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An Evaluation of Development Bank Efficiency and Its Determinants: A Two-Stage DEA Approach

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Abstract

Purpose: This study evaluates the efficiency of development banks worldwide and identifies its determinants, focusing on whether multilateral development banks differ in efficiency from multilateral development banks.

Research Methodology: Using S&P Global financial data on 98 development banks across five regions from 2010 to 2024, the study applies a two stage approach. Output oriented Data Envelopment Analysis (DEA) under constant returns to scale estimates technical efficiency, and bootstrapped tobit regression examines institutional type, net interest margin, bank size, loan to deposit ratio, nonperforming loans and return on assets as determinants.

Results: The average efficiency score of 0.569 indicates substantial input slack, as banks could reduce inputs by 43.1% without lowering outputs. Multilateral development banks are significantly less efficient than national counterparts, reflecting governance complexity across jurisdictions. Bank size and the loan to deposit ratio have strong positive effects, whereas net interest margin and return on assets are insignificant. Unexpectedly, nonperforming loans are positively associated with efficiency, suggesting that socially oriented lending to riskier borrowers can enhance developmental impact.

Conclusion: Structural balance sheet characteristics, rather than conventional profitability metrics, primarily drive the efficiency of development banks.

Limitation: The analysis relies on a single DEA and tobit framework and on financial indicators of individual banks, without accounting for statistical noise, macroeconomic dynamics or climate and green investments.

Contribution: The study offers evidence from multiple regions comparing multilateral and national development banks within a unified framework, with policy implications for governance reform, liquidity management and scale strategies.

Keywords: *Banking Efficiency, Development Banks, DEA, Non-Performing Loans, Tobit Regression*

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1. Introduction

As distinctive public financial institutions, development banks play a pivotal role in addressing market failures by providing long-term financing for high-risk development projects that commercial banks typically avoid due to profit concerns, such as infrastructure, education, agriculture, and climate change (Griffith-Jones & Ocampo, 2018). Beyond their financial function, development banks also serve as crucial policy instruments, contributing to the achievement of the Sustainable Development Goals (SDGs) through concessional financing for social and environmental projects (Hu et al., 2022;

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Marodon, 2022). In the context of many countries seeking effective public finance solutions to foster economic recovery and sustainable transformation, the role of development banks has become increasingly vital and widely recognized in policy-making.

Therefore, assessing the efficiency of development banks should be regarded as a prerequisite, yet it remains insufficiently explored. Given their dual objectives of ensuring financial performance while simultaneously pursuing developmental goals-the evaluation of these institutions' efficiency is inherently complex, and traditional financial indicators such as ROA or CIR cannot be directly applied (Xu et al., 2021). One effective approach in bank efficiency assessment is the two-stage Data Envelopment Analysis (two-stage DEA), a widely adopted analytical framework in efficiency studies, particularly within banking and finance. This approach enables a distinction between efficiency stemming from the transformation of inputs into outputs and that influenced by environmental factors, thereby offering a more comprehensive and nuanced assessment of performance (Badunenko & Tauchmann, 2019; Wanke et al., 2016).

While the efficiency of commercial banks has been extensively examined across various contexts, the performance of development banks remains a relatively underexplored area in the academic literature (Xu et al., 2021). With the dual mission of maintaining financial sustainability while pursuing socio-economic development objectives, development banks operate under a far more complex framework than profit-oriented commercial banks. Therefore, conventional financial indicators such as Return on Assets (ROA) and Cost-to-Income Ratio (CIR), which are designed to capture profitability and operational efficiency in competitive markets, fail to accurately reflect the true performance of these institutions (Gil-Jardón et al., 2024; Xu et al., 2021). Moreover, although factors such as ROA, Net Interest Margin (NIM), bank size (SIZE), Loan-to-Deposit Ratio (LDR), Non-Performing Loans (NPL), and CIR have been widely recognized as key determinants of financial performance in commercial banks, their mechanisms of influence within development banks may differ substantially due to variations in institutional objectives, governance structures, and policy environments (Hu et al., 2022; Lutfi & Suyatno, 2019; Satyagraha et al., 2022). However, this distinction has not yet been adequately addressed in existing studies. Clarifying these differences in the underlying mechanisms of performance determinants is therefore essential to extend the theoretical framework of bank efficiency and to provide empirical evidence that can inform policies aimed at enhancing the efficiency of development banks in achieving their developmental mandates.

