

THE IMPACT OF GREEN CREDIT ON THE FINANCIAL EFFICIENCY OF JOINT STOCK COMMERCIAL BANKS

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Received: 9 April 2026; Revised: 10 May 2026; Accepted: 16 May 2026

ABSTRACT

Green credit plays a pivotal role in guiding and optimizing capital flows toward environmentally sustainable production and business sectors. This study evaluates efficiency levels and the impact of green credit on joint stock commercial banks from 2020 to 2024. Employing the DEA-Malmquist Total Factor Productivity (TFP) index and its decomposition components, the analysis measures technical efficiency and technological progress across 10 selected institutions. The results show that not all banks providing green credit have high total factor productivity (TFP). The results indicate that joint stock commercial banks utilize input resources relatively efficiently, as reflected by a high average technical efficiency index. The Malmquist productivity index is employed to examine changes in the productivity of joint stock commercial banks over time. The research findings indicate that changes in the Malmquist productivity index are primarily driven by technological change (techch).

Keywords: Performance, technical efficiency, Data Envelopment Analysis, Malmquist index.

1. INTRODUCTION

As a bridge between financial stability and climate risk, green credit directs financial resources toward ecologically responsible and climate-resilient initiatives [1]. [2] posit that green credit constitutes a long-term strategy, enabling banks to reorient their credit portfolios toward sustainability while facilitating access to preferential financing for environmentally responsible enterprises. In Vietnam, the State Bank of Vietnam has promoted green credit development through Directive No. 03/CT-NHNN (2015), which seeks to encourage investments in environmentally sustainable projects. Additionally, the 2020 Environmental Protection Law establishes explicit regulations on green credit, mandating that financed projects contribute to natural ecosystem preservation and efficient utilization of natural resources. Thus, green credit not only advances environmental protection but also fosters green economic growth and Vietnam's sustainable development objectives. For commercial banks, it mitigates credit risks, lowers non-performing loan ratios, and strengthens financial capacity alongside market reputation.

The intense competition within the banking underscores the necessity of evaluating the operational efficiency of banks. Such assessments are critical not only for corporate managers but also for investors who seek high returns. Among various available methodologies for measuring firm efficiency, Data Envelopment Analysis (DEA) has gained widespread recognition as a powerful and flexible non-parametric methodology for performance evaluation. As highlighted by [3], DEA enables the relative assessment of the efficiency of

individual decision-making units (DMUs) by comparing them within a defined peer group operating under similar conditions. This approach is particularly effective in application domains where multiple inputs are utilized to produce multiple outputs, allowing for a comprehensive evaluation of each unit's operational performance in relation to the best-performing entities within the same environment.

The food companies with strong ESG strategies often attract investment and are highly valued in the market, which promotes growth and stability of stocks and brand value, creating a competitive advantage in the financial market. Therefore, it can be said that ESG plays an important role as an indicator, helping stakeholders understand how food companies manage risks and take advantage of opportunities in all three aspects of environment, society and governance. Therefore, this study examines the business efficiency of 10 banks listed on the Ho Chi Minh City Stock Exchange, with the objective of identifying the most efficient banks and assessing whether those banks have published Environmental, Social, and Governance (ESG) reports. In this study, the DEA-Malmquist Total Factor Productivity (TFP) index has been employed as the analytical framework to assess changes in productivity over time. This method is particularly well-suited for panel data analysis, as it facilitates the tracking of performance dynamics across multiple time periods. As recommended by [4], the DEA-Malmquist index not only quantifies the overall shift in productivity but also allows for a detailed decomposition of this change into two key components: technical change, which reflects shifts in the production frontier due to innovation or technological progress; and technical efficiency change, which captures variations in a decision-making unit's ability to utilize existing resources effectively relative to the frontier.

2. LITERATURE REVIEW

Efficiency frontier analysis comprises parametric and non-parametric approaches. Parametric methods estimate production or cost functions as optimal benchmarks through regression, requiring substantial sample sizes. In contrast, Data Envelopment Analysis (DEA)—a non-parametric technique—derives a sample-wide efficient frontier from financial institutions' data, offering flexible evaluations of multi-input, multi-output performance, particularly for complex production relationships [5-6].

