Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 9, 1437-1453
2025
Publisher: Learning Gate
DOI: 10.55214/2576-8484.v9i9.10141
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Efficiency, technological progress and productivity growth of Vietnamese commercial banks in the period 2008–2024: A Malmquist index approach

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Abstract: This study evaluates the efficiency and productivity growth of 22 Vietnamese commercial banks over the period 2008–2024 using a non-parametric approach. Applying the output-oriented Malmquist Productivity Index under constant returns to scale (CRS), we decompose total factor productivity (TFP) into efficiency change (EC) and technical change (TC). The results show that EC values remained close to unity for most banks, indicating relatively stable managerial performance. However, TC values varied significantly across institutions, suggesting that technological progress is the primary driver of TFP divergence. Among the 22 banks, only six achieved positive TFP growth, led by NVB, SEAB, and ABB—banks that demonstrated strong adaptability through technical improvements. In contrast, HDB, BIDV, and VPB recorded notable declines in productivity, largely due to lagging technological progress rather than inefficiency. These findings emphasize the critical role of digital transformation and innovation in sustaining long-term productivity. The study contributes updated empirical evidence on banking performance in Vietnam and offers strategic implications for bank executives and policymakers aiming to enhance competitiveness in a rapidly evolving financial environment.
Keywords: *DEA, Digital transformation, Efficiency, Malmquist index, Productivity, Technical change, Vietnamese banks.*

1. Introduction

In the process of economic transformation, the banking sector plays a vital role as a financial intermediary and stabilizing force within the national economy. In Vietnam, the banking system has undergone significant changes over the past two decades, both in terms of organizational structure and technological modernization. The last ten years have seen an active wave of mergers and acquisitions, leading to the consolidation of commercial banks and the reshaping of market dynamics.

Simultaneously, both globally and domestically, the banking industry has experienced profound shifts driven by regulatory reforms and the advancement of technology. The integration of Industry 4.0 innovations, digital banking platforms, fintech solutions, and new financial instruments has radically transformed banking operations. These technological developments have reshaped the production technology of banks, raising important questions regarding their impact on banking efficiency and productivity.

A key issue, therefore, is how such structural and technological changes have influenced the performance of banks. In a seminal review, Berger and Humphrey in Berger, et al. [1] provided a comprehensive overview of efficiency measurement techniques in the banking sector and emphasized the importance of both parametric and non-parametric approaches. Among these, Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) have become the most widely applied methods to estimate banking efficiency.

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History: Received: 14 August 2025; Revised: 4 September 2025; Accepted: 8 September 2025; Published: 22 September 2025
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This study aims to apply non-parametric methods, particularly the Malmquist Productivity Index under constant returns to scale (CRS), to assess the efficiency, technological progress, and total factor productivity (TFP) growth of Vietnamese commercial banks during the period 2008–2024. This timeframe captures an important phase of restructuring in the Vietnamese banking sector, marked by institutional consolidation and the rise of digital transformation.

Studies on productivity in the banking sector have traditionally focused on comparisons of cost ratios. Several cost-based indicators have been developed, each addressing a specific dimension of banking operations. However, given that banks utilize multiple inputs to generate multiple outputs, researchers have questioned the appropriateness of simple aggregations and instead examined suitable forms of input-output modeling [2].

Although early efforts attempted to estimate average practice cost functions, such approaches often failed to reflect the productivity levels of the best-performing banks. These limitations of the "classical" productivity approach have led to alternative methods that incorporate multiple inputs and outputs, as well as the concept of relative efficiency.

A major advancement in this domain is the frontier-based analysis, which classifies decision-making units into efficient and inefficient performers relative to a constructed frontier. The most widely adopted non-parametric method is Data Envelopment Analysis (DEA), introduced by Charnes, et al. [3]. DEA utilizes linear programming to form a piecewise linear frontier enveloping the efficient units and measures the relative efficiency of all others against it.

In Vietnam, DEA-based research remains relatively limited. Early domestic contributions include who examined banking efficiency and super-efficiency. Expanding the empirical landscape, Minh, et al. [4] analyzed the performance of 32 commercial banks in Vietnam during the period 2001–2005 using a super-efficient DEA model under variable returns to scale (VRS). The study adopted the slack-based measure and performed a series of sensitivity tests by allowing simultaneous changes in input–output subsets. The authors further applied Spearman's rank correlation and Kendall's tau-b to compare rankings derived from Tone's method and the Andersen-Petersen approach. Their findings revealed strong consistency in banking, suggesting robustness in relative efficiency assessment regardless of DEA specification.

2. Methodology

2.1. Production Efficiency

Measuring the level of absolute efficiency is generally not feasible due to the absence of a universally applicable production function that defines the maximum output for all banks within the same industry. To address this limitation, Farrell [5] proposed a method for evaluating relative efficiency, which compares a bank's performance with that of the best-performing banks sharing similar characteristics within the industry. This approach enables efficiency to be assessed even in the absence of a known production frontier.

Farrell's framework further decomposes overall efficiency into two distinct components: technical efficiency and allocative efficiency. Technical efficiency reflects a bank's ability to produce the maximum feasible output given the available inputs and current technology. In contrast, allocative efficiency examines whether, once a bank is technically efficient, it also selects the optimal combination of inputs based on given input prices—thereby minimizing costs [6].

Figure 1 provides a simplified graphical illustration of these two dimensions of efficiency under the assumption of constant returns to scale in banking production. The figure visually distinguishes between technical inefficiency (due to input-output mismatch) and allocative inefficiency (due to suboptimal input mix given price constraints), highlighting the conceptual importance of both in measuring performance.

