Jurnal Perencanaan Pembangunan:
The Indonesian Journal of Development Planning
Volume VII No. 3 - December 2023/Page: 313 - 333
https://doi.org/10.36574/jpp.v7i3.409
Article

The Contribution of Road Construction on Regional Economic Development in Indonesia

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Submitted: 2022-12-30 | Accepted: 2023-12-31 | Published: 31th December 2023

Abstract

The development process in Indonesia's provinces is expected to contribute to regional economic growth. This research aims to evaluate road construction's impact on regional economic development and the spatial spillover effect in 34 Indonesian provinces. This paper constructs Spatial Autoregressive Model (SAR), Spatial Durbin Model (SDM), Spatial Autocorrelation Model (SAC), Spatial Error Model (SEM), and Generalised Spatial Random Effect Model (GSPRE) for 34 provinces in Indonesia from 2010 to 2020 to capture the effect of road construction on regional economic development and spatial spillover effect. Compared to other models, the spatial Durbin model has the minimum Akaike information criterion (AIC) value, indicating that it is the most suited model. The result indicates that road infrastructure has little impact on regional economic development. Moreover, road development has a negative value and negligible spatial spillover effect.

Keywords: road development; spatial spillover; economic growth.

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1. Introduction

Indonesia is an archipelago nation that consists of numerous islands. The country has 34 provinces with different geographical features amongst regions. Additionally, the development procedure for one region is distinct from that of other regions. It generates inequities among the states. The government builds roads and bridges to connect various locations. The infrastructure of roads and bridges is essential to social movements.

According to the Ministry of Public Works and Housing (2019), the road infrastructure in Indonesia is expanding. 91.90 percent, or 43,208.98 kilometers of the national road, are in good condition, while 8.10 percent, or 3,808 kilometers, are not. Bangka Belitung has the most significant proportion of good road at 99.22%, followed by D.I. Yogyakarta at 99.04% and Bali at 98.93%. On the other side, Banten has the lowest proportion of excellent roads, with 76. According to Statistics Indonesia (2020), the annual GDP growth rate between 2010 and 2019 was 5.33 percent. The construction industry contributes 9.99% of each GDP increment in this scenario. National road construction is one of the construction industries that impact GDP.

1.1. Background of Problems

The Indonesian government has prepared a Long-Term National Development Plan from 2005 to 2025. This strategy aims to stimulate economic expansion. Infrastructure is one of the listed sectors for this project. As a consequence, the number of construction roads is increasing every year. The road's excellent condition positively affects economic growth since it facilitates the interprovincial transfer of products and services. It will raise the level of regional and income-based competitiveness. In addition, the development of road infrastructure has a spatial spillover impact.

According to Krugman (1991), the expansion of road infrastructure enhances regional ties. On the other hand, since there are no trade obstacles, it also creates a divide between regions. Fan and Kang (2008) state that road investment promotes China's economic growth. The findings indicate the road significantly impacts economic growth and poverty reduction. This work generates provincial-level geographical data for China between 1982 and 1999. The results indicate that different road slopes will lead to varying degrees of poverty reduction. Low-quality roads contribute more to poverty reduction than high-quality roads. In China's eastern and central regions, the massive economic boom produced by road investment is evident. Moreover, the southwest region contributes the most to the elimination of poverty.

1.2. Research objective and Brief Section

This study examines road infrastructure development's contribution to regional economic growth in 34 provinces in Indonesia from 2010 to 2020. Moreover, this study assesses the spatial spillover effect of road construction in 34 provinces in Indonesia. This paper is organized as follows. The introduction covers the progress of road infrastructure in Indonesia, the research subject, and the objectives of this work. The theoretical framework described in Section 2 describes the contribution of transportation and road infrastructure to economic growth. The approach for measuring the spatial spillover impact between provinces is presented in Chapter 3, along with analytical data and models. The estimation results are presented in Section 4, which covers the spatial models and displays the spatial dependence across the region using the Global Index Moran test. This research uses spatial econometric models to determine the optimal method for calculating the link between road infrastructure construction and economic development. The recommendation section closes the study in Section 5.

2. Theoretical Framework

2.1. Transport infrastructure, Road infrastructure, and Economic Growth

Numerous studies have determined that transportation infrastructure improvement, namely road construction, contributes to economic expansion. According to Schafer and Victor (2000), population expansion, urbanization, and the necessity for vehicle-based mobility are accelerating the construction of road networks in nations that are still developing. Each year, developing nations spend one trillion dollars on infrastructure development and road construction, and the World Bank (2014) supports infrastructure supply to satisfy this demand.

Farhadi (2015) investigates the public infrastructure, primarily transportation infrastructure, in 18 Organisation for Economic Cooperation and Development (OECD) nations from 1870 to 2009 using panel data. The result demonstrates that infrastructure for specific sectors, such as roads, highways, trains, airports, and inland waterways, influences economic growth positively. Infrastructure development increases the level of labor productivity.

Wang, Yang, and Deng (2022) evaluated the Yangtze River Delta's transportation infrastructure from 2007 to 2018 using data from the region's 41 prefectures. The paper develops a spatial Durbin model (SDM) for data analysis utilizing three weight matrices and establishes a statistically significant geographical agglomeration pattern between transportation infrastructure development and economic growth. Moreover, transportation development has a beneficial spatial spillover effect and adds to the economic development of neighboring regions.