Data Envelopment Analysis (DEA) represents a mathematical programming approach for evaluating relative efficiency across institutions using multiple inputs and outputs, computing weighted output-input ratios for decision-making units (DMUs) via linear programming. Its conceptual roots trace to Farrell's production frontier model, which distinguished technical efficiency (maximizing output from fixed inputs) from allocative efficiency under constant returns to scale (CRS). Charnes et al. formalized DEA by extending this to multi-input/output CRS frameworks, while Banker et al. introduced variable returns to scale (VRS) models, decomposing efficiency into pure technical and scale components. This study employs DEA for its non-parametric rigor, bypassing parametric production function assumptions.

In other words, DEA dispenses with a priori assumptions regarding input-output functional forms or preassigned weights, enhancing its adaptability for assessing decision-making units (DMUs) in complex, heterogeneous settings [7–8]. Unlike traditional financial ratios that capture partial performance dimensions, DEA delivers a holistic, multi-factor evaluation of efficiency [6–7]. This robustness positions it ideally for dissecting productivity in intricate organizational landscapes.

When examining time-series analyses, most scholars tend to conceptualize efficiency in terms of total factor productivity (TFP) and employ the distance function framework [8] to measure changes in productivity (or efficiency) over time. [9] applied productivity indices derived from Shephard's distance function to develop a theoretical framework for measuring

productivity and its changes, which subsequently evolved into the Malmquist productivity index approach. The Malmquist index enables the comparison of efficiency across different time periods.

[10] identified assets, cost of sales, and selling, general, and administrative expenses (SG&A) as key input variables for their DEA analysis. SG&A encompasses items such as salaries, employee benefits, and advertising expenditures. Both cost of sales and SG&A represent core components of operating expenses and are thus considered critical targets for optimization. In this context, assets and total operating costs - comprising cost of sales and SG&A - were employed as input variables, consistent with prior DEA studies in the field [11-13]. Similar input selections, including assets and operating costs, have also been adopted in DEA applications across other sectors [14-15]. For output variables, [5] selected sales and operating income. Sales, as a direct and intuitive indicator of business performance, have been widely used in DEA research to represent output [14]. Operating income - calculated as sales minus cost of sales and SG&A captures the firm's ability to efficiently manage inputs such as fuel and labor. Accordingly, it serves as a robust proxy for measuring operational efficiency and has been similarly applied in previous DEA studies. Therefore, in this study, the author approaches from the perspective of revenue and cost, so the author chooses three input variables as Total net fixed assets (X1), Deposits from customers (X2), Employee costs (X3) and two output variables as net interest income (Y1); Income from investments in other entities (Y2).

3. METHODOLOGY

This study utilizes DEA methodology to assess operational efficiency among 10 banks from 2020–2024 (Table 1). These are the ten commercial banks with the highest outstanding green credit balances in the first quarter of 2025, alongside net interest income patterns for joint stock commercial banks (Table 2), with emphasis on technical efficiency and Malmquist productivity indices. Resource utilization analysis employs a non-parametric framework, operationalized through DEAP 2.1 software.

Table 1. The list of joint stock commercial banks used for analysis and evaluation from 2020 - 2024

Code	Name company	Code	Name company
BIDV	Joint Stock Commercial Bank for Investment and Development of Vietnam	BAB	Bac A Commercial Joint Stock Bank
CTG	Vietnam Joint Stock Commercial Bank For Industry And Trade	HDB	Ho Chi Minh City Development Joint Stock Commercial Bank
VCB	Joint Stock Commercial Bank for Foreign Trade of Vietnam	NAB	Nam A Commercial Joint Stock Bank
MBB	Military Commercial Joint Stock Bank	TCB	Vietnam Technological and Commercial Joint Stock Bank
AGR	Vietnam Bank for Agriculture and Rural Development	ACB	Asia Commercial Joint Stock Bank

Source: Vietstock (2025)

Table 2. The Net interest income of joint stock commercial banks from 2020 – 2024

Unit: VND (billion)

	2020	2021	2022	2023	2024
BIDV	35,797	46,823	55,960	56,136	58,003
CTG	35,580	41,788	47,792	52,957	62,403
VCB	36,285	42,273	53,246	53,621	55,406
MBB	20,278	26,200	36,023	38,684	41,152
AGR	43,661	47,041	60,190	55,965	66,554
BAB	2,031	2,117	2,513	2,389	3,321
HDB	11,898	13,891	18,012	22,184	30,857
NAB	2,604	4,283	5,119	6,647	7,938
TCB	18,751	26,699	30,290	27,691	35,508
ACB	14,582	18,945	23,534	24,960	27,795

Source: Vietstock (2025)