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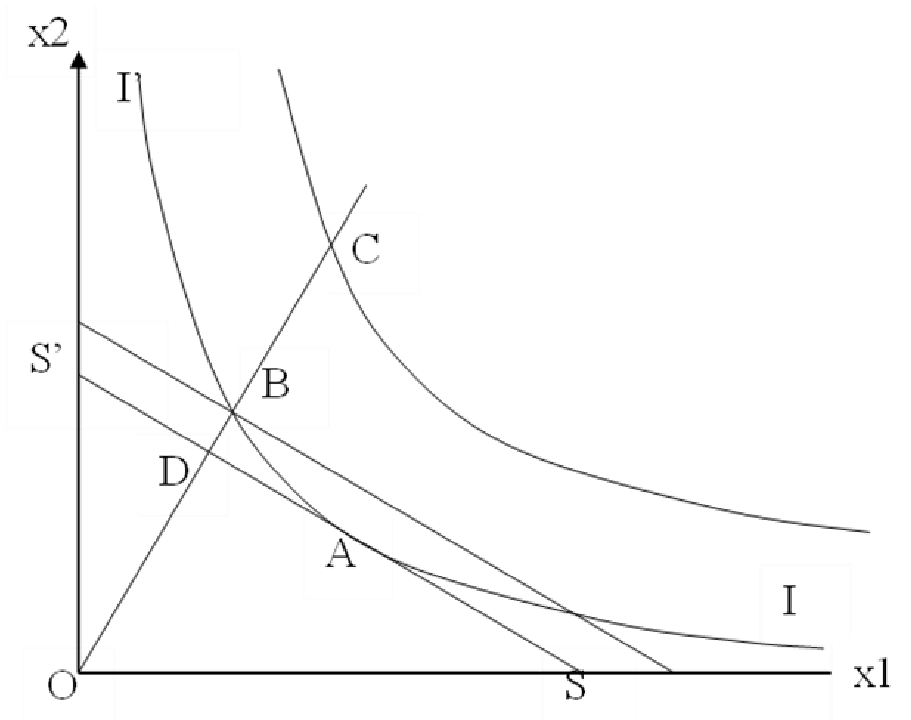

Figure 1.
Technical and allocative efficiency.
(**Source:** Banker, et al. [6]).

In Figure 1, the curve labeled IAI′ represents the isoquant of a bank, depicting all combinations of two inputs, x_1 and x_2, that can produce a given level of output. The straight line SS′ represents the isocost line, which reflects combinations of inputs that yield equal total cost, given relative input prices.

It is assumed, consistent with standard microeconomic production theory, that banks possess a concave production function with respect to these inputs. Under the behavioral assumption of cost minimization, a bank operating optimally will choose a point on the isoquant where the marginal rate of technical substitution (MRTS) equals the input price ratio. This optimal point is identified as point A, where the bank minimizes its input cost for the given level of output.

Meanwhile, point B represents a technically efficient production point, where the bank uses the minimum input quantities necessary to achieve the same level of output on the isoquant IAI′. However, if the bank instead operates at point C, it uses more inputs than necessary to achieve the same output, and is thus technically inefficient. The extent of technical inefficiency is quantified by the ratio OC/OB, indicating the proportional excess of input use compared to the efficient benchmark at point B.

Even if a bank achieves technical efficiency at point B, it may still incur allocative inefficiency if the combination of inputs does not minimize cost, given the input prices. Point A, which lies on both the isoquant and isocost line SS′, is the cost-minimizing point. The allocative efficiency is thus measured by the ratio OD/OB, where OD is the cost at point A and OB is the cost at point B.

Consequently, the overall productive efficiency of a bank is the product of its technical efficiency and allocative efficiency, and can be expressed as:

$$\text{Productive Efficiency} = \left(\frac{OB}{OC}\right)\cdot\left(\frac{OD}{OB}\right) = \frac{OD}{OC}$$

This formulation captures the combined impact of input-saving efficiency and cost-minimizing behavior, and provides a comprehensive measure of banking performance.

Edelweiss Applied Science and Technology
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2.2. Technical Efficiency and the Production Frontier

Following the general discussion on productive efficiency, this section focuses specifically on technical efficiency, which measures a bank's ability to maximize output given a fixed set of inputs and current technology. A bank with a technical efficiency (TE) score of 1 is considered fully efficient—operating on the production frontier and achieving the highest output level feasible relative to its peers. Contrary, a TE score less than 1 indicates that the bank is operating below the frontier and has potential to improve its performance.

Figure 2 provides a graphical illustration of technical efficiency using a simplified production function with one input and one output. Points A, B, C, D, E, and F represent banks with different input–output combinations. The production frontier is defined by the piecewise curve ACD, representing the most efficient combinations. Banks operating on the frontier (eg, points A, C, and D) are considered technically efficient, while those below the frontier (points B, E, and F) are inefficient.

The ray from the origin illustrates constant returns to scale. A bank located on both the frontier and the ray—point C—achieves maximum technical efficiency, combining both pure technical efficiency and scale efficiency. In contrast, banks at points A and D are technically efficient but do not lie on the rays, indicating they are not operating at optimal scale. Meanwhile, banks at points B and F have input levels matching those of technically efficient banks (C and D, respectively) and therefore exhibit scale efficiency, but they do not reach the frontier, indicating inefficiencies in their operations.

Finally, point E reflects a bank that is inefficient both in terms of scale and net technical efficiency, as it lies below the frontier and shares no input levels with any bank on the frontier. This graphical analysis illustrates how technical efficiency can be decomposed into pure technical efficiency and scale efficiency, providing insight into different banking sources of inefficiency within the sector.