Because it connects one region to another, road infrastructure, a subset of transportation infrastructure, is crucial for economic growth. Furthermore, it plays a crucial role in the distribution of products and services. According to Graham (2007), infrastructure can, directly and indirectly, affect regional growth. In addition, it decreases labor costs and capital expenditures, boosts employment, and encourages private investment.

Zhou, Tong, and Wang (2021) evaluate the impact of road infrastructure development in China using county-level panel data from 2014 to 2018. Their findings indicate that China has made significant strides in building its road system. In addition, road construction contributes significantly more to reducing poverty than, for instance, railway construction. The results indicate that infrastructure drives economic growth and reduces poverty, particularly in impoverished places.

Using data from the Ministry of Finance, NPC, Department of Roads, and Ministry of Physical Infrastructure, Gharti (2022) examines the causation between road infrastructure development and poverty in Nepal. In addition, it studies the impact of road construction development on GDP growth. The results indicate that road construction reduces Nepal's poverty rate and stimulates economic expansion.

2.2. Spatial Spillover Effect and Economic Growth

According to Boarnet (1998), a "spatial spillover effect" arises when transportation infrastructure upgrades contribute to a region's growth. Moreover, Krugman (1991) argues that the presence of road infrastructure may have spatial spillover effects. They suggest that the construction of roads contributes to the redistribution of space, especially concerning input factors. In addition, road improvements may boost the distribution of goods and services throughout diverse regions. However, it may also negatively affect the regions, mainly if there are no barriers between them, which could generate a "core-periphery" economic growth gap.

Li, Wen, and Jiang (2017) examine the spatial spillover impacts of transportation infrastructure along China's New Silk Road Economic Belt. The data is compiled from 31 adjacent provinces and New Silk Road Economic Belt zones. The authors find that transportation infrastructure frequently functions as an interregional network. The enhancement of a region's transportation infrastructure may have a direct impact on its economic growth. Additionally, it indirectly affects the economic growth of neighboring districts.

Yu et al. (2013) examine the influence of spatial spillover at the county and national level in China using an SDM model from 1978 to 2009, separated into three shorter periods: 1978 to 1990, 1991 to 2000, and 2001 to 2009. The findings exhibit a positive spatial spillover effect at the national level every time. Moreover, at the regional level, the performance of transport infrastructure is inconsistent over time. The study demonstrates that changes in regional spillovers are highly correlated with China's mobility of production components during the past few decades.

Using a global database, Komo et al. (2021) examine the spatial spillover effect of road building in 2010. The data include nighttime light photography, population information, and a global road construction database. The dataset is built to produce worldwide grid-based data. The least squares method, spatial error models, spatial lag model, and spatial Durbin model are examined, and the results indicate that the SDM model is the best suitable method. In addition, road infrastructure generates a positive geographical spillover impact in this model, although the direct effect has a negative value.

Nguyen (2022) examines the spatial spillover impact on economic development in Vietnam driven by transportation infrastructure. The data are collected at the provincial level from 2000 to 2019 inclusive. The data indicate that transport infrastructure has a positive spatial spillover effect at the national level. From 2010 to 2019, transportation infrastructure also delivers a positive geographical spillover effect at the regional level, particularly for the northern region. The spatial spillover effect is demonstrated through production factor changes in Vietnam during the previous two decades.

Arbues, Banos, and Mayor (2015) examine the direct and spatial spillover impacts of transport infrastructure, including road, railway, airport, and port facilities, on 47 Spanish peninsular provinces' economic development. The estimated production function is represented by a Spatial Durbin Model, maximum likelihood estimator, and extended technique of moments estimators. The result indicates that road infrastructure has a beneficial influence on output, particularly in the region where the infrastructure is located and in neighboring regions. Overall, the consequences of the other modes of transportation are insignificant.

Karim, Suhartono, and Prastyo (2020) examine the impact of Indonesia's transportation infrastructure on the country's overall economic expansion in 2017 across 34 provinces. In this research, spatial lag of X model (SLX), spatial autoregressive model (SAR), spatial error model (SEM), spatial autoregressive combined model (SAC), spatial Durbin model (SDM), and spatial autoregressive combined mixed model (SAC model) are selected for calculation. The data demonstrate that transportation infrastructure contributes positively and significantly to economic development. In addition, economic progress in one province of Indonesia fosters economic expansion in other regions.

3. Results and Discussion

3.1. Data

From 2010 through 2020, this report compiles statistics from Statistics Indonesia and the Ministry of Public Works and Housing. The data was compiled as a panel data collection from 34 provinces in Indonesia. This paper assembles the Gross Regional Domestic Product, Foreign Direct Investment, Domestic Direct Investment, Labor Force, Education, Manufacturing, and Road Construction data for each year and province. They are using data screening to create a balanced data set. The complete data set has 374 observations spanning eleven years.