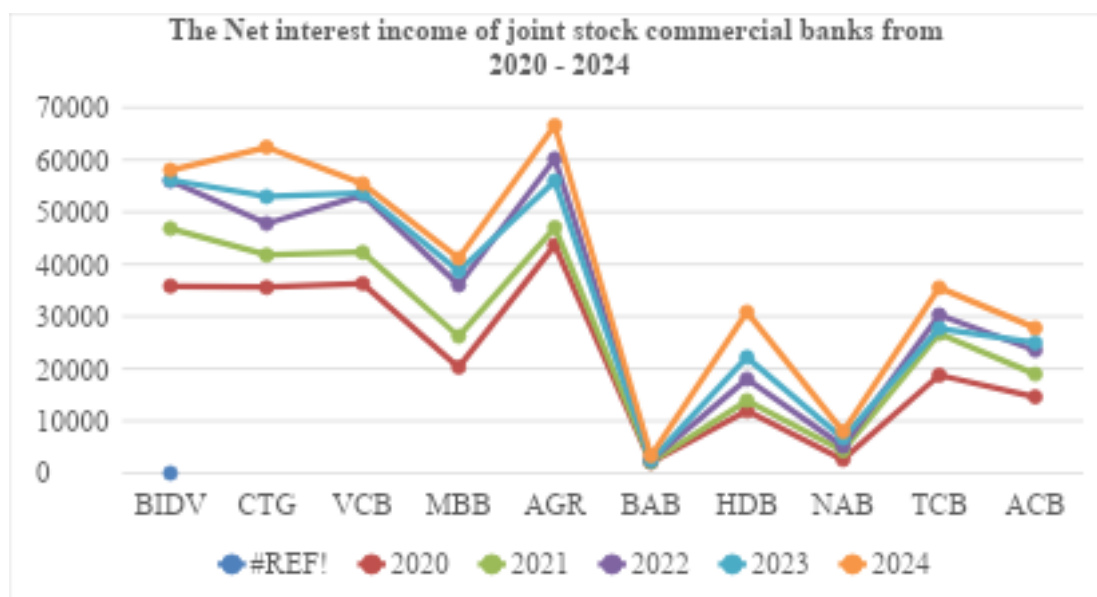


Figure 1. The Net interest income of joint stock commercial banks from 2020 – 2024

Source: Vietstock (2025)

3.1. Data Envelopment Analysis – DEA

In this study, the Data Envelopment Analysis (DEA) method is employed as a linear programming technique to assess how each firm performs relative to its peers within the sample. The technique constructs an efficient frontier, formed by the best-performing firms, against which the less efficient firms are benchmarked. Efficiency scores range from 0 to 1, with a score of 1 indicating a firm that is fully efficient. A basic DEA model is formulated as a problem of efficiency maximization, utilizing output weights (u) and input weights (v) for i inputs (x) and j outputs (y). By normalizing the sum of input weights to 1, the optimal efficiency score of a given company can be expressed through the following algebraic formulation:

$$\text{Max}_{uv} (u y_j) \text{ với } v x_i = 1$$

$$U y_i - v x_i < 0 ; u, v > 0$$

3.2. Malmquist productivity index (MPI)

The Malmquist Productivity Index (MPI) measures efficiency changes between decision-making units or within the same unit across periods by comparing output-input ratios. This study applies MPI analysis to quantify shifts in technical efficiency and technological progress throughout the observation period, leveraging distance functions derived from Data Envelopment Analysis (DEA).

Data Envelopment Analysis (DEA) incorporates the Malmquist index, originally developed by [16], quantifies productivity shifts by comparing total factor productivity between consecutive periods (t and $t+1$) using input-output configurations. This geometric measure decomposes changes into efficiency gains and technological progress for banking institutions. Its computation relies on distance functions derived from Data Envelopment Analysis frontiers.

$$M_0(X_{t+1}, Y_{t+1}, X_t, Y_t) = \left(\frac{d_0^t(X_{t+1}, Y_{t+1})}{d_0^t(X_t, Y_t)} * \frac{d_0^{t+1}(X_{t+1}, Y_{t+1})}{d_0^{t+1}(X_t, Y_t)} \right)^{1/2} \quad (1)$$

Technical efficiency changes under constant returns to scale (CRS) can be decomposed into scale efficiency and pure technical efficiency under variable returns to scale (VRS), providing insight into whether productivity shifts stem from optimal scale operations or enhanced management practices. This breakdown employs distance functions benchmarked against VRS technology frontiers, accommodating heterogeneity in scale effects across decision-making units (DMUs). Scale efficiency is subsequently derived from the ratio of CRS to VRS efficiency measures.