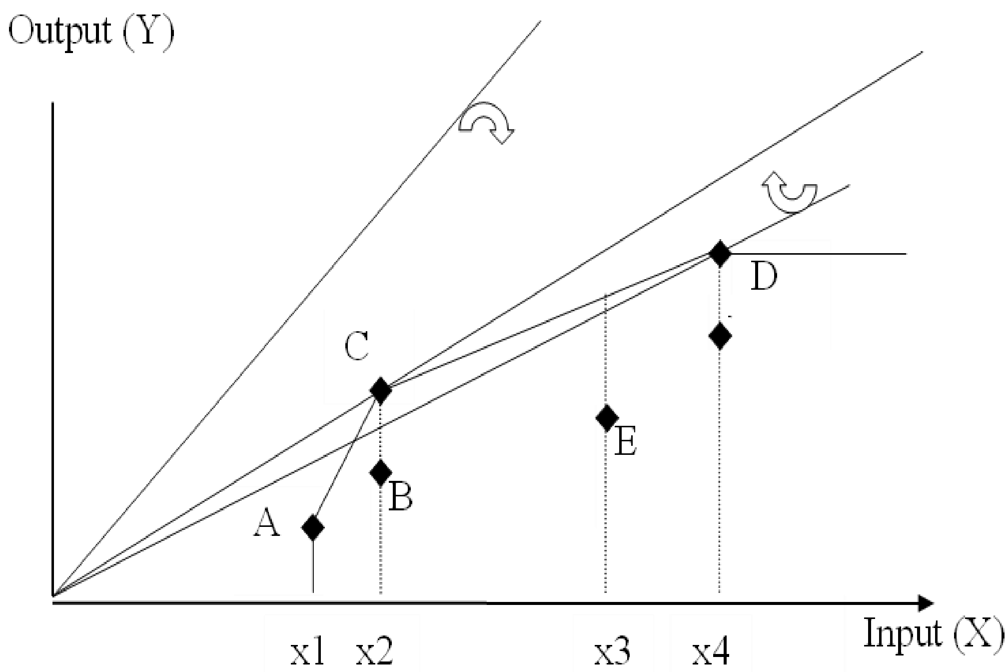

Figure 2.
Technical efficiency.

Subsequent studies on relative efficiency, building on Farrell's foundational framework, have mainly focused on the estimation of the production function—also referred to in some contexts as production technology—and the identification of its structural form.

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Parametric methods such as SFA assume a specific functional form and include a composed error term to separate inefficiency from statistical noise. In contrast, non-parametric methods like DEA construct the efficiency frontier directly from observed data without imposing any prior functional structure. Both approaches offer complementary insights, with parametric models better suited for hypothesis testing and statistical inference, and non-parametric models offering greater flexibility in modeling multi-input, multi-output production environments.

This relevant DEA (linear programming) paradigm will be briefly explained. For each DMU, we suppose that each bank has K inputs and M outputs. The inputs and outputs for the ith DMU are represented by the vectors and, respectively. We seek to determine the ratio of all outputs to all inputs for each bank (DMU), like $\frac{\sum_{k=1}^{K} u_{ik} y_{ik}}{\sum_{m=1}^{M} v_{im} x_{im}}$, where u_i and v_i are weight vectors. To choose the optimal weights, the following problem is proposed:

$$\frac{\sum_{k=1}^{K} u_{ik} y_{ik}}{\sum_{m=1}^{M} v_{im} x_{im}}$$

with constraints

$$\frac{\sum_{k=1}^{K} u_{ik} y_{ik}}{\sum_{m=1}^{M} v_{im} x_{im}} \le 1$$

$$u_{ik},\ v_{im} \ge 0$$

$$i = 1, 2, \ldots N$$

There are infinitely many solutions with this model's representation, as is well known. You can prevent this by adding a constraint $\sum_{m=1}^{M} v_{im} x_{im} = 1$, and obtain the multiplier form of the linear programming problem:

$$\sum_{k=1}^{K} u_{ik} y_{ik} \to \min$$

with constraints

$$\sum_{m=1}^{M} v_{im} x_{im} = 1$$

$$\sum_{k=1}^{K} u_{ik} y_{ik} - \sum_{m=1}^{M} v_{im} x_{im} \le 0$$

$$u_{ik},\ v_{im} \ge 0$$

$$i = 1, 2, \ldots N$$

Charnes, et al. [3] derive an equivalent envelope form from the dual property of this linear programming problem:

$$\min_{\theta,\lambda} \theta_i$$

with constraints

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$$\sum_{j=1}^{N} \lambda_j y_{kj} \geq y_{ki}, k = 1,2,\ldots,K$$
$$\sum_{j=1}^{N} \lambda_j x_{mj} \leq \theta_i x_{mi}, m = 1,2,\ldots,M$$
$$\lambda_j \geq 0$$
$$i = 1,2,\ldots,N$$

2.3. The Malmquist Productivity Index

Let x_t and y_t represent the input and output vectors for a bank at time t. The output distance function $D_t^t(x_t,y_t)$ measures the maximal proportional feasible expansion of output vector y_t, given input vector x_t and the production technology available at time t.

Formally, the output distance function is defined as:

$$D_t^t(x_t,y_t) = \inf\left\{\theta > 0 : \left(\frac{y_t}{\theta}\right) \in P_t(x_t)\right\}$$

where:

- θ is a scalar representing the proportion by which the output vector must be contracted to lie on the production possibility set $P_t(x_t)$ at time t,
- $P_t(x_t)$ is the output set for input x_t at time t, ie, the set of all output vectors produceable by x_t at time t,
- If $D_t^t(x_t,y_t) = 1$, the DMU lies on the frontier (technically efficient),
- If $D_t^t(x_t,y_t) < 1$, the DMU is inefficient.

This function allows for non-parametric estimation using DEA, where $D_t^t(x_t,y_t)$ is obtained as the solution to a linear programming problem under Constant Returns to Scale (CRS) or Variable Returns to Scale (VRS).

In the computation of the Malmquist Productivity Index, two additional distance functions play a crucial role in capturing the technological change component. These are referred to as cross-period distance functions:

- $D_t^{t+1}(x_{t+1},y_{t+1})$: the distance of the period t+1 observation evaluated against the period t technology.
- $D_{t+1}^t(x_t,y_t)$: the distance of the period t observation evaluated against the period t+1 technology.

Forward-looking cross-distance:

$$D_t^{t+1}(x_{t+1},y_{t+1}) = \inf\left\{\theta > 0 : \left(\frac{y_{t+1}}{\theta}\right) \in P_t(x_{t+1})\right\}$$

This function measures how well the future observation (from t+1) would have performed under the technology available at time t.