3.2. Empirical Analysis

3.2.1 Spatial Economic Models

This study investigates the relationship between road infrastructure and regional economic development in 34 Indonesian provinces. The central premise of this study is the conventional Cobb-Douglass production model, regarded as the most viable instrument for assessing the economic productivity of public infrastructure. This production function is as follows: (Canning 1999).

$$Y_{it} = A_{it}K_{it}^{\propto} HC_{it}^{\beta}Inf_{it}^{\gamma}U_{it} \tag{1}$$

Where Y_{it} Is real GRDP, A_{it} It is the total factor of productivity. K_{it}presents the stock of capital, HC_{it} the capital of humans Inf_{it} It presents the capital of infrastructure. U is the term of error. i is the index of provinces, and t is the time index. Thus, this production function can calculate the correlation between road infrastructure and economic expansion.

This study implies geographical dependence between provinces, which indicates that each region contributes not only to the economic growth of its areas but also to the growth of adjacent provinces. According to Ho and Hensher (2016), the first law of Tobler states that the conditions of one place or region correlate with the potential of another place or territory. In addition, this study employs 34 provinces applying a spatial econometrics model.

According to Anselin (1988), the spatial econometric technique can address spatial dependence and variability in regional-level datasets. A spatial econometric model changes a linear regression by incorporating geographical interaction effects. The following formula describes a standard model of linear regression without spatial interaction for spatial data:

$$Y_t = X_t\beta + \ \mu + \ \epsilon_t t_N + \varepsilon_t \tag{2}$$

Y_tIt is represented by a N x 1 vector containing a single observation for the variable of dependent for each element of the sample (i= 1,…., N) for time t (t=1,…., T). X_t represents an N x K matrix of exogenous explanatory of exogenous variables connected with the K x 1 vector β during time t. $\varepsilon_t = (\varepsilon_{1t}, \ldots., \varepsilon_{Nt})'$ is a term for a disturbance vector. ε_{it} presenting error term with an independent and identical distribution with variance σ^2 and zero mean for every i. $\epsilon_t t_N$ Represents a vector of size N x 1 that denotes spatial and time-particular impacts, which can be viewed as either fixed or random effects. For each spatial unit and timespan, a dummy variable is merged in the fixed effects model (except for one on preventing absolute multicollinearity). Furthermore, μ_i and ϵ_t , they are variables with independent and identical distributions, zero means, and variance $\sigma_\mu^2 \sigma_\epsilon^2$ when referred to as random variables in the random effects model.

The impacts of spatial interaction can be grouped into three categories. First is the impact of endogenous interaction, which assesses if a unit's dependent variable i is reliant on the dependent variable (j) of another unit j (j≠) and conversely. This condition can be represented through WY_t, where W is the spatial weight matrix, with size N x N and a positive value. This matrix illustrates the pattern of dependency across sample units. Second is the effects of exogenous interaction, wherein the dependent variable on element i is contingent on the explanatory from another part j (j ≠ i) and represented by WX_t. when K represents the number of defining elements, the number of effects of exogenous interaction is also K. The last is a correlation effect across the terms of error that might occur and be defined by Wu_t. This condition shows that units may exhibit similar behavior due to shared undiscovered properties or comparable uncontrolled situations.

Elhorst (2017) explains that models with one or two forms of spatial interaction are referred to by various names; for example, the spatial autoregressive model (SAR), which considers the effect of endogenous interaction on WYt, and the spatial error model (SEM), which reflects the effect of correlation across the terms of error. Wut, the spatial lag of X model (SLX) consists of the interaction of exogenous effects WXt, the spatial autoregressive combined (SAC) consisting of WYt and Wut, the spatial Durbin model (SDM) consisting of WYt and Wut, and the spatial Durbin error model (SDEM) consisting of WYt and Wut.

Bellotti, Hughes, and Mortari (2017) recognize five main spatial data models: the Spatial Autoregressive Model (SAR), the Spatial Durbin Model (SDM), the Spatial Autocorrelation Model (SAC), the Spatial Error Model (SEM), and the Generalised Spatial Random Effect Model (GSPRE). The spatial Autoregressive (SAR) model is the initial model. This model presents the following fundamental model:

$$Y_t = \rho WY_t + X_t\beta + \mu + \epsilon_t \tag{3}$$

In the random effects model, it is presumed that μ ~ N (0,σ_μ^2). In the fixed effects model, the parameter μ is a vector parameter that should be adjusted. Bellotti, Hughes, and Montari (2017) assume as basic premises that ϵ_{it}~ N (0,σ_μ^2) and E ($\epsilon_{it}\epsilon_{js}$) = 0 for I ≠ j or t ≠ s.

The spatial Durbin model is the second model. The Spatial Durbin model is a version of the SAR model that incorporates explanatory variables that are spatially weighted. The SDM could be expressed as follows:

$$Y_t = \rho WY_t + X_t\beta + WZ_t\theta + \mu + \epsilon_t \tag{4}$$

Where W defines a spatial weight matrix.

The spatial autocorrelation model is the third model (SAC). Also known as the spatial autocorrelation model with spatial autocorrelation error, SAC. This model alters the spatial autoregressive (SAR) as follows:

$$Y_t = \rho WY_t + X_t\beta + \mu + v_t \quad (5)$$

$$v_t = \lambda Mv_t + \epsilon_t \quad (6)$$

M is a spatial weights matrix that may or may not equal W.