4. RESULTS

This analysis adopts an output-oriented Malmquist DEA framework (i.e., focused on output maximization) incorporating data from two output variables as net interest income (Y1); Income from investments in other entities (Y2) and three input variables as Total net fixed assets (X1), Deposits from customers (X2), Employee costs (X3) for 10 banks was tracked across a five-year span (2020-2024). The input and output were described in VND millions.

The DEA-Malmquist Total Factor Productivity (TFP) index is a dynamic efficiency metric used to assess productivity changes between two periods, typically from period t to period $t+1$. A Malmquist index of 1 denotes stable productivity levels across periods, while values exceeding 1 signal productivity enhancements — either due to enhanced technical efficiency — while a value less than 1 reflects a decline in performance, indicating either reduced efficiency or technological regress. This interpretation also applies to each component of the index, where values above, below, or equal to 1 denote improvement, deterioration, or stability, respectively [17].

As 2020 serves as the base year, the Total Factor Productivity (TFP) index and its components are presented starting from 2021 onward. The average TFP change index for the period 2020 – 2024 is 1.017, indicating a 1.7% increase in TFP over the five years.

The primary cause of this increase is a 2.5% increase in technological change (techch), although there was a 0.8% reduction in Technical efficiency change (effch), 0.8% reduction in Scale efficiency change (sech) and maintain Pure technical efficiency change (pech). Therefore, The average TFP index increase primarily due to improvements in technological change (techch).

Looking at the productivity change over the years shows that, over the entire study period, the productivity change index increased by 1.8% in 2021; 16.6% in 2022 and 3.1% in 2024 compared to the reference year 2020 (Table 3). Besides, productivity declined in all other

years, with the most significant drops occurring in 2023 (−12.5%). The notable increase in 2022 and 2024 were primarily driven by technological change (techch). However, the decline in TFP in 2023 was primarily driven by a substantial decrease in technological change (techch) of 18.7%, indicating a setback in technological progress, despite improvements in both Technical efficiency change (effch), Pure technical efficiency change (pech) and Scale efficiency change (sech).

Table 3. Malmquist index summary of annual means

Year	Technical efficiency change (effch)	Technological change (techch)	Pure technical efficiency change (pech)	Scale efficiency change (sech)	Total factor productivity (TFP) change (tfpch)
2021	0.972	1.047	1.013	0.959	1.018
2022	0.976	1.196	0.993	0.983	1.166
2023	1.076	0.813	1.003	1.073	0.875
2024	0.950	1.085	0.992	0.957	1.031
Mean	0.992	1.025	1.000	0.992	1.017

Source: Analysis results from DEAP 2.1 software

The Total Factor Productivity Change (tfpch) during the study period is over than 1 (TFP = 1.017), mainly reason due to the change in technological progress (techch) reaching only 1.025. This can be explained by the fact that technological progress has been fully realized during this period and many banks have accelerated digital transformation. Thus, the factor of technological change is of great importance in contributing to the improvement of total factor productivity (TFP).

Table 4 presents the aggregated Malmquist index results, summarizing the average performance of 10 selected banks over the 2020–2024 period. The table includes key components of productivity change: efficiency change, technical change, pure technical efficiency change, scale efficiency change, and total factor productivity (TFP) change. Among the banks analyzed, once demonstrated an improvement in mean annual technical efficiency (effch > 1), four maintained the same level of efficiency (effch = 1), and five experienced a decline (effch < 1). These findings suggest that only a minority of banks succeeded in enhancing their managerial efficiency—specifically their ability to convert inputs into outputs (Y1, Y2)—while the majority either stagnated or regressed in this regard.

An analysis of mean annual technological change revealed that six banks exhibited technological advancement (techch > 1), while four experienced a decline (techch < 1). This suggests that most of banks actively modernized their operations, likely through the adoption of cutting-edge technologies to enhance service delivery. For scale efficiency change, once bank increased (sech > 1), four banks remained unchanged (sech = 1) and five banks decreased (sech < 1) their mean annual scale efficiency change.