Backward-looking cross-distance:

$$D_{t+1}^t(x_t,y_t) = \inf\left\{\theta > 0 : \left(\frac{y_t}{\theta}\right) \in P_{t+1}(x_t)\right\}$$

This function evaluates how well the past observation (from t) would perform under the updated technology at time t+1.

Interpretation in Malmquist Index

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Together, these two cross-period distances reflect shifts in the production frontier:

- If $D_t^{t+1}(x_{t+1}, y_{t+1}) < 1$, it indicates that the future observation performs better under the future technology than it would under the past technology → technological progress.
- If $D_{t+1}^{t}(x_t, y_t) > 1$, it implies that the past observation performs worse under the future technology → further evidence of frontier advancement.

The technological change (TC) component of the Malmquist index is then computed as:

$$TC = \left[\frac{D_t^{t+1}(x_{t+1}, y_{t+1})}{D_{t+1}^{t}(x_t, y_t)}\right]^{1/2}$$

This geometric mean formulation accounts for asymmetries in technology shifts and stabilizations cross-period comparisons.

2.4. Full Malmquist Index Using Output Distance Functions

With the distance functions defined, the Malmquist Productivity Index (MPI) between time t and t+1 can be expressed as:

$$M(x_t, y_t, x_{t+1}, y_{t+1}) = \left[\frac{D_t^{t}(x_t, y_t)}{D_{t+1}^{t+1}(x_{t+1}, y_{t+1})}\right] \cdot \left[\frac{D_t^{t+1}(x_{t+1}, y_{t+1})}{D_{t+1}^{t}(x_t, y_t)}\right]^{1/2}$$

Where:

- The first term measures efficiency change (EC): how much closer or further the DMU is to the frontier from t to t+1,
- The second term measures technological change (TC): the shift of the frontier itself between the two periods.

This decomposition provides a complete view of whether productivity growth arises from internal improvements (catching up) or from external innovation (technological progress).

3. Specification of Inputs and Outputs for Banks

Before analyzing bank-level productivity and efficiency indicators, it is necessary to clearly define the functional objectives of a commercial bank and, based on those, determine the appropriate inputs and outputs. There has long been debate in the literature regarding what constitutes valid outputs in banking. Banking outputs include "transaction services and portfolio management services provided to depositors while performing intermediation." This definition implies that the scope of bank outputs may be quite broad and depends heavily on the financial development of the economy. As such, both the breadth (diversity) and depth (complexity) of financial services vary across countries and over time, requiring context-specific input–output selection.

In the literature, three main methodological approaches are commonly used to define banking production:

1. Asset Approach: This perspective considers banks primarily as financial intermediaries between depositors and borrowers. Under this approach, loans and other earning assets are treated as outputs, while deposits and other liabilities are considered inputs [7].
2. User-Cost Approach: Inputs and outputs are classified based on the net financial contribution of each asset or liability item. If the return on an asset exceeds its opportunity cost (or if the cost of a liability is less than its opportunity cost), it is categorized as an output; otherwise, it is an input [8]. While theoretically elegant, this method is sensitive to interest rate fluctuations and suffers from practical challenges in measuring marginal revenue and cost.
3. Value-Added Approach: Both assets and liabilities may exhibit output characteristics, but only those that contribute clearly to value creation are classified as outputs. This approach actually

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uses operating cost shares rather than theoretical pricing models and has been widely used in empirical banking research [1, 9].

The value-added approach also allows for the differentiation of functional roles performed by banks. Taranova, et al. [10] identified five essential objectives in effective bank management: profit maximization, risk management, service provision, intermediation, and utility creation. For simplicity, these can be grouped into two broader functions: (1) profit maximization (including risk control), and (2) service delivery (including intermediation and utility) [11]. In reality, most banking operations involve both functions, and this duality is reflected in model construction [12]. No explicit weights are assigned; rather, the influence of both functions is inherently incorporated. In some cases, separate output sets may be constructed to emphasize one function over the other.

Building on the above conceptual insights, prior empirical work, and taking into account the structure and limitations of the available data, this study adopts the asset approach to specify inputs and outputs for both the DEA efficiency model and the Malmquist productivity analysis.

Based on the financial intermediation role of banks, the model includes three key outputs and four input variables:

- Outputs:
- Y_1 : Total loans
- Y_2 : Securities holdings
- Y_3 : Operating income
- Inputs:
- X_1 : Fixed assets
- X_2 : Total deposits
- X_3 : Operating expenses
- X_4 : Number of employees (labor)

The inclusion of labor reflects the real-world production process in banking, where human capital plays a central role in both service quality and operational management.

The dataset used in this study was constructed from manually collected financial information obtained from the annual reports of 22 Vietnamese commercial banks for the period 2008–2024 . The dataset includes a balanced set of 7 key indicators , covering both outputs and inputs relevant to bank operations. The full sample spans 17 years , enabling the assessment of long-term trends in efficiency and productivity under different economic and regulatory conditions.

This consistent and rich dataset enables the application of both DEA (Data Envelopment Analysis) and the Malmquist Productivity Index , with input–output configurations that reflect real-world banking operations in Vietnam. The data coverage also captures critical transitions in the banking sector, including consolidation, digitalization, and post-restructuring adjustments after the global financial crisis and COVID-19 pandemic.

Table 1 presents a list of 22 Vietnamese commercial banks used in the study, including the full English name of each bank (column "Name of bank") and the corresponding abbreviation code (column "DMU" – Decision Making Unit). Each DMU code represents a decision-making unit in the efficiency and productivity growth analysis model, which is often used to mark on the horizontal axis of charts or tables of results. The use of abbreviations such as CTG, VPB, TCB, BIDV... facilitates data processing and comparison of results with specific banking entities. This is an important basis for analyzing operational efficiency, comparing productivity and assessing technological changes among banks during the research period from 2008 to 2024.

