditional to modern, more knowledge-intensive sectors, as evidenced by Gindling and Newhouse (2014) and Adediyan and Omorenuwa (2021). In other words, education plays a role in improving workforce quality and the competitiveness of productive sectors.

Demographic and spatial factors also significantly influence the direction of structural transformation. Population growth strengthens the industrial and trade sectors, as outlined by Song and Van Geenhuizen (2014), while urbanization acts as a major catalyst for structural change, increasing the concentration of non-agricultural economic activities in urban areas (Jedwab and Vollrath, 2015; Liu et al., 2020).

Overall, this study confirms that inclusive and sustainable structural transformation can only be achieved through a synergy between infrastructure connectivity, education investment, and effective urban governance. The combination of these three factors forms a crucial foundation for an economic shift toward a more modern, productive, and highly competitive structure.

Conclusion

The main findings of this study indicate that the labor force proportion model is the most representative approach in describing the structural transformation of the regional economy in Indonesia. This model is able to comprehensively reflect the shift in the workforce from traditional sectors (agriculture) to modern sectors (industry, trade, and services), which is a key characteristic of the national economic modernization process.

Overall, the structural transformation process in Indonesia requires a multidimensional approach that integrates the development of port and logistics infrastructure, improving the quality of education and workforce skills, and adaptive and sustainable urbanization governance. The synergy of these three aspects can strengthen national economic competitiveness, increase regional productivity, and encourage inclusive and equitable growth.

Based on the research findings and identified limitations, several recommendations can serve as a reference for further research and the formulation of regional economic development policies. First, it is necessary to expand the time horizon of the analysis to capture long-term dynamics and the influence of economic cycles, global crises, and changes in national policies on the structural transformation of the workforce. Second, future research should utilize more comprehensive indicators to measure port accessibility, such as actual travel distance, travel time, and multimodal connectivity (toll roads, railways, airports, and feeder ports). This approach will provide a more accurate picture of the influence of physical and digital connectivity on regional economic transformation. Third, analyses of productivity and efficiency of labor allocation between sectors need to be integrated to assess the extent to which labor shifts contribute to increased value-added and the quality of economic growth, rather than simply changes in sectoral composition.

Furthermore, it is recommended to conduct comparative analyses across regions, for example between Java and outside Java or between large islands such as Sumatra, Kalimantan, Sulawesi, and Papua, to identify distinct patterns of structural transformation based on the geographic and economic characteristics of each region. Further research should also expand the analytical model by incorporating additional strategic variables, such as digital technology developments, foreign direct investment (FDI) flows, and regional fiscal policies, to yield a more comprehensive understanding of the drivers of inclusive and sustainable economic transformation. With this development direction, it is hoped that subsequent studies will be able to provide sharper empirical and policy contributions, strengthen the basis for formulating data-based development strategies, and support the agenda of a national economic transformation that is equitable and highly competitive.

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