The Economics and Finance Letters
2026 Vol. 13, No. 4, pp. 229-242
ISSN(e): 2312-430X
ISSN(p): 2312-6310
DOI: 10.18488/29.v13i4.5332
© 2026 Conscientia Beam. All Rights Reserved.

Spatial dependence in the efficiency of Indonesian regional development banks: A two-stage DEA-SAR Tobit analysis

Galih Ramadhan Febrianto[1+]
Ghozali Maski[2]
Putu Mahardika Adi Saputra[3]
David Kaluge[4]

[1,2,3,4]*Department of Economics, Faculty of Economics and Business, University of Brawijaya, Indonesia.*
[1]*Email: galihramadhanf@student.ub.ac.id*
[2]*Email: ghozalimaski@ub.ac.id*
[3]*Email: putu@ub.ac.id*
[4]*Email: davidk@ub.ac.id*

(+ Corresponding author)

Article History
Received: 2 July 2026
Revised: 14 September 2026
Accepted: 5 October 2026
Published: 29 October 2026

Keywords
Data envelopment analysis
Efficiency
Regional development banks
SAR Tobit
Spatial spillover.

JEL Classification:
C14; C21; C33; G21; R12.

ABSTRACT

This study analyzes the technical efficiency and spatial dependence of the 27 Regional Development Banks (RDBs) in Indonesia from 2013 to 2022. A two-stage quantitative design was used. First, using Data Envelopment Analysis under the intermediation approach, the inputs used to estimate annual efficiency were third-party funds, total costs, and fixed assets, while the outputs were loans, interest income, and non-interest income. Second, Moran's I was used to examine spatial autocorrelation in the DEA scores, while pooled SAR and SEM Tobit models were used to estimate spatial dependence and the relationships between regional and bank-specific characteristics and latent efficiency. A row-standardized first-order Queen contiguity matrix was used to represent spatial links; units with no contiguous neighbors had zero rows. Mean efficiency was 0.970, declined to 0.946 in 2020, and recovered to 0.984 in 2022. In 2018, 2020, and 2021, significant positive values of spatial autocorrelation were found. The SAR Tobit model also performed better than the non-spatial pooled Tobit model (LR = 8.944, p = 0.0028), and the spatial-lag coefficient was positive and significant (ρ = 0.025, p = 0.003). There was a negative relationship between non-performing loans and latent efficiency and a positive relationship between the loan-to-deposit ratio and latent efficiency. At the 10% level, GRDP per capita, capital adequacy, and the cost-to-income ratio exhibited weaker relationships. The results indicate that a dual strategy is needed: bank-level risk management and intermediation enhancement, along with coordinated benchmarking, digital collaboration, and peer learning through OJK, ASBANDA, provincial shareholders, and RDB management.

Contribution/Originality: This study advances banking-efficiency research by integrating input-oriented VRS DEA, Moran's I, and a censored SAR Tobit model for all 27 Indonesian RDBs. It provides new empirical evidence of contiguity-based efficiency dependence, clarifies bank-specific determinants, and translates the findings into coordinated regulatory, shareholder, and managerial actions across regions in Indonesia.

1. INTRODUCTION

In Indonesia's financial system, Regional Development Banks (RDBs) hold a unique position. These regionally owned banks mobilise public deposits, provide credit, manage government finances, and support other economic activities in their respective regions. They can therefore be viewed as both commercial enterprises and regional development tools (Zunairoh, Wijaya, Mahadwartha, & Murhadi, 2023). According to ASBANDA (the Association

© 2026 Conscientia Beam. All Rights Reserved.

of Regional Development Banks), Indonesia has 27 RDBs. In December 2021, their total assets amounted to IDR 870.53 trillion, making them significant contributors to regional financial intermediation and development.

Although all Indonesian RDBs have a similar institutional mandate, they operate under heterogeneous conditions. Significant differences in operating performance may result from regional variations in economic structure, population, infrastructure, fiscal capacity, technology adoption, customer characteristics, and bank size. Therefore, the level of efficiency in intermediation cannot be quantified solely in terms of assets, deposits, or loan volume. Rather, efficiency should be gauged by how well each bank utilizes the resources available to it to produce financial products.

Economists have used Data Envelopment Analysis (DEA) to measure relative technical efficiency owing to its ability to accommodate several inputs and outputs while placing no restrictions on the production function (Charnes, Cooper, & Rhodes, 1978; Farrell, 1957). This study adopts the intermediation approach, which considers banks as institutions that transform deposits, bank resources, and tangible assets into loans and income-generating activities (Sealey & Lindley, 1977). This approach is suitable for the RDBs, whose main role is to mobilize regional funds and allocate them to productive financial activities.

Earlier studies have employed DEA, SFA, and two-stage regressions to gauge the efficiency of banks in Indonesia. Hadad, Santoso, Ilyas, and Mardanugraha (2003) assessed the efficiency of Indonesia's banking industry, while Puspita and Shofawati (2019) used two-stage DEA to examine Islamic RDBs. Zahra and Darwanto (2019) found that capital adequacy was positively correlated with the loan-to-deposit ratio and RDB efficiency. The intermediation function was also found to be one of the determinants found by Puspasari, Priyarsono, and Sasongko (2020) while Satyagraha, Purwono, and Sari (2022) highlighted capital, credit risk, and technological investment. However, the effects of bank-specific and regional factors vary across samples, time periods, and estimation methods.

More importantly, previous studies of RDBs in Indonesia consider each bank a separate decision-making unit. Nonspatial second-stage models and conventional DEA models assume that the efficiency of a single RDB is not correlated in any way with the efficiency of other banks operating in surrounding areas. This premise can be deemed restrictive because RDBs are located in geographically constrained economies connected through trade and infrastructure, migratory labour, financial flows, and public policies. Omitting these relationships may lead to a flawed theoretical understanding of efficiency, obscure groups of banks in various geographical regions that are either efficient or inefficient, and limit policy advice.

The importance of geographical interaction is consistent with Tobler (1970) first law of geography: near things are more alike than distant things. RDBs' efficiency spillovers may take the form of shared regional shocks; competition for deposits and borrowers; the imitation of managerial and digital innovations; employee movement; benchmarking; and collaboration among neighbouring regional governments. This is confirmed by international studies. Tabak, Miranda, and Fazio (2013) found that banks sharing a similar geographical setting had similar levels of efficiency. Glass, Kenjegaliev, and Kenjegalieva (2020) observed spatial spillovers in banks' economies of scale and product mix, while Zhao, Kenjegalieva, Wood, and Glass (2020) and Zhao, Tian, Kenjegalieva, and Wood (2024) demonstrated that local markets and spatial relationships influence banking productivity.