DOI: 10.55214/2576-8484.v9i9.10141
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Table 1.
List of 22 Vietnamese commercial banks used in the study, including the full English name of each bank (column "Name of bank") and the corresponding abbreviation code (column "DMU" – Decision Making Unit).

Name of bank	**DMU**
Vietnam Joint Stock Commercial Bank for Industry and Trade	CTG
Vietnam Joint Stock Commercial Bank for Foreign Trade	VPB
Vietnam Technological and Commercial Joint Stock Bank	TCB
Bank for Investment and Development of Vietnam	BIDV
Military Commercial Joint Stock Bank	MBB
Vietnam Prosperity Joint Stock Commercial Bank	VBP
Saigon Thuong Tin Commercial Joint Stock Bank	STB
Asia Commercial Bank	ACB
Vietnam Export Import Commercial Joint Stock Bank	EIB
Saigon – Hanoi Commercial Joint Stock Bank	SHB
Maritime Commercial Joint Stock Bank	MSB
Ho Chi Minh City Development Joint Stock Commercial Bank	HDB
Tien Phong Commercial Joint Stock Bank	TPB
Vietnam International Commercial Joint Stock Bank	VIB
Southeast Asia Commercial Joint Stock Bank	SEAB
Orient Commercial Joint Stock Bank	OCB
An Binh Commercial Joint Stock Bank	ABB
Nam A Commercial Joint Stock Bank	NAB
Kien Long Commercial Joint Stock Bank	KLB
Saigon Bank for Industry and Trade	SGB
National Citizen Commercial Joint Stock Bank	NVB
Petrolimex Group Commercial Joint Stock Bank	PGP

4. Results and Discussion

We ran the model for 16 consecutive periods, namely from 2008 to 2024, corresponding to the periods: 2008–2009, 2009–2010, 2010–2011, …, 2023–2024. Each period consists of two consecutive years (t and t+1), which allows the calculation of the output gap functions and the Malmquist index according to the standard formula. In total, there are 16 calculations for each bank to determine: Efficiency Change (EC), Technical Change (TC) and Malmquist TFP Index, then, taking the geometric mean of these 16 periods to analyze the long-term performance of each bank. Below we analyze some typical periods.

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Table 2.
Technical efficiency, technological progress and Malmquist index for the period 2008-2009.

idDMU	DMU	Year_t	year_(t+1)	EC	TC	Malmquist
1	CTG	2008	2009	1	0.546	0.739
2	VPB	2008	2009	1	1.004	1.002
3	TCB	2008	2009	1.298	1.585	1.434
4	BIDV	2008	2009	1	0.888	0.942
5	MBB	2008	2009	1	0.522	0.723
6	VBP	2008	2009	1	1,021	1.01
7	STB	2008	2009	1.035	0.839	0.932
8	ACB	2008	2009	1.125	0.829	0.966
9	EIB	2008	2009	0.981	0.872	0.925
10	SHB	2008	2009	1,067	0.747	0.893
11	MSB	2008	2009	0.982	0.742	0.854
12	HDB	2008	2009	1.36	1,215	1,286
13	TPB	2008	2009	1	0.238	0.487
14	VIB	2008	2009	0.96	0.826	0.891
15	SEAB	2008	2009	1.183	2.707	1.79
16	OCB	2008	2009	0.983	1,053	1,017
17	ABB	2008	2009	1.454	1.183	1,312
18	NAB	2008	2009	0.986	0.713	0.838
19	KLB	2008	2009	0.624	0.47	0.542
20	SGB	2008	2009	1.047	1.211	1.126
21	NVB	2008	2009	0.856	0.811	0.833
22	PGP	2008	2009	1.211	0.789	0.977

The results of calculating the Malmquist index for 22 Vietnamese commercial banks in Table 2 during the period of 2008–2009 show a clear differentiation among banks in improving operational efficiency and technological innovation. In terms of the technical efficiency change index, most banks achieved a value of 1 or higher, demonstrating the ability to maintain or improve their relative position compared to the efficient frontier. Notably, some banks have very high EC levels such as ABB (1.454), HDB (1.36) or SEAB (1.183), showing significant improvements in the ability to use inputs effectively. However, there are still cases with low efficiency such as KLB (0.624), NVB (0.856) or EIB (0.981), reflecting inefficiency in operations, which may come from management factors or high operating costs compared to the output generated.

In terms of technological change, the results show a large difference between banks. While SEAB achieved a very high TC (2.707), showing that this bank has made great strides in technological innovation, invested in processes or applied advanced management methods, on the contrary, many other banks are lagging behind in technology such as TPB (0.238), KLB (0.470) or MB (0.522). This reflects the uneven level of access and application of innovation among banks, especially in the context after the 2008 global financial crisis, when the requirement for technological modernization and risk management has become more urgent than ever.

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Table 3.
Technical efficiency, technological progress and Malmquist index for the period 2009-2010.

idDMU	DMU	year_t	year_(t+1)	EC	TC	Malmquist
1	CTG	2009	2010	1	0.949	0.974
2	VPB	2009	2010	1	0.877	0.937
3	TCB	2009	2010	0.913	0.794	0.852
4	BIDV	2009	2010	1	1,059	1,029
5	MBB	2009	2010	1.173	2.414	1.683
6	VBP	2009	2010	1	1.118	1,058
7	STB	2009	2010	0.787	1.052	0.91
8	ACB	2009	2010	0.955	0.714	0.826
9	EIB	2009	2010	0.871	0.857	0.864
10	SHB	2009	2010	0.775	0.898	0.834
11	MSB	2009	2010	1	0.63	0.794
12	HDB	2009	2010	0.747	0.755	0.751
13	TPB	2009	2010	1	0.843	0.918
14	VIB	2009	2010	1	0.431	0.657
15	SEAB	2009	2010	0.845	0.49	0.644
16	OCB	2009	2010	0.902	1.101	0.997
17	ABB	2009	2010	0.819	0.955	0.884
18	NAB	2009	2010	0.784	0.952	0.864
19	KLB	2009	2010	1	0.959	0.979
20	SGB	2009	2010	0.899	1.078	0.985
21	NVB	2009	2010	1	0.921	0.96
22	PGP	2009	2010	0.862	0.942	0.901