For development banks, the number of studies on efficiency remains relatively limited compared to commercial banks. The main reason lies in the distinctive operational models and objectives of development banks, which make it difficult to directly apply assessment frameworks designed for commercial banks. Moreover, data on the operations and performance of development banks are often opaque or rarely disclosed, resulting in short data series and a limited number of analytical variables. According to Xu et al. (2021), many development banks are not obliged to report performance according to market standards, forcing researchers to rely on internal reports or data from international organizations such as the World Bank or Organisation for Economic Co-operation and Development (OECD), which are constrained in terms of granularity. Some notable studies have sought to overcome this limitation by developing evaluation criteria that combine financial efficiency with developmental impact. For instance, Abidin et al. (2021) in Indonesia compared the efficiency of commercial banks and regional development banks, finding that development banks typically exhibited lower efficiency and were significantly affected by factors such as ROA and NPL ratios. In such research, the two-stage DEA model has been regarded as a comprehensive analytical tool for efficiency assessment. Nevertheless, existing studies still face certain limitations, such as short data spans, exclusion of large-scale banks, and the lack of consideration for macroeconomic or local contextual factors. This gap underscores the need for more comprehensive studies that both measure efficiency and explore its determinants in development banks. Building on this gap, the present study extends the analysis by measuring the efficiency of development banks worldwide using the Two-Stage DEA method, examining whether institutional type [Multilateral Development Banks (MDBs) vs National Development Banks (NDBs)] and bank-level factors, namely NIM, SIZE, LDR, NPL and

ROA, are associated with efficiency, and drawing policy implications to enhance operational performance and strengthen the role of development banks in the economy.

This study contributes to advancing the theoretical and practical governance framework of development banks in three main dimensions. First, it clarifies the concept of "efficiency" in development banks under the dual objectives of achieving both financial sustainability and developmental impact. It also classifies the determinants of efficiency into three major groups. The first group concerns balance sheet structure, which SIZE, LDR and capital adequacy. The second group relates to asset quality, represented by NPL. The third group comprises profitability indicators, namely ROA and NIM. In doing so, the study also takes into account institutional differences between MDBs and NDBs. Second, regarding empirical evidence, the study constructs and harmonizes a multi-regional dataset of 98 development banks covering the period 2010-2024, and conducts a systematic comparison between MDBs and NDBs within a unified measurement framework. The variable multilateral is employed in the second-stage analysis to capture institutional type when examining the determinants of efficiency. The study further tests the effects of structural indicators (SIZE, LDR), asset quality (NPL), and profitability measures (ROA, NIM). The results show that MDBs are less efficient than NDBs, SIZE and LDR have positive effects, while ROA and NIM are statistically insignificant; NPL exhibits a positive coefficient. Third, in terms of policy and practice, the findings are translated into operational recommendations, emphasizing the prioritization of appropriate monitoring indicators, optimization of balance sheet structure and liquidity discipline, and strengthening of credit risk management to enhance the developmental effectiveness of these banks.

2. Literature Review and Hypothesis/es Development

2.1 Theoretical framework of development banks

Unlike commercial banks, development banks possess distinct characteristics as their operations are non-profit and inherently linked to social missions. Consequently, development banks often face challenges in balancing financial efficiency with the social objectives they pursue. Therefore, the efficiency of development banks should be assessed from multiple perspectives. Bank efficiency comprises four dimensions: technical efficiency (the optimal use of inputs), scale efficiency (cost advantages from increased scale), price efficiency (minimizing input costs without reducing output quality), and allocative efficiency (selecting an optimal input–output mix at given prices) (Ahmad et al., 2020; Fukuyama et al., 2020).

To date, numerous studies have examined the impact of various factors on bank efficiency in general and on the efficiency of development banks in particular. Abidin et al. (2021) found that return on assets exerts a positive and significant influence on both small- and medium-sized development banks, while the non-performing loans ratio negatively affects the technical efficiency of medium-sized development banks. This implies that banks with higher ROA achieve greater efficiency because efficient banks are capable of generating higher profits. Conversely, when the non-performing loans ratio increases, banks incur additional costs to resolve bad loans, which in turn reduces efficiency. Similarly, Lutfi and Suyatno (2019), using a two-stage DEA and panel regression approach, showed that capital and the loan-to-deposit ratio positively affect the efficiency of regional development banks. By contrast, the NPL ratio has a negative effect, reducing the efficiency of development banks. Furthermore, Herdhayinta and Rudolfus (2019) demonstrated that factors such as total assets (bank size), LDR, NIM, and central bank interest rate positively affect the profitability of regional development banks. In contrast, operating expenses to operating income, inflation, total core capital, and capital adequacy ratio show negative relationships with the profitability of development banks. Milenkovic et al. (2022) also found that bank size positively influences efficiency, whereas bank type and Merger and Acquisition (M&A) activity exert negative effects.

Overall, two main approaches have been employed to measure bank efficiency, namely the accounting approach and the econometric approach (Ahmad et al., 2020). The accounting approach relies on financial ratios such as ROA, Return on Equity (ROE), and the current ratio, and primarily evaluates

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organizational efficiency using historical data. In contrast, the econometric approach employs mathematical and statistical models to estimate technical efficiency or profit frontiers and is more complex than the accounting approach. Econometric methods are generally divided into two groups, namely parametric methods, such as Stochastic Frontier Analysis (SFA), the Thick Frontier Approach (TFA) and the Distribution Free Approach (DFA), and non-parametric methods, such as DEA and Free Disposal Hull (FDH). Parametric methods employ cost, production, or revenue functions to estimate production technology and have the advantage of separating inefficiency from random noise (Badunenko & Kumbhakar, 2016; Lai & Kumbhakar, 2018). However, these methods depend heavily on assumptions regarding functional forms and error distributions; if these assumptions are violated, the results may be biased or misleading (Guo et al., 2018; Sakouvogui et al., 2021). By contrast, non-parametric methods mainly rely on linear programming and do not impose a specific functional form (Kaffash & Marra, 2017).