However, it is still unknown whether there are geographical clusters in the efficiency of Indonesian RDBs and whether the efficiency of one RDB is systematically related to that of neighbouring RDBs. This study aims to fill this gap by analysing 27 RDBs in Indonesia from 2013 to 2022. Technical efficiency is calculated in the first stage using an input-oriented DEA model, under the assumption of variable returns to scale (VRS) and the intermediation approach. The inputs include third-party funds, total costs, and fixed assets, while the outputs include loans, interest income, and non-interest income. The VRS specification also allows for variations in the operating scale of the RDBs studied (Banker, Charnes, & Cooper, 1984).

At the second stage, a spatial autoregressive Tobit model is used to estimate efficiency spillovers, with spatial autocorrelation assessed using Moran's I. The spatial component captures the interdependence among neighbouring

© 2026 Conscientia Beam. All Rights Reserved.

RDBs, and the Tobit specification accommodates DEA scores ranging from zero to one. In the model, the control variables are Gross Regional Domestic Product per capita, Capital Adequacy Ratio, Non-Performing Loans, Cost-to-Income Ratio, and Loan-to-Deposit Ratio. A row-standardised first-order queen-contiguity matrix is used to represent spatial relationships, with two territories considered neighbours if they share a boundary or vertex. If a territory has no neighbouring territories, the corresponding row in the matrix and the spatial-lag value are set to 0.

This paper investigates the existence of significant spatial dependence in RDB efficiency in Indonesia and the association between the efficiency of an RDB and that of other RDBs in contiguous or neighbouring territories, after adjusting for regional and bank-specific characteristics. The study's theoretical, empirical, methodological, and practical contributions lie in its integration of DEA, Moran's I, queen-contiguity weights, and SAR Tobit estimation to examine efficiency clustering and spillovers among RDBs in Indonesia. It also highlights the importance of regional benchmarking, knowledge transfer, shared digital infrastructure, and coordinated risk management. The remainder of this paper is organised as follows. Section 2 reviews the literature. Section 3 describes the data and methodology. Section 4 presents and discusses the empirical results. Section 5 concludes the study, and Section 6 outlines the policy implications.

2. LITERATURE REVIEW

2.1. Technical Efficiency and the Intermediation Approach

Technical efficiency is the capacity of a decision-making unit to obtain the maximum possible output from the same quantity of inputs or to produce the same output using the smallest quantity of inputs (Farrell, 1957). Data Envelopment Analysis (DEA) is a non-parametric technique for measuring relative efficiency in the absence of a predetermined production function (Charnes et al., 1978). Banker et al. (1984) expanded DEA by introducing the variable returns to scale model, which distinguishes between pure technical efficiency and scale effects. This specification is suitable for RDBs, as they operate at different scales under varying regional conditions.

Banking efficiency studies commonly distinguish between the production and intermediation approaches. The intermediation approach considers banks to be institutions that convert deposits, operating resources, and assets into loans and income-generating activities (Sealey & Lindley, 1977). This strategy is appropriate for RDBs, as their main responsibility is to mobilise regional funds and allocate them to credit and productive assets. The same input-output structure has been used in previous banking efficiency studies (Andries, 2011; Řepková, 2015; Zahra & Darwanto, 2019).

2.2. Evidence of Indonesian Banking Efficiency

The efficiency of Indonesian banks has been studied using DEA, SFA, and two-stage models. Hadad et al. (2003) and Puspita and Shofawati (2019) reported an efficiency gap in Indonesia's banking industry using two-stage DEA in the case of Islamic RDBs. The study by Zahra and Darwanto (2019) found substantial variation in efficiency among RDBs in Indonesia and indicated that capital adequacy and the loan-to-deposit ratio positively influence efficiency. Puspasari et al. (2020) and Satyagraha et al. (2022) also emphasized the roles of capital, credit risk, and technological investment. Banking performance in terms of capital, asset quality, operating costs, and liquidity is also linked to banking efficiency, although the results differ across samples and approaches (Marsondang, Purwanto, & Mulyati, 2020; Sulaeman, Moelyono, & Nawir, 2019; Widiarti, Siregar, & Andati, 2015).

Some of these discrepancies are due to methodological decisions. DEA allows for many inputs and outputs but does not require a functional form and typically considers deviations from the frontier as inefficiency. SFA can separate random shocks from inefficiency, but it imposes assumptions on the functional form and the distribution of the error. In addition, typical second-stage regressions are based on the assumption of spatial independence. Therefore, previous research can only shed light on the determinants of banks and cannot determine whether there is any correlation between RDB efficiency and the performance of banks located near similar banks.

© 2026 Conscientia Beam. All Rights Reserved.

2.3. Spatial Dependence and Banking Efficiency

Spatial dependence is based on Tobler's first law of geography, which states that closer objects are more similar than those that are farther apart (Tobler, 1970). A spatial weight matrix is used to represent this relationship in spatial econometric models. A spatial autoregressive model assumes that an outcome in one area is associated with a weighted outcome in other areas, whereas a spatial error model assumes that spatial dependence is based on unobserved elements of the error term (Elhorst, 2014; LeSage, 1999). Qu and Lee (2012) provide a basis for spatial limited-dependent-variable analysis based on limited results.

Efficiency spillovers may occur between RDBs via a number of channels. Neighboring banks, competition for deposits and borrowers, imitation of managerial and digital innovation, exchange of knowledge between banks through employee mobility, benchmarking, common training, and cooperation with neighboring banks are all subject to regional shocks. Spatial dependence could therefore reflect direct interaction between banks and similar responses to such regional factors.

Empirical studies have endorsed the importance of geography to banks. Tabak et al. (2013) report that banks in similar local environments exhibited similar efficiency characteristics. Glass et al. (2020) identified a geographical aspect of banking scale and product-mix economies in the U.S. The local market conditions and spatial relationships have been found to affect the performance and productivity of Chinese regional banks (Zhao et al., 2020; Zhao et al., 2024). Financial spillovers and feedback effects of connected markets were also recorded by Fang, Jing, Shi, and Zhao (2021).