The spatial error model is the fourth model. Regarding the error, this approach focuses on the spatial autocorrelation model (SAC). The model appears below.

$$Y_t = X_t\beta + \mu + v_t \quad (7)$$

$$v_t = \lambda Mv_t + \epsilon_t \quad (8)$$

The last model is the generalized spatial random effect (GSPRE), which is depicted as follows:

$$Y_t = X_t\beta + \mu + v_t \quad (9)$$

$$v_t = \lambda Mv_t + \epsilon_t \quad (10)$$

$$\mu = \phi W\mu + \eta \quad (11)$$

A generalized spatial random effect is a development of the spatial error model, denoted by vector μ and spatially connected to the effect of the panel. It is presumed that the errors in vectors μ and ϵ_t They present independent, normally distributed errors. Hence, the model should be a RE configuration that includes $\mu = (I - \phi W)^{-1}\eta$ and $v_t = (I - \lambda W)^{-1}\epsilon_t$.

This study follows Karim et al. (2020), who evaluated Indonesian provinces in 2017 using seven geographical models. Following Belloti, Hughes, and Montari (2017), this study evaluates the SDM (Spatial Durbin Model), SAR (Spatial Autoregressive model), SEM (Spatial Error Model), SAC (Spatial Autocorrelation model), and GSPRE (generalized spatial random-effects model) for 34 Indonesian provinces from 2010 to 2020.

The models adopted by Belloti, Hughes, and Montari (2017) are presented as follows.

Spatial Autoregressive Model (SAR)

$$ln\ GRDP_{it} = \rho\ Wy + \beta_0 + \beta_1 lnFDI + \beta_2\ lnDDI + \beta_3 lnEmploy + \beta_4 lnUnemploy + lnStudent + \beta_5 lnManuf + \beta_6 lnGotEXp + \beta_7 \text{lnConstWork} + \beta_8 \text{lnRoadInfra} + \varepsilon_i \quad (12)$$

Spatial Error Model (SEM)

$$Y_{it} = \rho\, Wy + \beta_0 + \beta_1 lnFDI + \beta_2\, lnDDI + \beta_3 lnEmploy + \beta_4 lnUnemploy + \beta_5 lnStudent + \beta_6 lnManuf + \beta_7 lnGotEXp + \beta_8 lnConstWork + \beta_9 lnRoadInfra + u_i \tag{13}$$

$$where\ u_i = \lambda W u_i + \varepsilon_i$$

Spatial Autocorrelation Model (SAC)

$$Y_t = \beta_0 + \beta_1\, lnFDI + \beta_2\, lnDDI + \beta_3\, lnEmploy + \beta_4\, lnUnemploy + \beta_5\, lnStudent + \beta_6\, lnManuf + \beta_7\, lnGotEXp + \beta_8\, lnConstWork + \beta_9\, lnRoadInfra + \mu + v_t \tag{14}$$

$$v_t = \lambda M v_t + \epsilon_t$$

Spatial Durbin Model (SDM)

$$Y_{it} = \rho Wy + \beta_0 + \beta_1\, lnFDI + \beta_2\, lnDDI + \beta_3\, lnEmploy + \beta_4\, lnUnemploy + \beta_5\, lnStudent + \beta_6\, lnManuf + \beta_7\, lnGotEXp + \beta_8\, lnConstWork + \beta_9\, lnRoadInfra + \theta_1 WlnFDI + \theta_2 WlnDDI + \theta_3 WlnEmploy + \theta_4 WlnUnemploy + \theta_5 W\, lnStudent + \theta_6 W\, lnManuf + \theta_7 W \quad \ln \quad lnGotEXp + \theta_8 W \mathrm{l} lnConstWork + \theta_9 W \mathrm{l} lnConstWork + \varepsilon_i \tag{15}$$

Generalized Spatial Panel Data

$$Y_t = \beta_0 + \beta_1 \beta_1\, lnFDI + \beta_2\, lnDDI + \beta_3\, lnEmploy + \beta_4\, lnUnemploy + \beta_5\, lnStudent + \beta_6\, lnManuf + \beta_7\, lnGotEXp + \beta_8\, lnConstWork + \beta_9\, lnRoadInfra + \mu + v_t \tag{16}$$

$$where\ v_t = \lambda M v_t + \epsilon_t \tag{17}$$

$$\mu = \phi W \mu + \eta \tag{18}$$

W represents the spatial weight matrix which has a size of 34 x 34.

The Akaike information criterion with the smallest value is selected to create estimation models with the most significant applicability. According to Burnham and Anderson (2002), the AIC is a straightforward and efficient method for selecting the model that most closely approximates the "actual" model. The method yielding the best results for a spatial econometric model is the one with the lowest AIC value.

3.2.1 Spatial Dependence

Based on Cliff and Ord (1970) and Anselin (1995), Moran's I can be expressed as follow :

$$I = \frac{\Sigma_{i=1}^{n} \Sigma_{j=1}^{j} w_{ij} z_i z_j}{\Sigma_{i=1}^{n} z_i^2} \tag{19}$$

Where n shows the number of districts, and z_i It is the number of regional I of the standard or mean-centered variable z. The ij_{th} member of the row-standardized spatial weight matrix W is denoted by W_{ij}.

The Global Moran Index, often known as Moran's I, could be utilized to analyze spatial interdependence. This calculation shows the average situation in all regions. The interval value utilized by the Global Moran Index spans from -1 to 1. A positive result indicates that a region shares the same features as another. In contrast, the negative number indicates a concentration of sites with shared characteristics. When the index value is zero, it indicates no relationship between the measured locations.