Among non-parametric approaches, DEA has become the most widely used in bank efficiency research. DEA applies linear programming techniques to estimate relative efficiency based on multiple inputs and outputs. Its basic assumption is isotonicity, meaning that increases in inputs may reduce efficiency while increases in outputs may improve efficiency. In cases where the opposite occurs, that is, when increases in outputs reduce efficiency or increases in inputs enhance efficiency, this is termed anti-isotonicity. To address such "undesirable" variables, DEA minimizes outputs and maximizes inputs (Halkos & Petrou, 2019). Although DEA lacks a stochastic component and thus treats all deviations as inefficiency, which makes it sensitive to noise, measurement errors, and outliers (Olesen & Petersen, 2016), its major advantage lies in not requiring a specific functional form, thereby offering greater flexibility with real-world data compared to parametric methods (Ahmad et al., 2020). Moreover, DEA has proven effective for analyzing complex production processes (Henriques et al., 2020), allowing simultaneous handling of multiple inputs and outputs to determine the efficiency frontier and identify best-performing units (Kaffash & Marra, 2017). It also provides quantitative insights into the amount of redundant resources that should be reduced or potential outputs that could be achieved if units operated at optimal efficiency (Aggelopoulos & Georgopoulos, 2017). Owing to these advantages, DEA is considered a suitable tool for measuring efficiency in the context of development banks, which operate under multiple objectives and social constraints, and it is the most frequently applied method in banking research (Emrouznejad & Yang, 2018).

Despite the widespread application of DEA in assessing the efficiency of financial institutions, many studies continue to apply DEA solely as a single-stage method to measure technical efficiency without further examining the relationship between efficiency and its determinants, leaving conclusions more descriptive than explanatory. Furthermore, since different types of banks pursue different objectives - either profit-oriented or socially oriented - many studies have yet to design efficiency models that incorporate input–output variables aligned with the distinctive missions of each bank type. In particular, the failure to adjust models for the efficiency of development banks risks producing biased evaluations of their performance.

2.2 Theoretical framework of banking efficiency

Banking efficiency refers to the extent to which a banking institution effectively utilizes its available resources to generate maximum feasible output while minimizing operational frictions (Ahmad et al., 2020). Within the broader financial system, efficiency is not limited to cost minimization but also reflects a bank's strategic adaptability, governance quality and responsiveness to evolving market dynamics (Bueno et al., 2024). In this regard, efficiency is closely tied to a bank's internal decision-making structure and its response to external institutional and market pressures (Ullah et al., 2023). While persistent inefficiency within banks has been empirically linked to elevated risk-taking behavior, thereby amplifying systemic vulnerabilities and undermining prudential oversight (Chepngenoh & Muriu, 2020). As such, enhancing efficiency is not merely a managerial imperative but a central concern for regulators and monetary authorities.

While the conceptual framework of banking efficiency applies across institutional forms, its relevance acquires distinct dimensions in the context of development banks, which are publicly owned or policy-mandated entities tasked with allocating capital to sectors neglected by market-based finance (Ocampo & Ortega, 2022). Unlike commercial banks, development banks are designed to absorb greater levels of risk, offer concessional financing, and operate with longer investment horizons in pursuit of structural transformation and social objectives (Griffith-Jones, 2022). These institutions pursue a dual mandate of achieving financial viability while fulfilling long-term developmental goals such as infrastructure financing, industrial upgrading, and climate resilience (Zhang, 2022). This duality introduces distinct governance and operational trade-offs, making the assessment of efficiency especially critical. Accordingly, a deeper examination of efficiency determinants in development banking is essential not only for evaluating institutional performance but also for strengthening governance mechanisms, enhancing resource allocation and improving the developmental impact of policy-based finance.

2.3 Institutional structure and banking efficiency: multilateral versus national development banks

Multinational development banks, such as the Asian Development Bank and the African Development Bank, are supranational financial institutions that operate across multiple sovereign jurisdictions. They mobilize pooled resources to finance projects that address common regional challenges while tailoring interventions to the specific needs of member countries (Ocampo & Ortega, 2022). Their mandates often encompass promoting climate resilience, supporting disaster-resilient infrastructure and enhancing capacity building (Bazbauers & Engel, 2021). In contrast, national development banks operate exclusively within a single country, aligning their strategies closely with domestic policy priorities and macroeconomic conditions. This narrower governance scope enables them to adapt more readily to the domestic business cycle and to respond more quickly to national economic shocks (Akyuwen et al., 2019).