However, those were conducted in an institutional setting that is different from the regionally owned banking system in Indonesia. Moreover, the current studies on RDB in Indonesia have not specifically studied whether the DEA efficiency scores are geographically dependent. This creates a crucial gap between traditional efficiency analysis, where banks are treated as independent entities, and spatial banking analysis, where performance can be regionally networked.

2.4. Determinants of RDB Efficiency

One regional and four bank-specific determinants are taken into account in this study. GRDP per capita is an indicator used to estimate the economic potential and demand for banking services in the area. When income in the area increases, deposits, loans, and transactions at banks may increase; however, the potential for higher efficiency can only be achieved when banks make optimal use of them (Garza-García, 2012; Sulaeman et al., 2019; Zahra & Darwanto, 2019).

The Capital Adequacy Ratio measures a bank's ability to absorb losses while continuing to operate and produce assets. Although an increase in capital can enhance stability and lending capacity, excess capital does not always result in increased efficiency when it is not utilized optimally (Dewi, 2024; Pambuko, 2016; Zahra & Darwanto, 2019).

The proportion of Non-Performing Loans indicates problems with asset quality. When the proportion of problem loans increases, the proportion of the bank's resources devoted to monitoring, provisioning, restructuring, and recovery of problem loans increases, and thus the bank's resources become less productive (Berger & DeYoung, 1997; Phung, Van Vu, & Tran, 2022; Widiarti et al., 2015).

The Cost-to-Income Ratio is a ratio of the costs of generating income. The greater the ratio, the greater the pressure on costs and the less efficient the operation is (Rozzani & Abdul Rahman, 2013; Widiarti et al., 2015; Zhou & An, 2016). This variable is taken as an input to DEA, and the aim is to determine whether relative pressure on operating costs has any explanatory power.

Finally, there is the Loan-to-Deposit Ratio, which is a measure of the intensity of financial intermediation. The higher the ratio, within prudent limits, the more deposits are turned into productive loans and income. However, too much lending compared with deposits can lead to an increase in liquidity and credit risks (Marsondang et al., 2020; Puspasari et al., 2020; Sulaeman et al., 2019).

© 2026 Conscientia Beam. All Rights Reserved.

Collectively, the available research suggests that regional effects, capital, credit risk, operating costs, and intermediation have an impact on the efficiency of banks, but the findings are not always consistent and are generally estimated with spatially independent variables. This research paper tries to address this shortcoming by combining input-oriented DEA and SAR Tobit estimation to examine the combined impacts of internal and regional economic conditions and the effectiveness of neighbouring banks on the efficiency of Indonesian RDBs.

3. RESEARCH METHODS

3.1. Research Design, Sample, and Data Sources

The present research uses a two-stage quantitative design. Technical efficiency in the first stage is calculated using an input-based Data Envelopment Analysis (DEA) model under the assumption of Variable Returns to Scale (VRS). The resulting DEA efficiency scores are then used as the dependent variable in a pooled Spatial Autoregressive (SAR) Tobit model to test the determinants of efficiency and spatial dependence among Indonesian Regional Development Banks (RDBs).

This paper employs a balanced sample of 27 RDBs, which were followed from 2013 to 2022, yielding a total of 270 bank-year observations. The units of observation are RDBs, which are considered to be Decision-Making Unit (DMU). There are 20 RDBs operate in one province, and seven operate in two provinces: Bank Riau Kepri, Bank Sumsel Babel, Bank Kaltimtara, Bank Sulselbar, Bank SulutGo, Bank Maluku Malut, and Bank Papua. Together, their areas of operation align with the uniform 34-province framework throughout the study period.

Data from the 27 RDBs at the bank level are derived from the audited annual financial statements and annual reports of the 27 banks from 2013 to 2022, obtained via the official websites of the corresponding banks and the Financial Services Authority (OJK). The information provided in these documents includes third-party funds, operating costs, fixed assets, loans, interest and non-interest income, capital, credit quality, operating-cost ratios, and intermediation ratios. The provincial statistical tables of Statistics Indonesia (BPS), namely the Gross Regional Domestic Product (GRDP) at current market prices and annual provincial population data, are used to obtain regional data.

GRDP per capita is measured using provincial GRDP per capita at current market prices. For RDBs representing a single province, the value of that province is used. For RDBs jointly owned by two provinces, the GRDP per capita variable is calculated as the simple arithmetic average of the two provincial GRDP per capita values. No logarithmic transformation or normalization is applied. The DEA monetary variables are retained in their reported monetary units, while CAR, NPL, CIR, and LDR are expressed in percentage points.

3.2. DEA Specification

The DEA model is based on the intermediation approach, in which banks are considered institutions that convert deposits and operating resources into loans and income-generating assets (Sealey & Lindley, 1977). This method is favored over the production approach because the latter focuses on the quantity and number of banking services provided to people, whereas the intermediation approach more directly reflects the principal role of RDBs in mobilizing public funds and allocating them to credit and earning assets. The inputs are third-party funds, total costs, and fixed assets, whereas the outputs are loans, interest income, and non-interest income. Table 1 presents the input and output variables employed in the DEA specification, together with their respective roles and operational definitions under the intermediation approach.

The choice of an input-oriented specification is based on the fact that RDB management has more control over resource use than over regional demand based on credit and banking income. The Constant Returns to Scale specification is less preferable than the VRS specification, since the RDBs vary significantly in terms of asset base, market coverage, operational capacity, and technological infrastructure. They may also be unable to operate at an

© 2026 Conscientia Beam. All Rights Reserved.

optimal scale due to regional, regulatory, and financial constraints. VRS thus quantifies pure technical efficiency without the influence of scale (Banker et al., 1984).

Table 1. DEA input and output variables under the intermediation approach.

Variables	Role	Definition
Third-party funds	Input	Demand deposits, savings, and time deposits mobilized from customers.
Total costs	Input	Personnel expenses and other operating expenses incurred by the bank.
Fixed assets	Input	Buildings, vehicles, information-technology equipment, ATMs, and other fixed assets.
Loans	Output	Total loans and financing extended to customers.
Interest income	Output	Income generated from loans and other interest-bearing assets.
Non-interest income	Output	Fee-based and other non-interest operating income.