According to Anselin (2003), the spatial weight matrix (W) can be formed by connecting all the sets of observations using the distributional distance component and all the regions close to one another in particular locations. The elements with positive values comprise the weight matrix. Additionally, the spatial weight matrix for a geographic place is generated on a 0-by-one matrix consisting of spatial unities. 0 and 1 represent the proximity between the two regional locations. Wij values greater than zero suggest neighbors, whereas Wij values equal to zero imply others (or diagonal elements w ii defined as zero). The spatial weight matrix (W) is computed using the distance between all regions, the distance between neighboring areas, and the inter-regional adjacency. In addition, according to Griffith (2017), spatial weights quantify the relative value of a link between two sites. Based on the concept, spatial weight has numerous specifications: contiguity, persistent distance, distance to nearest neighbors, a predetermined distance range, and spatial involvement.

According to Drukker (2003), a Wooldridge test can be applied to the panel dataset to evaluate the robustness of the model. Wooldridge's test uses the residuals from a first-differences regression and is resistant to heteroscedasticity. Additionally, the Wald test can be used to detect heteroskedasticity.

According to Frondel and Vance (2010), two models with fixed and random effects are frequently used in panel data econometric models. In the fixed-effects method, time-invariant, non-observable factors for each observation are either explicitly represented by a variable or dummy or eliminated via time-demeaning. In contrast, the time-invariant non-observable elements are treated as changes in the random effects model. In addition, the interaction assumption between time-invariant non-observables and the regressor is null. The Hausman (1978) test is used to estimate the proper estimation model, either the fixed or random effect model, as described in greater detail below.

Determine the hypothesis:

Ho: In the panel data model, there is no interaction between the term of error with variables of independence. In this case, the appropriate approach is Random effects. $Cov\ (a_t, x_{it}) = 0$

H1: In the panel data model, there is an interaction between the term of error with independent variables. In this case, the appropriate model is fixed effects. $Cov\ (a_t, x_{it}) \neq 0$

In the analysis applied, if the result of the Hausman test is more prominent than the critical value, the null hypothesis is rejected.

The following section summarises the findings of geographical dependence among provinces using the Global Moran Index and the most suitable model to determine a correlation between road infrastructure and other economic development indicators. Initially, simple least-squares were utilized. However, the findings revealed significant bias. Panel data were compiled and applied to the regression estimation to avoid partial data in the model.

4. Conclusion and Recommendation

A Wooldridge and Breusch-Pagan test was used to examine the model's robustness and heteroskedasticity. The Wooldridge test yields F(1,33) = 127.910 and Probability > F = 0. The result indicates that the null hypothesis is rejected, and the model has an issue with serial correlation. In addition, the fact that the Wald test reveals Prob>chi2 = 0 indicates that the null hypothesis is rejected and that heteroskedasticity exists.

A Hausman test was used to evaluate whether a fixed or random effect model should be applied. When the result of the p-value is significantly less than 0.1, the null hypothesis should be rejected. It indicates that the effects are fixed. The estimator could accept the null hypothesis if the p-value is more significant than 0.1. The outcome of the Hausman test for the panel data model is presented in Table 1.

Table 1. Hausman's (1978) specification test

Column number	(1)
	Coef.
Chi-square test value	40.865
P-value	0

With a determined p-value of 0.000, the Hausman test indicates that the null hypothesis is rejected, and the fixed effects model is regarded as the optimal strategy for the panel dataset. The global Moran Index is utilized to determine the presence of provincial dependency between provinces. The spatial linkages between regions were evaluated in this study through a series of phases.

First, following Anselin (2003), the spatial weight matrix was constructed to establish the spatial correlation between provinces. Given that there are 34 provinces in Indonesia, the spatial weight matrix for this study is 34 by 34. The Global Moran Index is then calculated using province GRDP data from 2010 to 2020. The results indicate that the Global Moran Index in 2010 was 0.269 (I), while the expected value of the Index (E) was -0.030 (Io). As I > Io (0.269% > -0.030), the geographical patterns of the GRDP throughout Indonesia exhibit a clustering distribution, indicating the existence of spatial dependence across these provinces. The global Moran's Index findings are provided in table 2. Notably, all values are positive and significant, consistent with previous research (Lottman, 2012; Karim, Suhartono, and Prastyo, 2020).

Table 2. Global Moran Index

Column Number	(1)	(2)	(3)	(4)	(5)
Variables	I	E(I)	sd(I)	z	p-value*
lnGRDP2010	0.269	-0.030	0.071	4.193	0.000
lnGRDP2011	0.268	-0.030	0.071	4.179	0.000
lnGRDP2012	0.264	-0.030	0.071	4.135	0.000
lnGRDP2013	0.262	-0.030	0.071	4.105	0.000
lnGRDP2014	0.262	-0.030	0.071	4.096	0.000
lnGRDP2015	0.258	-0.030	0.071	4.050	0.000
lnGRDP2016	0.255	-0.030	0.071	4.006	0.000
lnGRDP2017	0.253	-0.030	0.071	3.978	0.000
lnGRDP2018	0.247	-0.030	0.071	3.893	0.000
lnGRDP2019	0.248	-0.030	0.071	3.908	0.000
lnGRDP2020	0.242	-0.030	0.071	3.822	0.000

*** $p<.01$, ** $p<.05$, * $p<.1$

The subsequent regression is in keeping with Belloti, Hughes, and Montari (2017). Table 3 displays the results of the regression studies for these five models: the geographic Durbin model, the spatial autoregressive model, the spatial error model, the spatial autoregressive combination model, and the generalized spatial panel data. In addition, Table 3 illustrates the relationship between road infrastructure development and other determinants of Indonesia's regional economic expansion.