Table 4. The Malmquist index summary of the firm means

Firm	Technical efficiency change (effch)	Technological change (techch)	Pure technical efficiency change (pech)	Scale efficiency change (sech)	Total factor productivity (TFP) change (tfpch)
BIDV	1.150	1.004	1.029	1.118	1.155
CTG	1.000	0.972	1.000	1.000	0.972
VCB	0.989	1.012	1.000	0.989	1.001

Firm	Technical efficiency change (effch)	Technological change (techch)	Pure technical efficiency change (pech)	Scale efficiency change (sech)	Total factor productivity (TFP) change (tfpch)
MBB	1.000	0.995	1.000	1.000	0.995
AGR	0.944	1.102	1.000	0.944	1.039
BAB	0.918	0.998	1.000	0.918	0.916
HDB	1.000	1.129	1.000	1.000	1.129
NAB	0.965	0.983	1.000	0.965	0.948
TCB	1.000	1.036	1.000	1.000	1.036
ACB	0.972	1.032	0.973	0.999	1.003
Mean	0.992	1.025	1.000	0.992	1.017

Source: Analysis results from DEAP 2.1 software

Of the 10 banks analyzed, six (BIDV, VCB, AGR, HDB, TCB, ACB) recorded TFP increases, with the highest gains observed in BIDV (15.5%), HDB (12.9%), AGR (3.9%), TCB (3.6%), ACB (3%), and VCB (1%), respectively. Although their TFP exceeded 1, ACB (3%) and VCB (1%) rank among those with the smallest improvements. TFP declined for the remaining four banks, with the sharpest drops in BAB (8.4%) and NAB (5.2%). Notably, despite BIDV, CTG, and VCB holding the largest green credit portfolios, only BIDV and VCB showed TFP growth, while CTG experienced a decline.

5. CONCLUSION

This study employed the DEA-Malmquist Productivity Index (DEA-MPI) to assess the performance of 10 banks listed on the Ho Chi Minh Stock Exchange over the five-year period from 2020 to 2024. The objective was to evaluate whether these companies maintain superior efficiency levels based on DEA metrics. A summary of the firms' average Malmquist index results is presented in Tables 2 and 3.

The first, the analysis shows that six banks achieved a Total Factor Productivity (TFP) score greater than 1, reflecting an improvement in their overall performance. In contrast, four banks recorded TFP scores below 1, indicating a decline in productivity.

The second, among all banks, AGM demonstrated the highest productivity growth with a TFP score of 1.192, while BAB exhibited the greatest decline, with the lowest TFP score of 0.916.

Third, this study identifies four banks with elevated net interest income: AGR, VCB, CTG, BIDV and AGR, VCB and BIDV scored TFP above 1 is ranked in descending order in Table 3. Most of banks with deteriorated performance ($tfpch < 1$) had a technological change score of less than 1 ($techch < 1$) except CTG; MBB; BAB; NAB.

This finding suggests that the size of a green credit portfolio does not automatically lead to higher overall efficiency; instead, it also depends on the quality of capital allocation, project appraisal capabilities, and each bank's risk-control capacity. In the Vietnamese context, this implies that green credit development should not merely focus on expanding outstanding loans but should also be accompanied by improvements in capital-use efficiency to enhance overall productivity. Thus, optimizing green credit strategies requires additional factors beyond mere portfolio size for enhanced banking efficiency.

Firstly, Banks should prioritize enhancing staff expertise in risk management and environmental impact assessment to ensure rigorous evaluation of green projects. Concurrently, establishing dedicated departments within commercial banks would strengthen

oversight of green credit implementation, guaranteeing adherence to environmental standards.

Second, Commercial banks should introduce preferential credit packages featuring competitive interest rates to stimulate engagement in environmental protection initiatives.

Third, Commercial banks should leverage cutting-edge technologies to boost transparency and efficiency in green credit management. Tools such as artificial intelligence (AI), Big Data, and the Internet of Things (IoT) can streamline data processing, oversee green projects, and evaluate environmental outcomes. This approach enhances appraisal accuracy and strengthens risk mitigation

Governments should establish precise criteria and classifications for green project evaluation across specific economic sectors, equipping credit institutions with standardized frameworks for project assessment and selection. Additionally, deploying environmental impact assessment tools - such as monitoring systems, GIS mapping, predictive modeling, and environmental audits - would bolster the efficacy and promotion of green credit initiatives.

The State Bank of Vietnam (SBV) should strengthen the legal framework and incentive mechanisms related to green credit. The SBV, in coordination with other state agencies, should develop and promulgate lists of green projects in specific sectors as well as criteria for determining green eligibility, thereby providing a basis for commercial banks to appraise and assess projects. At the same time, the introduction of incentive mechanisms such as preferential interest rates, guarantees, and capital support would help motivate commercial banks to implement green credit more effectively.

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