Source: Andries (2011); Řepková (2015); Sealey and Lindley (1977); and Zahra and Darwanto (2019).

Where X is the m N input and Y s N output matrix of N RDBs, where x_i and y_i are the input and output of RDB_i. The input-oriented BCC/VRS model can be specified as follows:

$\min \theta$

subject to: $Y\lambda \geq y_i$

$X\lambda \leq \theta x_i$

$1'\lambda = 1$

$\lambda \geq 0$

The scalar θ is the technical efficiency score and lies between 0 and 1. A value of one means that an RDB is on the efficiency frontier, whereas a value below one indicates the percentage decrease in inputs that could be realized without decreasing the level of observed output. The vector λ forms a convex combination of similar RDBs.

3.3. Explanatory Variables

The second-stage model incorporates one regional and four bank-specific variables. GRDP per capita reflects the local economic potential and the need for financial services. CAR is the capacity of the bank to take in the losses and sustain its productive assets. NPL is an indicator of credit risk and resources needed to deal with problem loans. CIR is a measure of operating-cost pressure as compared to operating income, and LDR is a measure of the intensity of conversion of deposits into productive lending. Table 2 presents the explanatory variables included in the second-stage regression model, along with their measurement definitions and data sources.

Table 2. Definition and source of explanatory variables.

Variables	Measurement	Source
GRDP per capita	Provincial GRDP at current market prices divided by population	BPS provincial GRDP and population tables
CAR	Bank capital divided by risk-weighted assets	RDB annual reports and published financial statements
NPL	Non-performing loans divided by total loans	RDB annual reports and published financial statements
CIR	Operating expenses divided by operating income	RDB annual reports and published financial statements
LDR	Total loans divided by third-party funds	RDB annual reports and published financial statements

3.4. Spatial Weight Matrix

A first-order queen-contiguity matrix is used to represent the spatial relationships between RDBs. Two RDB territories are considered neighbors if they have a common boundary or a common vertex between their operational

© 2026 Conscientia Beam. All Rights Reserved.

regions. In the case of RDBs in which two provinces are modeled, the component provinces are considered to be a single operational territory, and it is adjacent when at least one of the component provinces lies adjacent to another RDB territory.

The binary spatial weights are defined as:

$w_{ij} = 1$, if RDB territories i and j share a boundary or vertex.

$w_{ij} = 0$, otherwise.

The diagonal elements are set to zero ($w_{ii} = 0$). For spatial units with at least one neighbor, the matrix is row-standardized by dividing each element by the sum of the corresponding row.

$$w_{ij}^{*} = w_{ij} / \sum_j w_{ij}$$

In the case of island territories or operational areas that do not have neighboring territories, the respective row is maintained as a zero row. This means that the spatial-lag value of that RDB is zero. This treatment shows that there is no adjacent spatial relationship and does not mean that the bank's technical efficiency score is zero.

3.5. SAR Tobit Model

DEA scores take values between zero and one, with a few observations lying on the efficiency frontier. The second-stage analysis thus uses a two-limit Tobit model. Fractional-response models estimate the conditional mean of observed fractions, even though they can account for proportional effects. The Tobit model is retained because this study develops efficiency as a latent index, with its observed value capped by the lower and upper efficiency boundaries. The spatial expansion also allows neighboring efficiency to enter the latent-efficiency relationship (Qu & Lee, 2012).

The pooled SAR Tobit model is specified as:

$$\theta^{*}_{it} = \rho \sum_j w_{ij} \theta_{jt} + z'_{it} \beta + \varepsilon_{it}$$

The observed efficiency score is defined as:

$$\theta_{it} = 0, if\ \theta^{*}_{it} \leq 0$$
$$\theta_{it} = \theta^{*}_{it}, if\ 0 < \theta^{*}_{it} < 1$$
$$\theta_{it} = 1, if\ \theta^{*}_{it} \geq 1$$

Here, θ^{*}_{it} is the latent efficiency index, θ_{it} is the observed DEA score, W is the row-standardized queen-contiguity matrix, and ρ measures spatial dependence. The vector z_{it} consists of GRDP per capita, CAR, NPL, CIR, and LDR; β represents their estimated coefficients; and ε_{it} is the disturbance term. A positive and statistically significant ρ indicates that higher efficiency among neighboring RDBs is associated with higher efficiency in the observed RDB. The model is estimated using maximum likelihood.

3.6. Panel Structure, Model Selection, and Diagnostic Procedure

A pooled Tobit specification is taken as the baseline for the analysis. Neither fixed- nor random-effects specifications are employed because of the identification and convergence issues arising from a small cross-sectional dimension, censoring at efficiency frontiers, and spatial dependence. Global Moran's I is first used to determine spatial dependence.

Likelihood-ratio tests are then used to compare the SAR Tobit and Spatial Error Model (SEM) Tobit specifications with a non-spatial pooled Tobit model. The SAR specification captures dependence in adjacent efficiency scores, but the SEM specification captures spatial dependence due to unobserved variables in the disturbance term. The pairwise correlation matrix, Variance Inflation Factors (VIF), and tolerance values are used to measure multicollinearity between the explanatory variables. Criteria indicating no serious multicollinearity include pairwise correlations under 0.80, VIF less than 5, and tolerance greater than 0.10. The empirical results chapter reports the diagnostic results.

© 2026 Conscientia Beam. All Rights Reserved.

4. RESULTS AND DISCUSSION

4.1. Technical Efficiency Over Time

The input-oriented VRS DEA results show that the RDBs in Indonesia tended to work near the relative efficiency frontier during the period 2013–2022. In 270 bank-year observations, technical efficiency had a mean of 0.970. The annual distribution still shows significant cross-bank and intertemporal variation, meaning that a number of RDBs might have had fewer third-party funds, operating costs, and fixed assets but still recorded loans and incomes. Table 3 presents the annual distribution of input-oriented VRS DEA efficiency scores for Indonesian RDBs during 2013–2022, including the average efficiency level, variation across banks as reflected by the standard deviation, the lowest efficiency score observed in each year, and the number of RDBs operating on the efficiency frontier.

Table 3. Annual input-oriented VRS DEA efficiency, 2013-2022.