According to Burham and Anderson (2002), the spatial econometric model with the minimum AIC value can be regarded as the most suitable method for the analysis. Based on the significance of the Akaike information criterion (AIC), the spatial Durbin model is the most appropriate model for evaluating the interaction between road infrastructure and other variables on regional economic development, as it has the lowest AIC value (-1447.966) among the five contenders. Consequently, this work will concentrate on the spatial Durbin model.

Estimations of direct and indirect effects can be derived using the spatial Durbin model. Initially, observe that the parameter has a negative and significant value of -0.323. This number is negative, indicating the repercussions of spatial interconnections throughout the province on regional economic development in Indonesia.

Secondly, the results of the SDM model indicate that the direct effects of manufacturing and government spending on economic growth have a substantial sign. In addition, the manufacturing sector's elasticity value is 0.199, and the importance of elasticity for government expenditures is 0.28, proving their exceptional steadiness. The coefficient of education (as assessed by the number of college students), the coefficient of the number of employees, the coefficient of people employed in the construction business, and the coefficient of road infrastructure all have a negative but minor value. The coefficients for the number of students are -0.008, -0.01, and -0.005 for construction workers and road infrastructure, respectively. The result demonstrates that education, the number of construction workers, and the construction of roads have negligible direct effects on Indonesia's regional economic growth. Despite these empirical factors, the estimated value of local and international direct investments' direct effects is positive and inconsequential. Foreign direct investment, domestic direct investment, the total number of employees, and the unemployment rate do not affect economic development because they are insignificant. The estimated FDI coefficient is 0.001, the DDI coefficient is 0.00, and unemployment is 0.00.

Third, foreign direct investment, unemployment, the number of college students, government spending, and construction employees have favorable but insignificant indirect effects. The foreign direct investment coefficient is 0.005, the unemployment coefficient is 0.011, the university student coefficient is 0.01, the government expenditure coefficient is 0.204, and the construction worker total coefficient is 0.008. In addition, manufacturing has an extensive and favorable score of 0.50. The number of employees, in comparison, has a negative and insignificant value of -0.008. In addition, domestic direct investment has a substantial negative value of -0.039.

Table 2. Result of spatial model test

Column Number	(1)	(2)	(3)	(4)	(5)
	(SDM)	(SAR)	(SEM)	(SAC)	(GSPRE)
	lnGRDP	lnGRDP	lnGRDP	lnGRDP	lnGRDP
lnFDI	.001	-.001	-.001	-0.001	-0.002
	(.002)	(.002)	(.002)	(.002)	(.803)
lnDDI	0	0	.001	-0.001	0.001
	(.002)	(.002)	(.003)	(.002)	(.442)
lnEmploy1	-.001	.001	.003	0.003	0.003
	(.002)	(.003)	(.003)	(.003)	(1.255)
lnUnemploy1	0	0	-.001	-0.000	-.001
	(.002)	(.003)	(.003)	(.002)	(.448)
lnStudent	-.008	-.014	-.008	-0.014	-.008
	(.011)	(.013)	(.012)	(.0013)	(12.768)
lnManuf	.199***	.188***	.155**	.198***	.155
	(.049)	(.052)	(.062)	(.048)	(19.892)
lnGotEXp	.285***	.323***	.395***	0.294***	.394
	(.107)	(.122)	(.114)	(.108)	(168.310)
lnConstWork	-.005	-.002	-.004	-0.002	-0.004
	(.004)	(.005)	(.004)	(.004)	(.653)
lnRoadInfra	-.001	-.001	-.001	-0.001	-0.001
	(.003)	(.003)	(.002)	(.003)	(.748)
_cons			11.893***		

			(1.859)		
Wx:lnFDI	.005				
	(.006)				
Wx:lnDDI	-.039***				
	(.012)				
Wx:lnEmploy1	-.008				
	(.007)				
Wx:lnUnemploy1	.011				
	(.009)				
Wx:lnStudent	.01				
	(.028)				
Wx:lnManuf	.504***				
	(.119)				
Wx:lnGotEXp	.204				
	(.159)				
Wx:lnConstWork	.008				
	(.012)				
Wx:lnRoadInfra	-.005				
	(.009)				
Spatial: rho	-.323*	.202		0.443	
	(.187)	(.187)		(.199)	
Spatial: lambda			.903***	-0.494	0.903
			(.05)	(.327)	(30.184)
Variance:sigma2_e	.001***	.001***	.002***	0.001	0.040
	(0)	(0)	(0)	(0)	
Variance:ln_phi			6.007***		
			(.448)		
Observations	374	374	374	374	374
R-squared	.825	.884	.893	.856	.893
AIC	-1447.966	-1395.465	-1391.247	-1402.712	-986.801

Standard errors are in parentheses **** p<.01, ** p<.05, * p<.1*

The estimation indicates that the value of the Global Moran's Index is positive and statistically significant. According to prior research (Karim, Suhartono, and Prasyta, 2020), Indonesia's economic growth rate relies significantly on geographic location. The estimation indicates that the spatial Durbin model is the most appropriate methodology in this circumstance. In addition, the coefficient is negative, demonstrating spatial autocorrelation throughout the province. This negative value in this estimation is unexpected, as it may indicate that rivalry across regions is greater than the cooperative factor, resulting in less provincial government coordination.