Combining both EC and TC factors in the Malmquist index shows that some banks have strong growth in total factor productivity such as SEAB (1.790), TCB (1.434), ABB (1.312) and HDB (1.286). These banks have not only improved the efficiency of resource use but also reached out to advanced technology, demonstrating a sustainable development strategy. In contrast, banks such as TPB (0.487), KLB (0.542), MB (0.723) and CTG (0.739) all showed a decline in total factor productivity, mainly due to weaknesses in improving operational efficiency and lack of technological innovation. Some special cases such as PGP (EC = 1.211, TC = 0.789) reflect the tendency that banks can improve their internal efficiency but without simultaneous technological improvements, overall productivity growth remains limited.

During the 2009–2010 period, the Malmquist index analysis results in Table 3 continued to reflect the differentiation in productivity and efficiency among Vietnamese commercial banks. In terms of technical efficiency, most banks maintained an EC level equal to or close to 1, indicating relatively stable operating efficiency compared to the frontier. Some banks continued to improve strongly, such as MBB (1.173), reflecting internal efforts in optimizing resources and operating processes. Meanwhile, HDB (0.747), SHB (0.775) or SEAB (0.845) recorded low EC levels, indicating a decline in internal management and inefficient use of inputs.

Regarding the technology progress index, many banks recorded positive growth, most notably MBB (2,414) - this is a sudden increase, possibly due to strong technological innovation or the application of a new core banking system. Banks such as BIDV (1.059), VBP (1.118) and SGB (1.078) also showed a positive shift in the technology frontier. However, many banks showed a clear lag in technology such as VIB (0.431), MSB (0.63) and SEAB (0.49) - this raises a warning about slow technological adaptation in a period when system modernization is becoming urgent.

Combining the two factors EC and TC into the total factor productivity index, some banks have impressive growth rates such as MBB (1.683), BIDV (1.029) and VBP (1.058) - showing comprehensive growth in both operations and technology. On the contrary, many banks still maintain TFP < 1, showing declining productivity levels such as HDB (0.751), ACB (0.826), EIB (0.864) or TCB (0.852) -

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 9: 1437-1453, 2025
DOI: 10.55214/2576-8484.v9i9.10141
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reflecting that although operations have improved somewhat, the level of innovation is not strong enough to boost overall productivity.

Table 4.
Technical efficiency, technological progress and Malmquist index for the period 2022-2023.

idDMU	DMU	year_t	year_(t+1)	EC	TC	Malmquist
1	CTG	2022	2023	0.976	0.856	0.914
2	VPB	2022	2023	0.988	0.894	0.94
3	TCB	2022	2023	1,002	1,078	1.04
4	BIDV	2022	2023	1	0.96	0.98
5	MBB	2022	2023	1.011	1.15	1,078
6	VBP	2022	2023	1	0.966	0.983
7	STB	2022	2023	1,041	1,024	1,033
8	ACB	2022	2023	0.961	0.93	0.945
9	EIB	2022	2023	1,012	1,067	1,039
10	SHB	2022	2023	1	0.821	0.906
11	MSB	2022	2023	1	0.715	0.845
12	HDB	2022	2023	1	1,013	1,007
13	TPB	2022	2023	1	1.16	1,077
14	VIB	2022	2023	1	0.744	0.862
15	SEAB	2022	2023	1	1,015	1,007
16	OCB	2022	2023	1	0.915	0.957
17	ABB	2022	2023	0.999	0.975	0.987
18	NAB	2022	2023	0.976	0.943	0.959
19	KLB	2022	2023	0.862	0.804	0.832
20	SGB	2022	2023	0.983	0.992	0.987
21	NVB	2022	2023	1,044	0.964	1,003
22	PGP	2022	2023	0.924	0.896	0.91

In the period 2022–2023, the results of the Malmquist index analysis (Table 4) continue to show a clear differentiation among Vietnamese commercial banks in maintaining and improving overall productivity. In terms of technical efficiency, banks with EC levels exceeding 1 such as MB (1.011) , STB (1.041) , EIB (1.012) and NVB (1.044) show that they not only maintain efficiency but also have clear improvements in operational management and resource optimization.

However, there are also banks with EC levels lower than 1 such as KLB (0.862) , PGP (0.924) or NAB (0.976) - this is a sign that some units are still facing difficulties in controlling costs or organizing effective operations, especially in the context of many economic fluctuations after COVID-19 and increasing interest rate pressure.

In terms of technological progress, the most outstanding results belong to MB (1.15) , TPB (1.16) and TCB (1.078) , showing that these banks continue to invest and adapt well to digital technologies, modernize core banking systems or upgrade operational capacity. On the contrary, some banks have low TC levels below 0.9 such as MSB (0.715) , SHB (0.821) or KLB (0.804) , showing delays in technological innovation or not keeping up with the development level of the industry.