Year	Mean	Std. dev.	Minimum	Efficient RDBs
2013	0.9730	0.0503	0.80	17
2014	0.9689	0.0479	0.80	15
2015	0.9744	0.0406	0.87	17
2016	1.0000	0.0000	1.00	27
2017	0.9581	0.0695	0.75	17
2018	0.9570	0.0593	0.82	14
2019	0.9596	0.0655	0.71	15
2020	0.9456	0.0761	0.64	13
2021	0.9796	0.0354	0.89	17
2022	0.9844	0.0259	0.91	18

The efficiency remained relatively steady in 2013-2015. In 2016, all 27 RDBs were located on the border of the annual DEA. This outcome refers to relative efficiency in the sample and year under observation and not absolute efficiency in all aspects of operation. The average efficiency then dropped in 2017 and 2020 and was lowest in 2020. The mean was 0.9456, the minimum was 0.64, and the greatest cross-bank dispersion was recorded. The degradation was accompanied by a significant economic and operational impact in 2020, but the research design does not show a causal effect of the pandemic. The recovery was broad-based in 2021 and 2022, with efficiency regaining, minimum scores increasing, and reduced dispersion indicating efficiency.

4.2. Spatial Patterns and Diagnostic Results

The highest pairwise correlation was 0.4769 between NPL and CIR, below the 0.80 criterion. The VIF and tolerance results are reported in Table 4.

Table 4. Multicollinearity diagnostic results.

Variables	VIF	Tolerance
GRDP per capita	1.4335	0.6976
CAR	1.3385	0.7471
NPL	1.1459	0.8727
CIR	1.1076	0.9029
LDR	1.0886	0.9186

All VIF values are below 5, and all tolerance values exceed 0.10. The explanatory variables can therefore be included simultaneously without evidence of serious multicollinearity.

© 2026 Conscientia Beam. All Rights Reserved.

Table 5. Global Moran's I statistics for input-oriented efficiency, 2018-2022.

Year	Moran's I	p-value	Inference
2018	0.2389	0.0660	Significant at 10%
2019	0.0680	0.2215	Not significant
2020	0.1428	0.0888	Significant at 10%
2021	0.2924	0.0337	Significant at 5%
2022	0.0357	0.3210	Not significant

Table 5 presents the results of the Global Moran's I statistics used to assess spatial dependence in input-oriented efficiency among Indonesian RDBs during 2018-2022. Positive and statistically significant spatial autocorrelation was detected in 2018, 2020, and 2021, with the strongest association in 2021 (Moran's I = 0.2924). The positive but insignificant results for 2019 and 2022 show that clustering was not persistent in every year. Spatial dependence is therefore dynamic and may change with regional conditions, common shocks, and the diffusion of operational practices.

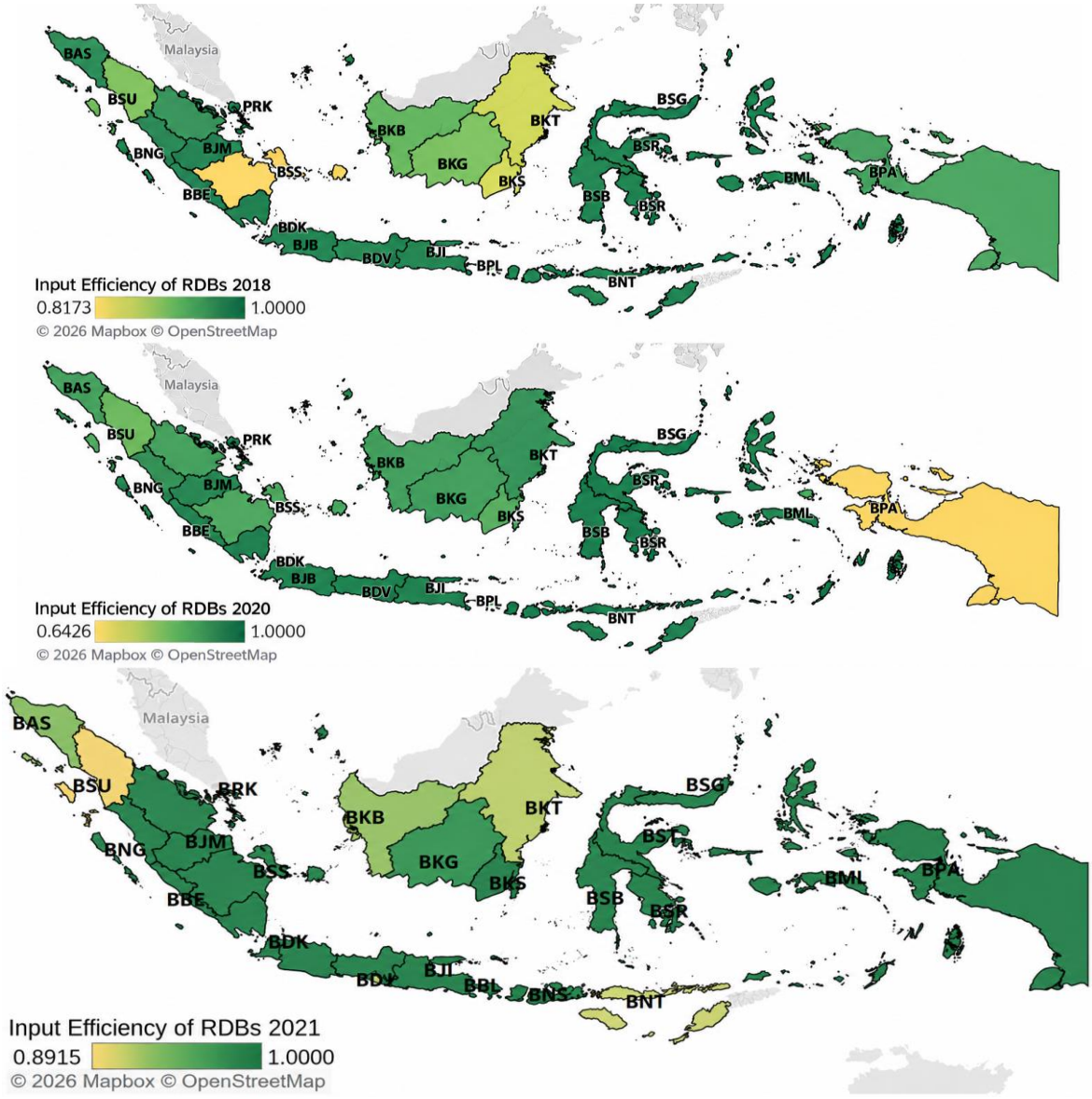

Figure 1. Spatial distribution of input-oriented RDB efficiency in years with significant Global Moran's I.