This situation is clarified by Griffith and Arbia (2010), who discover that, in some instances, the value of spatial autocorrelation is negative due to the competitiveness on the geographical surface, territorial, and market area. Myrdal (1957) adds that the negative value for spatial autocorrelation is determined by the effect of "backwash," in which the economic development in one region is exacerbated by that in a nearby region due to the migration of skilled labor, hence reducing the growth potential. In addition, Bloningen et al. (2004) demonstrate that spatial autocorrelation has a negative value when interregional competition surpasses cooperation. In contrast to previous research (Karim, Suhartono, & Prastyo, 2020) that utilized spatial autocorrelation analysis to establish the spatial dependence of economic development, they discovered positive spatial autocorrelation.

In this paper, the coefficient for road construction's direct and indirect effects is negative and insignificant. The coefficients for the direct effect are -0.001, whereas the coefficients for the indirect effect are -0.05. The coefficient of direct effect indicates that when the gross regional domestic product rises by 1 percent, road building is likely to fall by 0.001 percent. Indirectly, when the gross regional domestic product increases by 1 percent, road development will reduce by 0.05 percent, or it may be concluded that increasing investment in road infrastructure may hinder the local economy. This study's negligible coefficient was unexpected, as it indicates that road infrastructure has little effect on economic growth or spillover to neighboring provinces. Since the federal government invests heavily in infrastructure, road construction is expected to affect economic development positively. These results indicate that the national term plan has no short-term impact on economic development, particularly road construction.

This study concludes that road construction has a negative spillover impact and adds little to economic development. According to Boarnet (1996, 1998), migratory patterns between regions may result in a negative value for the spillover effect. When the roads in Indonesia are in decent shape, most of the population migrates to urban areas with better employment possibilities. This study differs from the findings of most earlier research, which concluded that road construction has a favorable and significant impact on economic development (Karim, Suhartono, and Prastyo, 2020). According to Hu and Luo (2017), road infrastructure positively affects economic growth. The development of roads has a favorable ripple impact on the economies of the surrounding areas, which stimulates economic growth; however, the distance between the places mitigates this effect. In addition, a previous study (Komo et al., 2021, Nguyen, 2022, Arbues, Banos, and Mayor, 2015) evaluates road construction through SDM. It concludes that road building positively affects economic growth and has a spillover effect on neighboring regions. However, the result is consistent with a prior study by Griffith and Arbia (2010), who found a negative spatial autocorrelation due to regional competition for land use and commercial district.

According to estimates, foreign direct investment has both direct and indirect positive impacts, but the latter is negligible. The coefficient for the direct effect is 0.001. Therefore a 1% rise in GRDP results in a 0.001% increase in FDI. The coefficient for the indirect effect is 0.005. Therefore a 1% increase in GRDP will result in a 0.001 increase in the spillover effect of FDI. This result is consistent with Hong's (2014) assertion that FDI favorably impacts economic growth. In addition, Makki and Somwaru (2004) demonstrate that FDI helps economic growth via market openness, fiscal policies, and monetary policies.

The coefficient of domestic direct investment's direct effect is zero. In addition, the indirect effect coefficient is negative and statistically significant at -0.039. The condition indicates that a 1% increase in GRDP will result in a 0.039% decline in domestic direct investment. Domestic direct investment in the neighboring provinces hinders economic growth. According to Bakari (2021), domestic direct investment damaged the short-term economic growth of Arab countries between 1990 and 2020. This result contradicts expectations because the domestic direct investment may contribute positively to economic growth.

The direct effect of provincial government spending is positive and significant, with a coefficient value of 0.199, whereas the indirect effect is positive but minor, with a coefficient value of 0.204. It means that while the GRDP grows by 1%, provincial government expenditures will rise by 0.365; when the regional domestic product grows by 1%, provincial government expenditures will rise by 0.204. Prior research (Arestis et al., 2021; Arvin et al., 2021; Attari and Javed, 2013) suggests that government expenditure positively influences economic development by improving the quality of public services, boosting consumer spending, and facilitating access to private investment.

Direct and indirect consequences of manufacturing are substantial and reasonable. The direct effect has a coefficient of 0.199, which indicates that when the gross regional domestic product improves by one percentage point, manufacturing increases by 0.199 percentage points. The coefficient of the indirect effect of manufacturing is 0.504, which indicates that when the gross regional domestic product rises by 1%, manufacturing will rise by 0.504. In addition, it may be assumed that manufacturing investment helps the economic growth of neighboring provinces. This result is consistent with findings from a prior study (Smeets, Cheng, and Haraguchi, 2016), showing the manufacturing sector promotes economic development positively. Manufacturing's contribution to the international gross domestic product (GDP) has not changed since 1970. The manufacturing sector is vital to stimulate less developed nations, which have sustained robust and consistent growth over the past few decades,

The number of employees has unfavorable direct and indirect effects, but these effects are negligible. The coefficient for the direct effect is -0.01, which indicates that a 1% increase in the gross regional domestic product will result in a 0.01 drop in employment. Thus, increasing the amount of GRDP cannot improve regional employment; however, regional employment may decline. In addition, the coefficient for the indirect effect is - 0.008, meaning that when the gross regional domestic product rises by 1 percent, the number of employees will fall by 0.008.