The fundamental institutional difference between these two banking models lies in their governance complexity. Multilateral development banks operate under multi-country governance structures with diverse political interests, which can slow decision-making processes and reduce operational agility (Humphrey, 2020; Wang, 2017). This governance complexity, which stems from the need to coordinate multiple principals with potentially divergent objectives, may introduce inefficiencies in resource allocation and project execution (Creutz, 2023). Conversely, national development banks, governed solely by their host country's policy framework, benefit from streamlined decision-making and greater flexibility in responding to domestic economic shocks (Akyuwen et al., 2019). These structural differences raise important empirical questions about relative efficiency.

Prior empirical studies in the banking literature suggest that these structural differences should translate into measurable efficiency differentials. Andrieș et al. (2018); Shaban and James (2018) and Patra et al. (2023) document that institutional classification systematically predicts banking efficiency in multiple contexts. Despite the theoretical basis for such differences, empirical evidence comparing the efficiency of MDBs and NDBs remains scarce. This study addresses this gap by investigating whether multilateral development banks exhibit higher or lower banking efficiency compared to national development banks. By adopting a multilateral dummy variable in the second stage of our analysis, this research contributes to our understanding of how institutional structure shapes operational efficiency in development finance.

Accordingly, the study proposes the following hypothesis:

Whether multilateral development banks exhibit higher or lower operational efficiency compared to national development banks

2.4 Bank-specific determinants and hypothesis development

Net Interest Margin (NIM) serves as a critical indicator of a bank's ability to manage interest-bearing assets and sustain profitability from core operations. A higher NIM typically signals greater efficiency

in transforming funding into interest-generating assets, as well as effective pricing and credit allocation practices (Islam & Nishiyama, 2016). However, the empirical literature presents divergent views on the efficiency implications of elevated NIM levels. On one hand, Sulaeman et al. (2019) suggest that high margins may stem from risk overpricing or inefficiencies in funding structures, particularly in markets with heightened credit risk or volatility. On the other hand, Maji and Saha (2024) and Takahashi and Vasconcelos (2024) find that wider interest spreads are conducive to improving cost efficiency and profitability. Against this backdrop, the present study incorporates NIM to empirically examine its effect on bank efficiency.

H_2: Net interest margin has a positive effect on the efficiency of development banks

Bank size, commonly proxied by total assets, constitutes a critical structural determinant of institutional performance. It reflects a bank's capacity to expand market reach, secure funding advantages and embed within systemic financial networks. The theory of economies of scale posits that as bank size increases, average production costs decline due to the spreading of overhead expenses, such as personnel, IT infrastructure, compliance and marketing, across a broader operational base, thereby enhancing profitability and strategic resilience (Blatter & Fuster, 2022). These structural advantages allow large banks to invest more effectively in innovation and absorb competitive pressures, which may translate into superior operational efficiency. Empirically, a substantial body of literature reports a robust positive association between bank size and banking efficiency. Larger banks are frequently found to exhibit higher technical efficiency, underpinned by superior governance, better risk-adjusted returns and more efficient intermediation processes (Benbachir, 2025; Diko, 2024; Istaiteyeh et al., 2024; Maji & Saha, 2024; Pasha, 2024). Building on this theoretical rationale and empirical consensus, the present study employs bank size in the model.

H_3: Bank size has a positive effect on the efficiency of development banks

The Loan-to-Deposit Ratio (LDR) is a widely recognized metric of asset transformation efficiency, reflecting the degree to which mobilized customer deposits are channeled into interest-generating loans. A higher LDR is theoretically posited to indicate more efficient capital deployment, as it reflects a bank's ability to maximize interest income while minimizing idle liquidity (Jatmiko, 2025). Empirical evidence has consistently confirmed a positive association between LDR and banking efficiency, with higher LDRs often linked to superior technical and profit efficiency resulting from improved resource utilization and reduced capital underuse (Abidin et al., 2021; Benbachir, 2025; Sulaeman et al., 2019). However, surpassing prudent LDR thresholds may precipitate financial vulnerabilities, including excessive credit expansion, inflationary pressure and increased exposure to liquidity risk (Adenuga et al., 2021). Accordingly, this study incorporates LDR to assess its effect on the operational efficiency of development banks.

H_4: The loan-to-deposit ratio has a positive effect on the efficiency of development banks

Non-Performing Loans (NPL) represent a critical indicator of credit portfolio quality and are widely used to assess the effectiveness of banks' credit risk management systems. From a theoretical standpoint, elevated NPL ratios are indicative of deteriorating asset quality, increased loan-loss provisions and diminished interest income (Alam, 2024). Many of empirical studies report a robust negative association between NPL and bank efficiency, attributing this relationship to deficiencies in credit screening, monitoring and recovery practices (Diko, 2024; Joaquim et al., 2024; Sulaeman et al., 2019). However, some recent findings offer alternative interpretations, noting that in specific institutional contexts - followed by aggressive growth strategies or risk-seeking behavior - higher NPL may not necessarily imply lower efficiency and might reflect a calculated risk-return trade-off (Abidin et al., 2021; Benbachir, 2025; Ganefi et al., 2024). Accordingly, this study incorporates NPL to quantify its impact on the operational efficiency of development banks.