Note: Darker green denotes higher relative efficiency, while lighter yellow denotes lower relative efficiency.

© 2026 Conscientia Beam. All Rights Reserved.

Figure 1 illustrates the spatial distribution of input-oriented RDB efficiency across Indonesian provinces in the years with statistically significant Global Moran's I values. The figure highlights the geographical variation in relative efficiency levels, where darker green areas represent higher efficiency scores and lighter yellow areas indicate lower efficiency scores. The 2018 map shows lower-efficiency territories in parts of Sumatra and Kalimantan alongside neighboring regions with similarly high scores. In 2020, the sharpest decline occurred in Papua, consistent with the national minimum of 0.64 and wider dispersion in Table 3. The 2021 map shows broad recovery, although lower scores remained in parts of Sumatra, Kalimantan, and Nusa Tenggara. The spatial configuration therefore changed over time rather than following a fixed geographical divide.

Table 6. Descriptive comparison of selected spatial groups.

Group	Obs.	Mean	Std. dev.	Minimum	Frontier share
Selected contiguous RDBs	40	0.9965	0.0192	0.88	95.0%
Selected geographically dispersed RDBs	40	0.9370	0.0889	0.64	42.5%

Note: The contiguous group comprises Bank BJB, Bank DKI, Bank Jateng, and Bank Jatim. The geographically dispersed group comprises Bank Sumut, Bank Kaltimtara, Bank Papua, and Bank Maluku Malut. The comparison is descriptive and is not interpreted as a causal test.

Table 6 presents a descriptive comparison of efficiency characteristics between the selected contiguous group and the geographically dispersed comparison group, including mean efficiency, efficiency variation, minimum values, and frontier observations. The mean efficiency was higher, the dispersion was smaller, and the proportion of frontier observations was substantially larger in the selected contiguous group than in the geographically dispersed comparison group. This finding supports the graphical indication that connected-corridor banks may exhibit more similar and stable efficiency patterns. However, these spatial differences are descriptive and do not necessarily imply a causal relationship, as geographical proximity alone may not determine efficiency outcomes. Therefore, a further formal assessment was conducted using spatial econometric modelling. Table 7 presents the spatial model selection results by comparing the SAR Tobit and SEM Tobit specifications with the pooled Tobit benchmark. The likelihood ratio (LR) test indicates that the SAR Tobit model significantly improves the baseline pooled Tobit model (LR = 8.944; p = 0.0028), suggesting that spatial dependence through neighbouring efficiency patterns should be incorporated into the model. In contrast, the spatial error parameter (λ) in the SEM Tobit specification is statistically insignificant (p = 0.4067), indicating limited evidence of unobserved spatial error correlation. These results support the use of the SAR Tobit framework as the preferred specification for examining the determinants of RDB efficiency after controlling for relevant explanatory variables.

Table 7. Spatial model selection results.

Comparison/model	Test or parameter	Estimate/statistic	p-value	Decision
SAR Tobit versus pooled Tobit	LR statistic	8.944	0.0028	SAR improves the baseline model
SEM Tobit	Spatial-error parameter (λ)	−0.057	0.4067	Spatial error is not significant

4.3. Spatial Model Selection and Efficiency Dependence

Table 8 presents the estimation results of the pooled SAR Tobit model for input-oriented RDB efficiency, including the spatial lag coefficient, regional economic conditions, and bank-specific characteristics. The likelihood-ratio test indicates that the inclusion of the spatial lag of efficiency significantly improves the pooled Tobit model. In comparison, the SEM spatial-error parameter is not significant. The pooled SAR Tobit model is therefore the best choice, as spatial dependence is linked to neighboring efficiency rather than to spatially correlated unobserved disturbances.

© 2026 Conscientia Beam. All Rights Reserved.

This difference has a material impact. A significant SAR parameter indicates that an RDB's efficiency is systematically related to the weighted efficiency of contiguous RDBs. A very large SEM parameter would instead imply spatial correlation between omitted shocks. The findings confirm the former and not the latter mechanism.

Table 8. Pooled SAR Tobit estimates for input-oriented efficiency.

Variables	Symbol	Coefficient	Std. error	p-value
Intercept	C	0.831	0.034	<0.001
Spatial lag of efficiency	ρ	0.025	0.008	0.003
GRDP per capita	X_1	0.000	0.000	0.085
CAR	X_2	0.001	0.001	0.092
NPL	X_3	-0.007	0.002	<0.001
CIR	X_4	0.000	0.000	0.077
LDR	X_5	0.001	0.000	0.001
Log(scale)	ln(σ)	-3.000	0.043	<0.001

4.4. SAR Tobit Estimates and Discussion

The coefficient of the spatial lag is positive and statistically significant at the 1% level. Though small in scale, it shows that the index of latent efficiency of an RDB is systematically linked to the weighted efficiency of adjacent RDBs. The result follows Tobler (1970) geographical suggestion and the evidence of spatial interdependence in banking efficiency, productivity, scale economies, and lending behavior (Glass et al., 2020; Tabak et al., 2013; Zhao et al., 2020; Zhao et al., 2024). The relationship may operate in the Indonesian setting through competition, imitation, employee mobility, benchmarking, common shocks, and institutional cooperation. The low coefficient indicates that internal bank management is not replaced by spatial channels but is supplemented by them.

NPL has a negative and statistically significant coefficient. Problem loans diminish the productive use of lending assets and require additional resources for monitoring, provisioning, restructuring, collection, and recovery. This finding aligns with the bad-management and bad-luck mechanisms described by Berger and DeYoung (1997) and with evidence of reduced bank efficiency due to deteriorating asset quality (Phung et al., 2022; Widiarti et al., 2015).

LDR is positive and significant at the 1% level. Within the intermediation approach, RDBs are more likely to be closer to the frontier in cases where a higher proportion of mobilized deposits are mobilized into productive lending. This finding aligns with Indonesian data that focuses on intermediation (Marsondang et al., 2020; Puspasari et al., 2020; Sulaeman et al., 2019). This is not to be construed in support of unchecked growth of LDR, since over-lending could increase liquidity and credit risks.