Overall, the total factor productivity index reflects comprehensive performance from both technical efficiency and technological progress. Banks with impressive productivity growth include MBB (1.078) , TPB (1.077) , TCB (1.04) and EIB (1.039) . In contrast, banks such as KLB (0.832) , MSB (0.845) or PGP (0.91) face many challenges in simultaneously improving operational efficiency and modernizing technology.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 9: 1437-1453, 2025
DOI: 10.55214/2576-8484.v9i9.10141
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Table 5.
Technical efficiency, technological progress and Malmquist index for the period 2023-2024.

idDMU	DMU	year_t	year_(t+1)	EC	TC	Malmquist
1		2023	2024	1	0.954	0.977
2		2023	2024	0.994	0.873	0.932
3		2023	2024	0.959	0.837	0.896
4		2023	2024	1	0.953	0.976
5		2023	2024	0.989	0.807	0.893
6		2023	2024	1	0.973	0.986
7		2023	2024	1.03	0.97	0.999
8		2023	2024	0.91	0.821	0.864
9		2023	2024	0.92	0.839	0.879
10		2023	2024	1	1.203	1.097
11		2023	2024	1	0.685	0.828
12		2023	2024	1	0.662	0.813
13		2023	2024	1.084	1.033	1.058
14		2023	2024	1	0.988	0.994
15		2023	2024	1.045	0.925	0.983
16		2023	2024	1	0.973	0.986
17		2023	2024	0.977	0.916	0.946
18		2023	2024	1.079	1.179	1,128
19		2023	2024	1.196	1.1	1.147
20		2023	2024	1.021	0.993	1,007
21		2023	2024	1.397	1.243	1.318
22		2023	2024	1.098	0.942	1.017

The period 2023–2024 (Table 5) – the end of the observation period in the study – continues to show significant changes in the efficiency and productivity of Vietnamese commercial banks. In terms of technical efficiency index, some prominent banks such as NVB (1.397), KLB (1.196) and NAB (1.079) show outstanding improvements in terms of operations.

On the other hand, some banks still show relative weakness in technical efficiency such as ACB (0.91), EIB (0.92) and TCB (0.959). This may stem from internal problems such as high operating costs, ineffective resource allocation strategies or being affected by an unfavorable business environment in 2023.

In terms of the technological change index – a proxy for the level of technological innovation and improvement – banks such as SHB (1.203), NAB (1.179), KLB (1.1) and especially NVB (1.243) show a strong shift in the technological frontier. This reflects strong investments in digital technology, e-banking, or business process improvement. On the contrary, some banks still have significantly low TC such as MSB (0.685) and HDB (0.662), raising questions about the system's ability to innovate technology and adapt to digital transformation requirements.

Combining the above two factors, the total factor productivity index comprehensively reflects the performance of the bank. Some banks achieved very high growth rates such as NVB (1.318), KLB (1.147), NAB (1.128) and SHB (1.097), while banks such as EIB (0.879), ACB (0.864), VPB (0.932) and VCB (0.932) recorded an overall productivity level below 1, indicating a slight decline in productivity in the context of market fluctuations.

ISSN: 2576-8484
Vol. 9, No. 9: 1437-1453, 2025
DOI: 10.55214/2576-8484.v9i9.10141
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Table 6.
Technical efficiency, technological progress and average Malmquist index for the period 2008-2024.

idDMU	DMU	EC	TC	Malmquist
1	CTG	0.999966	0.923316	0.960865
2	VPB	1.004577	0.901526	0.951698
3	TCB	0.999727	0.929064	0.963902
4	BIDV	1	0.887193	0.941842
5	MBB	1.00002	0.968696	0.980744
6	VBP	1	0.94641	0.972807
7	STB	0.999418	1.018225	1.008818
8	ACB	1.002569	0.982712	0.992497
9	EIB	0.999912	1.047435	1.023366
10	SHB	0.984822	0.929663	0.956829
11	MSB	0.998847	0.990365	0.994767
12	HDB	0.999896	0.842789	0.91808
13	TPB	1.005074	0.919035	0.960857
14	VIB	0.997397	0.962156	0.979721
15	SEAB	1.002732	1.046631	1.024446
16	OCB	0.992556	1.021951	1.007159
17	ABB	1.007269	1.040725	1.023814
18	NAB	0.989456	0.940766	0.964749
19	KLB	0.994272	0.97893	0.986524
20	SGB	1.014278	1.031685	1.022789
21	NVB	1.016499	1.080606	1.047978
22	PGP	1.016915	0.974752	0.99569

After aggregating the results from 16 consecutive periods (Table 6), the average Malmquist index provides a more comprehensive view of the long-term trend in efficiency and productivity growth of commercial banks in Vietnam. In general, banks have an EC level fluctuating around the value of 1 , indicating relatively stable performance compared to the efficient frontier over time. Banks such as TPB (EC = 1.0051) , SGB (1.0143) , NVB (1.0165) and PGP (1.0169) have an average EC above 1 – this reflects good management capacity and continuous improvement in operating efficiency in the long term.

However, the TC index – representing the ability to innovate technology and shift the production frontier – has a larger difference between banks. Some units such as NVB (TC = 1.0806) , SGB (1.0317) and SEAB (1.0466) show a clear level of investment in technology and digital transformation. Meanwhile, some large banks such as BIDV (0.8871) , HDB (0.8428) and VPB (0.9015) have a significantly lower average TC level, indicating that the speed of approaching technological innovation is still slow or ineffective.

total factor productivity index – the product of EC and TC – reflects the combined results of both operational efficiency and technological progress. Banks with high average Malmquist scores include NVB (1.0480) , SEAB (1.0244) , EIB (1.0234) , SGB (1.0228) , and ABB (1.0238) . This is a group of banks with real productivity growth in the long term. In contrast, some large banks such as CTG (0.9609) , VPB (0.9517) , BIDV (0.9418) , and HDB (0.9181) have average productivity lower than 1 – reflecting a trend of declining productivity due to not keeping up with the growth rate of the industry or lacking strong reforms.