H_5: Non-performing loans have a negative effect on the efficiency of development banks

Return on Assets (ROA) is a fundamental profitability metric reflecting a bank's capacity to generate net income relative to its total asset base. In the context of development banks, where institutions must

reconcile profitability objectives with regulatory and developmental mandates, ROA is particularly salient as it captures both financial performance and asset utilization effectiveness. Empirical research has consistently established a positive linkage between ROA and bank efficiency, highlighting that institutions with stronger return profiles tend to operate with more cost-effective structures, greater earnings stability and improved resilience to adverse market conditions (Benbachir, 2025; Ganefi et al., 2024; Istaiteyeh et al., 2024; Joaquim et al., 2024; Pasha, 2024; Takahashi & Vasconcelos, 2024). Anchored in this empirical consensus and theoretical relevance, this study incorporates ROA to estimate its effect on the efficiency of development banks.

H₆: Return on assets has a positive effect on the efficiency of development banks

3. Research Methodology

3.1 Control variable

Based on the hypotheses developed, the second-stage model examines institutional type (MDB) together with five bank-specific variables, namely NIM, SIZ, LDR, NPL and ROA, as determinants of Bank Efficiency (EFF). The definitions, measurements, expected signs and supporting references of these variables are summarised in Table 1.

Table 1. Variable specification

Variable	Notation	Measurement	Expected Sign	Reference
Bank Efficiency	EFF	First-stage DEA		
Mulitilateral Development Bank	MDB	1 for multinational banks, 0 for national banks	-	
Net Interest Margin	NIM	Formula 1 : $\frac{Netinterestincome}{Earningassets}$		
Bank Size	SIZ	Formula 2: $ln_{(Totalassets)}$		
Loans-to-Deposit Ratio	LDR	Formula 3: $\frac{Netloans}{Totaldeposits}$	+	Sulaeman et al. (2019); Abidin et al. (2021); Benbachir (2025)
Non-Performing Loans	NPL		–	Sulaeman et al. (2019); Joaquim et al. (2024); Diko (2024); Ganefi et al. (2024); Benbachir (2025)
Return on Assets	ROA	Formula 4: $\frac{Netincome}{Totalassets}$	+	Abidin et al. (2021); Istaiteyeh et al. (2024); Joaquim et al. (2024); Ganefi et al. (2024); Pasha (2024); Takahashi and Vasconcelos (2024); Benbachir (2025)

3.2 Data

Table 2. Analysed development banks

Region	Number of Banks	Percentage of Banks
Asia-Pacific	34	34.7%
Western European, Northern American and other States*	28	28.6%
Latin American and Caribbean States	17	17.3%
Africa	13	13.3%
Eastern European	6	6.1%

Region	Number of Banks	Percentage of Banks
Total	98	

Based on Table 2, the final sample consists of 98 development banks, with the highest concentration located in the Asia-Pacific region. This study employs a financial dataset of development banks randomly collected on a global scale. After filtering out entities that do not conform to the definition of development banks and those with insufficient information for analytical purposes, 98 development banks remained for analysis. The analysis covers the period from 2010 to 2024, as earlier years were excluded due to limited data availability. Financial information for the development banks was obtained from the S&P Global database.

This study employs a financial dataset of development banks randomly collected on a global scale. After screening out entities that do not align with the definition of development banks and those with insufficient information for analytical purposes, the final sample consists of 98 development banks, with the highest concentration located in ABC. The analysis covers the period from 2010 to 2024, as data prior to 2010 were excluded due to limitations in data availability. Financial information on development banks was obtained from the S&P Global database.

3.3 Methodology

3.3.1 Data Envelopment Analysis

Data Envelopment Analysis (DEA) is employed to measure the relative efficiency of development banks in transforming financial resources into developmental outputs. The analysis is conducted in R Studio using an output-oriented Constant Returns to Scale (CRS) model, which evaluates how effectively each bank expands its outputs given a fixed level of inputs. This orientation aligns with the operational mission of development banks, emphasizing output maximization in support of economic and social objectives rather than strict input minimization. The CRS assumption is appropriate in this context because these institutions operate under comparable mandates and policy frameworks, allowing proportional scaling between inputs and outputs. DEA non-parametric nature avoids imposing a predefined functional form on the production frontier, making it suitable for assessing performance across banks with heterogeneous operating conditions. The resulting efficiency scores, ranging between zero and one, serve as the dependent variable for the second-stage analysis.

3.3.2 Bootstrapped Tobit Regression

Given that the DEA efficiency scores are censored within the range between 0 and 1, and often cluster at unity, standard linear models such as OLS are unsuitable due to bias and inconsistency in parameter estimation. To overcome this limitation, a Tobit regression model is estimated using Stata 17 to identify the determinants of efficiency among development banks. The Tobit framework assumes a latent efficiency variable that is only partially observed, allowing it to account for the bounded nature of DEA scores while producing consistent and interpretable results. This approach has become standard in two-stage DEA analyses because it appropriately models the limited dependent variable and recognizes that some institutions operate at full efficiency. Bootstrapped standard errors are applied to enhance the robustness and accuracy of the inference.