GRDP per capita and CAR are very positive but only significant at the 10 percent level. GRDP offers poor evidence that regional economies with greater power increase transactions and credit demand, enabling current capacity to be utilized more efficiently (Garza-García, 2012). CAR indicates that capital buffers are capable of aiding in lending and absorption of losses; however, capital enhances efficiency only when it is converted into productive assets. The weak positive coefficient of CIR at the 10 percent level also needs to be taken with a grain of salt. The total costs already include a DEA input, and some operating expenditure could reflect a short-term investment in digitalization, service expansion, or risk-management systems instead of just inefficiency.

The tailored two-limit spatial Tobit routine would indicate the structural coefficients and spatial-dependence parameters. GRDP per capita, CAR, NPL, CIR, and LDR coefficients represent relationships with the latent efficiency index of the observed RDB territory. The neighboring-efficiency channel is reflected in the parameter ρ, and spatial dependence in unobserved disturbances is reflected in λ in the SEM. These are not the direct, indirect, and total marginal effects characterised in traditional linear spatial models. To achieve a complete decomposition of censored outcomes, extra post-estimation steps are needed to combine both spatial feedback and censoring probabilities; these are not produced by the estimator in this case.

© 2026 Conscientia Beam. All Rights Reserved.

5. CONCLUSION

This paper unites input-oriented VRS DEA, Moran's I, and pooled spatial Tobit models to investigate the technical efficiency of 27 Indonesian RDBs from 2013 to 2022. The average efficiency was high at 0.970; however, the time profile was uneven: efficiency decreased to 0.9456 in 2020 and then increased to 0.9844 in 2022. Moran's I identified significant positive clustering in 2018, 2020, and 2021.

The model-comparison evidence points to spatial dependence in neighboring efficiency rather than in spatially correlated disturbances. The SAR specification enhances the pooled Tobit baseline, and the value of ρ is positive and significant, but the value of λ (SEM) is not significant. This finding ought to be seen as a positive spatial correlation, which is in line with efficiency spillovers, rather than as a causal marginal impact. NPL is found to be negatively correlated with latent efficiency, and LDR is found to be positively correlated. GRDP per capita, CAR, and CIR provide less convincing evidence at the 10 percent level.

Theoretically, the study demonstrates that the efficiency of RDBs is embedded in geographically structured interdependence and does not depend solely on individual banks. It adds empirical evidence on temporal dynamics and contiguity-based clustering to the entire RDB population; contributes methodologically by integrating DEA with censored SAR and SEM Tobit comparisons; and contributes practically by demonstrating that internal risk and intermediation reforms ought to be accompanied by coordinated region-to-region learning.

The findings are limited in a number of ways. DEA is a relative, not an absolute, measure of efficiency, and it is also sensitive to the choice of inputs and outputs and the frontier against which efficiency is compared on an annual basis. The queen-contiguity matrix represents administrative adjacency, but not economic or institutional connections, and zero rows omit the impacts of proximity to isolated areas. The pooled model fails to account for unobserved bank effects, the customized estimator fails to produce a standard direct, indirect, and total marginal-impact decomposition, and the findings are correlational rather than causal. Future studies ought to experiment with alternative and time-varying weight matrices, construct robust censored spatial-panel estimators, estimate censoring-adjusted effects, and compare technical, cost, and profit efficiency.

6. POLICY IMPLICATIONS

OJK and ASBANDA ought to complement bank-by-bank supervision with regional benchmarking and organised peer learning. RDBs with strong credit evaluation, electronic systems, treasury functions, or branch optimisation may act as reference organisations for contiguous banks through cooperative training, work sharing, joint centres of excellence, and unified performance tabs.

RDB management is supposed to combine effective intermediation with stringent control of credit quality. The positive LDR coefficient facilitates the more productive conversion of deposits into lending, whereas the negative NPL coefficient indicates that growth not accompanied by proper screening, monitoring, early-warning systems, restructuring, and recovery can reverse efficiency advantages. LDR needs to be optimized, not maximized, by management and should be aligned with viable regional sectors and value chains in lending.

As the main shareholders, provincial governments ought to tie capital support to plausible business plans, governance enhancement, risk management, technological capacity, and quantifiable productive lending. Interprovincial collaboration can facilitate cross-boundary interoperable payments of public services, cross-boundary cybersecurity and data infrastructure, and cross-boundary financing programs, with transparent governance and data-protection policies.

The Island RDBs and territories that will not have any neighbors will also need a differentiated strategy, since their spatial-lag values will be zero by design. Geographical separation should be overcome through formal institutional networks, digital collaboration, and structured peer matching. Each RDB should retain accountability for the quality of assets, liquidity, capital, governance, and operations, but regional coordination will need to supplement these efforts.

© 2026 Conscientia Beam. All Rights Reserved.

Funding: This study received no specific financial support.
Institutional Review Board Statement: Not applicable.
Transparency: The authors confirm that this manuscript provides an honest, accurate, and transparent account of the research. All relevant aspects of the study have been reported, and any deviations from the original research plan have been appropriately disclosed. The study was conducted in accordance with relevant research and publication ethics guidelines.
Data Availability Statement: The data supporting the findings of this study are available from the corresponding author upon reasonable request.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

REFERENCES

Andries, A. M. (2011). The determinants of bank efficiency and productivity growth in the Central and Eastern European banking systems. *Eastern European Economics, 49*(6), 38-59. https://doi.org/10.2753/EEE0012-8775490603

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. *Management Science, 30*(9), 1078-1092. https://doi.org/10.1287/mnsc.30.9.1078

Berger, A. N., & DeYoung, R. (1997). Problem loans and cost efficiency in commercial banks. *Journal of Banking & Finance, 21*(6), 849-870. https://doi.org/10.1016/S0378-4266(97)00003-4

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429-444. https://doi.org/10.1016/0377-2217(78)90138-8

Dewi, E. R. (2024). The influence of bank size, loan-to-deposit ratio, and capital adequacy ratio on the efficiency level of conventional banks in Indonesia. *INKUBIS: Jurnal Ekonomi dan Bisnis, 6*(1), 1-7. https://doi.org/10.59261/inkubis.v6i1.81

Elhorst, J. P. (2014). Spatial panel data models. In *Spatial econometrics: From cross-sectional data to spatial panels* (pp. 37–93). Berlin, Germany: Springer.