The direct effect for construction workers is negative and insignificant at - 0.005. Therefore, construction employees drop by 0.005 for every 1% increase in GRDP. In the context of the spillover effect, while GRDP is expanding, employment tends to decline, negatively impacting the economic development of neighboring provinces. This result is not anticipated based on the assumption that as the GRDP increases, the unemployment rate lowers and contributes positively to economic growth. This condition is consistent with Zulu and Banda's (2015) finding that the labor force has a detrimental impact on short-term economic growth. Pini (1997) concludes that employment flexibility fell between 1979 and 1995 and 1960 and 1979, particularly in France and Sweden and Italy and Sweden.

The construction workers have a positive but insignificant indirect effect coefficient of 0.008. This result indicates that the number of construction employees will grow by 0.08% for every 1% increase in GRDP. The economy's expansion is causing an increase in construction workers. This result is consistent with the findings of Zulu and Banda (2015), who found that the number of workers in South Africa and Mauritius had a significant and beneficial effect on economic growth.

In addition, the number of unemployed has no direct influence, as the estimation-derived coefficient has zero value. In addition, the indirect effect has a positive value but is not statistically significant at 0.01. This research indicates that when the gross regional domestic product rises by 1 percent, employment rises by 0.11 percent. According to Hasan (2015), Nigeria's economic development growth from 2004 to 2011 could not alleviate unemployment, poverty, or inequality. This result contradicts Okun (1963), who concluded that economic development and unemployment are inversely connected. In addition, Phillips (1958) shows that rising inflation contributes to a decline in unemployment, whereas Dayioglu and Aydin (2020) discover that rising economic growth drives a decline in unemployment.

The projected direct effect of the number of pupils is negligible and negative, at -0.08. This outcome agrees with Benhabib and Spiegel (1994). According to cross-country estimates by Benhabib and Speigel, education affects economic development (1994). In contrast, the number of students has a positive indirect effect with a value of 0.01. However, this value is not statistically significant. This research indicates that the number of pupils grows by 0.1% when the gross regional domestic product increases by 1%. This outcome is consistent with Sterlacihni (2008). According to Sterlacihni (2008), education favors economic growth in European regions, with an increasing number of students contributing positively to regional economic development.

5. Conclusion and Recommendations

The calculation's results demonstrate that the spatial Durbin Model is the most effective spatial model, as its Akaike information criterion value is the lowest among those.. In addition, the Global Moran Index reveals spatial relationships among Indonesia's regions. In conclusion, each element has distinct direct and indirect consequences on Indonesia's economic development.

The estimation's results indicate that road construction has no significant impact on the regional economic growth of a province's neighboring provinces. Foreign direct investment helps positively, both directly and indirectly, despite the low estimate. The direct effect of domestic direct investment is zero, whereas the indirect effect has a negative and considerable value. In contrast, government spending has a favorable and significant impact on economic development directly and indirectly. In addition, the production process has a direct impact that contributes significantly and positively. Through indirect impacts, construction workers have an excellent effect.

The initial results imply numerous policy implications. First, Indonesia has a high spatial dependency between provinces, which suggests that the expansion of one province contributes to negative growth in other provinces. Consequently, provincial governments should coordinate more with other provinces when enacting policies to eliminate disparities between jurisdictions.

Second, the findings suggest that the construction of roads has a negative ripple impact. Because Indonesia is composed of numerous islands, distances between provinces can vary considerably. For instance, circumstances in Java differ from those in Kalimantan and Papua.. Moreover, the amount of money the federal government supplies to each province for road infrastructure construction varies considerably. To address this issue, the federal government should study appropriate financial allocations that would have a favorable effect on the rate of economic expansion in various regions.

Additionally, provincial governments should invest in new road infrastructure, particularly in eastern Indonesian provinces such as Papua, Sulawesi, and Kalimantan, to enhance the distribution of goods and services within their respective provinces. If economic activity grows, a positive ripple effect will contribute to the economy's expansion. Moreover, the provincial governments in the Java island, particularly in provinces that have grown their road infrastructure at a pace of more than 70 percent, should preserve the current level of their road infrastructure to expedite the distribution of goods and services.

Thirdly, the provincial government should prioritize domestic and international investment. To draw investment into the region, the federal and provincial governments should endeavor to increase the number of partner nations for domestic and international investment. Additionally, employment possibilities must be accessible in each province and offered by the provincial government. The government might prioritize increasing construction, manufacturing, and agricultural employment. It could encourage people to remain in their home provinces and discourage labor migration. This condition would lessen disparities throughout the province. Additionally, the government should strengthen both the quality and quantity of higher education institutions, particularly in regions with a limited number of colleges and universities, as higher education contributes significantly to economic development.

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