4. Results and Discussions

4.1 Descriptive

Table 3. Descriptive statistics

Variable	Variable	Obs	Mean	Std. Dev.	Min	Max
DEA Inputs	DEP	1062	5447542.5	18112661	2.176	2.210e+08
DEA Inputs	FXA	1397	134852.79	433072.99	31.723	4237514.7
DEA Inputs	EQT	1441	8086872.5	21902497	9171.778	1.903e+08
DEA Outputs	LOA	1434	38506638	1.174e+08	19126.181	1.186e+09

Variable	Variable	Obs	Mean	Std. Dev.	Min	Max
DEA Outputs	SEC	1370	12867598	37731496	4.024	4.178e+08
Efficiency Score	EFF	1011	0.569	0.352	0.054	1
Efficiency Determinants	REG	1470	0.184	0.387	0	1
Efficiency Determinants	NPL	1103	8.258	12.446	.002	94.726
Efficiency Determinants	ROA	1340	1.008	4.637	-37.151	139.814
Efficiency Determinants	LDR	1049	329.005	2070.005	0.211	24017.18
Efficiency Determinants	SIZ	1440	15.698	2.241	10.698	21.063
Efficiency Determinants	NIM	1269	2.904	3.435	-5.823	33.424

Descriptive statistics are presented in Table 3. Since DEA constructs an efficiency frontier by solving linear programming problems across all Decision-Making Units (DMUs), every DMU must not have missing values for their inputs and outputs. Therefore, only 1011 observations of efficiency score are calculated. The mean EFF value of 0.569 suggests that, on average, the sampled development banks are operating at 56.9% efficiency, or the average bank could reduce its inputs by 43.1% while maintaining the same output levels, if it is optimized. The relatively high standard deviation of 0.352 and the extremely low value of the minimum value, 0.054, suggest that the efficiency scores of the sampled banks experience significant volatility, and a notable number of banks are clustered at, and near, the efficiency frontier. The mean value of REG being 0.184 indicates that multilateral banks take up 18.4% of the sample, approximately 18 out of the 98 banks.

4.2 Discussion

The Tobit regression results reveal that the variable REG has a negative and highly statistically insignificant impact on the performance of Multilateral Development Banks (MDBs) during the study period, a result that fails to support H_1. This means that MDBs tend to operate less efficiently compared to National Development Banks (NDBs) or Regional Development Banks (RDBs). Based on the study of Kellerman (2019), this may be due to the fact that MDBs operate across many countries with significant differences in legal environments, economic, political, cultural, and social conditions, thereby making governance processes more complex and organizational structures more duplicative, which in turn leads to higher operating costs. Meanwhile, RDBs operate within a limited region or country, and their capital sources mainly come from low-cost funds provided by local governments, which help reduce administrative and logistics costs, thereby increasing their performance (Satyagraha et al., 2022). In addition, the regression results are consistent with the study of Kersting and Kilby (2016), according to which, complex governance structures and multinational political constraints often make the decision-making process of MDBs less flexible, and capital allocation objectives are heavily influenced by political or diplomatic factors, limiting their ability to exploit economies of scale and allocate resources efficiently.

The findings show that the variable NPL has a positive coefficient and is statistically significant at the 5% level, implying that higher non-performing loan ratios are associated with higher measured efficiency in the study, thereby failing to support H_5. This relationship goes against the conventional expectation that higher NPLs reduce efficiency. However, for development banks that operate with social objectives and often lend to clients who cannot access funds from commercial banks or other financial institutions, or take on high-risk but strategic projects that create long-term development impacts such as infrastructure or credit for disadvantaged regions, these projects may increase the reported NPL ratio but improve the overall performance of development banks (Mazzucato & Penna, 2016). This trend is consistent with the studies of Fernández-Arias et al. (2020) when analyzing the performance of development finance institutions, arguing that efficiency in terms of development criteria does not necessarily align with asset quality by commercial standards.

It is observed that the variable ROA has a negative coefficient and is statistically insignificant at the 5% level, indicating that higher ROA does not necessarily correspond to higher performance of development banks, thus failing to support H_6. This result is consistent with the Multiple Objectives Theory, which argues that balancing profit objectives (ROA) with development objectives often entails conflicts. Accordingly, Humphrey (2016) argued that development banks are inherently

multi-objective institutions, having to ensure financial sustainability while fulfilling their social mission by financing high-risk projects with long-term developmental value, and that the conflict between these two objectives is precisely the reason why development banks' performance is limited. Thus, focusing on improving ROA in the short term may lead banks to restrict concessional lending or reduce participation in projects with long-term developmental benefits but low profitability, thereby reducing performance according to development criteria. Furthermore, if microfinance institutions depend heavily on external funding, they may be pressured to shift their clientele toward lower-risk individuals to ensure repayment. The pursuit of profit objectives may cause development banks to deviate from their original mission, lose their initial target clients, reduce service quality, and erode their distinctive role compared to commercial banks, ultimately failing to fulfill their social mission (Mia & Lee, 2017).