Fang, Y., Jing, Z., Shi, Y., & Zhao, Y. (2021). Financial spillovers and spillbacks: New evidence from China and G7 countries. *Economic Modelling, 94*, 184-200. https://doi.org/10.1016/j.econmod.2020.09.022

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society. Series A (General), 120*(3), 253–281.

Garza-García, J. G. (2012). Determinants of bank efficiency in Mexico: A two-stage analysis. *Applied Economics Letters, 19*(17), 1679-1682. https://doi.org/10.1080/13504851.2012.665589

Glass, A. J., Kenjegaliev, A., & Kenjegalieva, K. (2020). Spatial scale and product mix economies in US banking with simultaneous spillover regimes. *European Journal of Operational Research, 284*(2), 693-711. https://doi.org/10.1016/j.ejor.2019.12.036

Hadad, M. D., Santoso, W., Ilyas, D., & Mardanugraha, E. (2003). *Efficiency analysis of the Indonesian banking industry: Application of the non-parametric Data Envelopment Analysis (DEA) method.* Jakarta, Indonesia: Bank of Indonesia.

LeSage, J. P. (1999). *The theory and practice of spatial econometrics.* Toledo, OH: University of Toledo.

Marsondang, A., Purwanto, B., & Mulyati, H. (2020). Measurement of efficiency and analysis of the internal and external bank factors influencing it. *Jurnal Manajemen dan Organisasi, 10*(1), 48-62. https://doi.org/10.29244/jmo.v10i1.28860

Pambuko, Z. B. (2016). Determinants of Sharia banking efficiency levels in Indonesia: Two-stage data envelopment analysis. *Cakrawala: Jurnal Studi Islam, 11*(2), 178-194.

Phung, Q. T., Van Vu, H., & Tran, H. P. (2022). Do non-performing loans impact bank efficiency? *Finance Research Letters, 46*, 102393. https://doi.org/10.1016/j.frl.2021.102393

Puspasari, A., Priyarsono, D. S., & Sasongko, H. (2020). Bank specific factors affecting the efficiency of regional development banks. *Jurnal Ilmiah Manajemen Fakultas Ekonomi, 6*(2), 171–186. https://doi.org/10.34203/jimfe.v6i2.2325

Puspita, H. S., & Shofawati, A. (2019). Determinants of the efficiency level of Sharia regional development banks (BPD) in Indonesia: Two-stage data envelopment analysis. *Jurnal Ekonomi Syariah Teori dan Terapan, 5*(10), 804-819. https://doi.org/10.20473/vol5iss201810pp804-819

© 2026 Conscientia Beam. All Rights Reserved.

Qu, X., & Lee, L.-F. (2012). LM tests for spatial correlation in spatial models with limited dependent variables. *Regional Science and Urban Economics*, *42*(3), 430-445. https://doi.org/10.1016/j.regsciurbeco.2011.11.001

Řepková, I. (2015). Banking efficiency determinants in the Czech banking sector. *Procedia Economics and Finance*, *23*, 191-196. https://doi.org/10.1016/S2212-5671(15)00367-6

Rozzani, N., & Abdul Rahman, R. (2013). Determinants of bank efficiency: Conventional versus Islamic. *International Journal of Business and Management*, *8*(14), 98–109. https://doi.org/10.5539/ijbm.v8n14p98

Satyagraha, F. T., Purwono, R., & Sari, D. W. (2022). An analysis of the performance of Regional Development Banks (RDB) in Indonesia: Stochastic frontier analysis approach. *Economies*, *10*(9), 228. https://doi.org/10.3390/economies10090228

Sealey, J. C. W., & Lindley, J. T. (1977). Inputs, outputs, and a theory of production and cost at depository financial institutions. *The Journal of Finance*, *32*(4), 1251-1266. https://doi.org/10.1111/j.1540-6261.1977.tb03324.x

Sulaeman, H. S. F., Moelyono, S. M., & Nawir, J. (2019). Determinants of banking efficiency for commercial banks in Indonesia. *Contemporary Economics*, *13*(2), 205–218. https://doi.org/10.5709/ce.1897-9254.308

Tabak, B. M., Miranda, R. B., & Fazio, D. M. (2013). A geographically weighted approach to measuring efficiency in panel data: The case of US saving banks. *Journal of Banking & Finance*, *37*(10), 3747-3756. https://doi.org/10.1016/j.jbankfin.2013.05.022

Tobler, W. R. (1970). A computer movie simulating urban growth in the Detroit region. *Economic Geography*, *46*, 234-240. https://doi.org/10.2307/143141

Widiarti, A. W., Siregar, H., & Andati, T. (2015). The determinants of bank's efficiency in Indonesia. *Bulletin of Monetary Economics and Banking*, *18*(2), 129-156. https://doi.org/10.21098/bemp.v18i2.520

Zahra, N., & Darwanto, D. (2019). The determinant of banking efficiency (Data envelopment analysis based on intermediation approach). *Jurnal Ekonomi Pembangunan: Kajian Masalah Ekonomi Dan Pembangunan*, *20*(1), 87-99. https://doi.org/10.23917/jep.v20i1.5799

Zhao, B., Kenjegalieva, K., Wood, J., & Glass, A. (2020). A spatial production analysis of Chinese regional banks: case of urban commercial banks. *International Transactions in Operational Research*, *27*(4), 2021-2044. https://doi.org/10.1111/itor.12732

Zhao, B., Tian, Y., Kenjegalieva, K., & Wood, J. (2024). Measuring the productivity of urban commercial banks in China. *International Review of Economics & Finance*, *93*, 477-489. https://doi.org/10.1016/j.iref.2024.05.029

Zhou, X., & An, Z. (2016). *The determinants of the efficiency of commercial banks*. Paper presented at the Proceedings of the First International Conference Economic and Business Management 2016, Paris, France: Atlantis Press.

Zunairoh, Z., Wijaya, L. I., Mahadwartha, P. A., & Murhadi, W. R. (2023). Regional development bank competition: Evidence from Indonesia. *Jurnal Keuangan dan Perbankan*, *27*(1), 33-44. https://doi.org/10.26905/jkdp.v27i1.9414

Views and opinions expressed in this article are the views and opinions of the author(s), The Economics and Finance Letters shall not be responsible or answerable for any loss, damage or liability etc. caused in relation to/arising out of the use of the content.

© 2026 Conscientia Beam. All Rights Reserved.