The Tobit regression results reveal that the LDR exhibits a positive and highly statistically significant association with the technical efficiency of development banks. This finding is fully consistent with H_4, which posits that a higher LDR reflects the effective allocation of mobilized funds into income-generating loans, thereby improving technical efficiency. The result is also consistent with prior empirical evidence (Benbachir, 2025), which underscores the LDR as a key indicator of asset transformation efficiency. A reasonably high LDR suggests that banks have minimized idle liquidity, enhanced their capacity to generate returns from mobilized funds, and optimized balance sheet structures (Cao et al., 2023). Within the context of development banks, this relationship is particularly salient given that these institutions typically mobilize concessional or public funds and are mandated to deploy them into long-term, high-risk projects in infrastructure, agriculture, or environmental sectors. Nonetheless, when exceeding safe thresholds, a high LDR may entail liquidity and credit risks, highlighting the necessity of maintaining an optimal LDR that simultaneously ensures efficient utilization of funds and system stability (Adenuga et al., 2021).

The Tobit regression results indicate that the NIM carries a negative coefficient and is statistically insignificant in relation to the technical efficiency of development banks. This suggests that although NIM is an important indicator of profitability from core banking activities, in the context of development banks it is not a decisive factor for technical efficiency. The result does not support H_2 regarding a positive association between NIM and efficiency, and is consistent with previous studies (Das Gupta et al., 2021), which argue that higher net interest margins do not necessarily imply greater efficiency, as banks with lower spreads may in fact operate more efficiently under competitive or cost-efficient environments. This outcome may be attributed to the specific nature of development banking. Unlike commercial banks, development banks typically apply concessional interest rates to support long-term projects rather than maximizing interest spreads (Fernández-Arias et al., 2020). In addition, they mobilize funds from non-market sources such as government budgets or concessional international borrowing, resulting in lower funding costs and pricing mechanisms that primarily reflect policy objectives rather than profit-maximizing or managerial efficiency considerations (Hu et al., 2022). These findings imply that technical efficiency in development banks is driven more by balance sheet structures (e.g., size, LDR) than by NIM. Moreover, the pursuit of higher NIM may even conflict with social development objectives, since raising lending rates to improve margins can undermine access to finance for public-interest projects. Therefore, managers should avoid treating NIM as the sole measure of efficiency and instead focus on the prioritization of capital allocation, operational optimization, and the maintenance of credit quality, even when NIM remains relatively low.

The Tobit regression results indicate that SIZE has a positive and highly statistically significant effect on the technical efficiency of development banks. This finding fully supports H_3 and is consistent with economies of scale theory as well as prior studies (Hughes et al., 2019), which suggest that larger banks are better able to spread fixed costs across a broader operational base, thereby improving overall efficiency. The positive impact of SIZE may operate through several channels. First, large banks often possess modern technological infrastructure, extensive branch networks, and advanced managerial capabilities, which enable them to reduce unit costs and enhance process efficiency

(Hughes et al., 2019; Wheelock & Wilson, 2018). Second, large banks tend to benefit from lower funding costs due to broader and more stable deposit bases, while simultaneously diversifying credit and investment portfolios to strengthen resilience against macroeconomic shocks (Hu et al., 2022; Tran, 2020). Third, large development banks are generally better positioned to attract and retain high-quality personnel by prioritizing employee development and welfare, which contributes to enhanced efficiency and overall performance (Ampong, 2024; Fukuyama et al., 2020). At the same time, they invest in advanced risk management systems supported by senior leadership, structured training, and a well-defined risk culture (Kunz & Heitz, 2021). The adoption of modern technologies further enhances data analytics and decision-making capacity, thereby improving operational efficiency and risk resilience (Chen et al., 2023; Do et al., 2022). However, the positive effect of SIZE is not always linear. Once scale surpasses a certain threshold, banks may experience diseconomies of scale, manifested in rising costs, declining profitability, cumbersome management structures, slower decision-making, and diminished focus on policy objectives. Consequently, expansion must be accompanied by internal process improvements and greater managerial flexibility in order to sustain efficiency (Avramidis et al., 2018). These findings suggest that strategies to enhance the efficiency of development banks may include selective consolidation, cross-border cooperation, or technological integration to optimize operations. Nevertheless, scale expansion must be complemented by robust governance mechanisms and clear performance metrics to ensure that the benefits of size are effectively translated into enhanced capacity to serve socio-economic development goals.

4.3 DEA

Table 4. DEA results summary

Region	Obs	Mean	Std. Dev.	Min	Max	Change
Western European, Northern American and other States*	279	0.690	0.313	0.169	1	-6.34%
Latin American and Caribbean States	223	0.590	0.373	0.061	1	49.43%
Eastern European	62	0.539	0.341	0.056	1	5.81%
Asia-Pacific	341	0.469	0.349	0.054	1	23.56%
Africa	106	0.543	0.319	0.104	1	-1.41%
Total	1011	0.569	0.352	0.054	1	15.73%

Due to the extensive DEA results, the full result cannot be shown. The summarized version is therefore presented in Table 4. Based on the mean value, the most efficient development banks concentrate in Western Europe, Northern America, and multilateral development banks comprising countries from different regions. However, these banks, along with African banks, tended to be less efficient, opposite to the worldwide general trend. Significantly, Latin American and Caribbean development banks experienced the most notable growth in efficiency, at 49.43%.

4.4 Correlation and VIF

Table 5. Pearson correlation matrix

	EFF	REG	NPL	ROA	LDR	SIZ	NIM
EFF	1.000						
REG	-0.148	1.000					
NPL	-0.008	-0.080	1.000				
ROA	-0.053	0.089	-0.163	1.000			
LDR	0.180	-0.038	-0.035	-0.019	1.000		
SIZE	0.295	0.082	-0.473	-0.061	0.132	1.000	
NIM	-0.257	-0.047	0.202	0.252	-0.095	-0.538	1.000

As shown in Table 5, the highest observed correlation coefficient between any two independent variables in the model is -0.538, specifically between SIZE and NIM. Since this value does not exceed the commonly accepted threshold of |0.8|, the results suggest that collinearity is not a concern in the regression model.

Table 6. VIF results

Variable	VIF	1/VIF
SIZE	1.769	0.565
NIM	1.513	0.661
NPL	1.354	0.738
ROA	1.134	0.881
LDR	1.022	0.979
REG	1.020	0.981
Mean VIF	1.302	.

As for the VIF results, presented in Table 6, no value exceeds the threshold of 10, especially for the mean VIF, therefore affirming the absence of multicollinearity.

4.5 Bootstrap

Table 7. Bootstrapped Tobit Regression Results

	β	Bootstrap std. dev.	Normal-based err.	*p*-value
REG	-0.216	0.027	-8.040	0.000 ***
NPL	0.004	0.002	2.210	0.027 **
ROA	-0.002	0.009	-0.230	0.821
LDR	0.002	0.000	4.410	0.000 ***
SIZE	0.096	0.015	6.420	0.000 ***
NIM	-0.016	0.013	-1.240	0.216
Obs	655	655	655	655
Uncensored	463	463	463	463
Left-censored	0	0	0	0
Right-censored	193	193	193	193
Replications	1000	1000	1000	1000

The regression results estimated using the Bootstrapped Tobit regression approach are presented in Table 7. The results show that NPL, LDR, and SIZE have a statistically significant positive effect on EFF. In contrast, REG exerts a significant negative influence on EFF. Meanwhile, ROA and NIM are found to have no significant effect on EFF, as their *p*-values exceed the 0.05 threshold. The estimation is re-conducted 1000 times to increase the accuracy.

5. Conclusions

This paper investigates the drivers of efficiency in development banks globally, applying a DEA–Tobit two-stage estimation framework. Multilateral Development Banks (MDBs) operate with lower efficiency than national counterparts, a pattern that may reflect the governance complexity and reduced adaptability inherent in multi-jurisdictional operations. The loan-to-deposit ratio and bank size emerge as strong and consistent positive drivers, in line with asset transformation and economies of scale, whereas net interest margin and return on assets show no statistically significant effect, implying that conventional profitability measures are insufficient to explain differences in efficiency among development banks. Non-performing loans exhibit a positive association with efficiency, suggesting that, within robust risk governance, moderate credit exposure may accompany more disciplined lending and resource allocation. Overall, structural balance sheet characteristics exert a more decisive influence on efficiency than profitability indicators.

These results carry several policy implications. Development banks should calibrate their loan-to-deposit ratios within prudent thresholds consistent with Basel III Liquidity Coverage Ratio and Net

Stable Funding Ratio, pursue scale economies through selective consolidation, cross-border cooperation and technology-enabled operational integration, and maintain credit quality oversight, forward-looking stress testing and targeted provisioning so that the positive link between non-performing loans and efficiency reflects prudent risk-taking rather than latent credit deterioration. This study is limited by its reliance on a single DEA–Tobit framework and bank-level financial indicators; future research could employ Stochastic Frontier Analysis to account for statistical noise, incorporate macroeconomic and financial dynamics such as business cycles, interest rate regimes and capital flow volatility, and examine how climate-related and green investments, as well as coordination with state-owned enterprises, shape the efficiency of development banks.

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Author Contributions

Dinh Huong Thao is the sole author of this article and was responsible for the conceptualisation, research design, data collection and curation, formal analysis, interpretation of the results, and the writing, review and editing of the manuscript.

Conflict of Interest

The author declares that there is no conflict of interest regarding the publication of this article.

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