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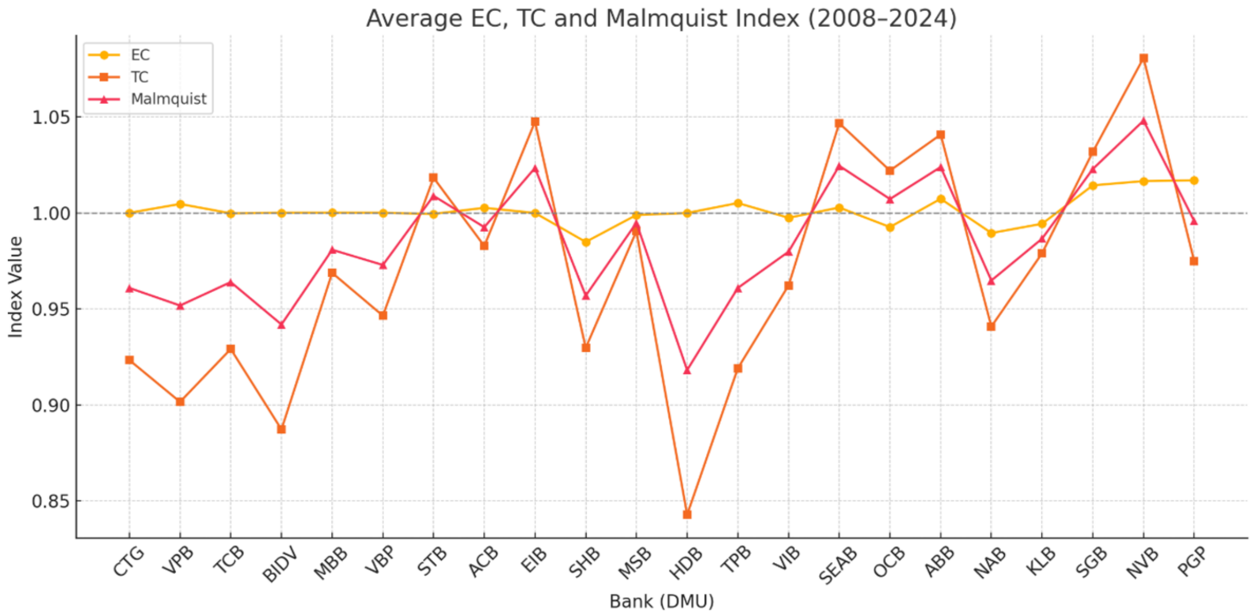

Figure 3.
Technical efficiency, technological progress index and average Malmquist index of 22 banks.

Figure 3 shows that the technical efficiency of banks is relatively stable around level 1, reflecting the ability to maintain long-term operational efficiency. However, the technological progress index fluctuates more strongly among banks, indicating large differences in the level of investment in innovation and digital transformation. Some banks such as NVB , SEAB , SGB and ABB have Malmquist levels > 1 , showing increased productivity due to a good combination of effective management and technology. In contrast, banks such as BIDV or HDB have decreased productivity due to limited technological progress.

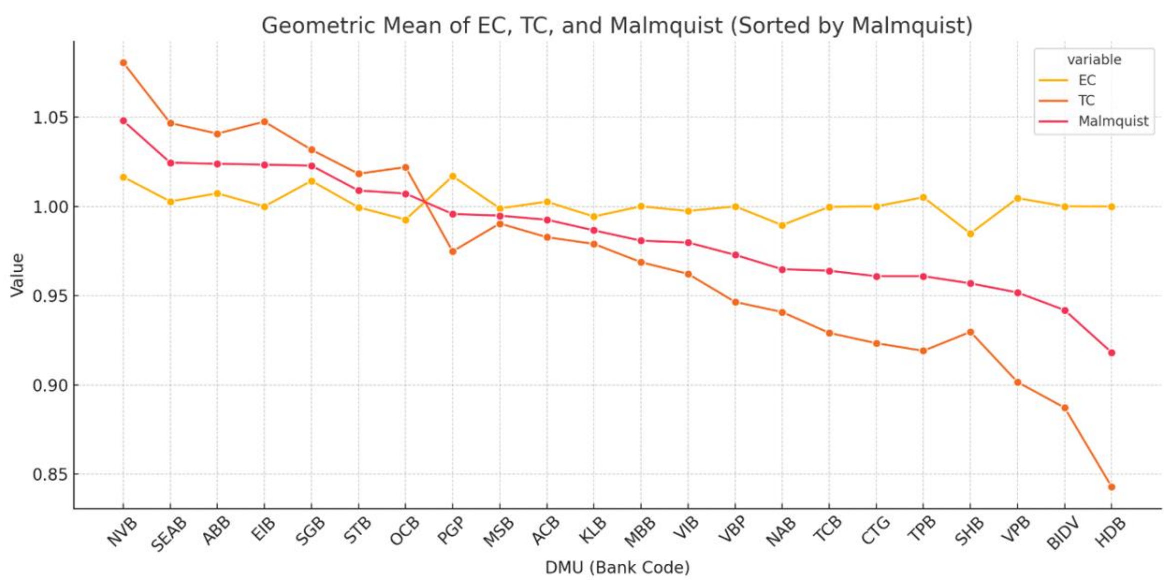

Figure 4.
Arrange banks in descending order of average Malmquist index.

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 9: 1437-1453, 2025
DOI: 10.55214/2576-8484.v9i9.10141
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Figure 4, which ranks banks in descending order of average Malmquist index, shows a clear divergence in productivity growth. Banks such as NVB , SEAB , ABB and EIB are in the top group, with outstanding productivity growth due to a good combination of technical efficiency and technological innovation. In contrast, banks such as BIDV and HDB have the lowest Malmquist scores, mainly due to a sharp decline in TC index, indicating limited technological innovation. This result emphasizes the key role of technological innovation in improving bank productivity.

5. Conclude

This study used the data envelopment analysis method and the Malmquist index to evaluate the technical efficiency, technological progress and productivity growth of 22 Vietnamese commercial banks during the period 2008–2024. Data collected from the financial statements and annual reports of banks showed significant productivity differentiation among banks. The results indicated that the technical efficiency of most banks remained around level 1, reflecting relatively stable management capabilities. However, large differences in technological progress were the main factor creating the gap in the total factor productivity index. Banks such as NVB, SEAB, ABB, EIB and SGB were prominent with strong productivity growth, while some large banks such as BIDV, HDB and VPB showed productivity decline due to technology not catching up. The results highlight the essential role of technology investment and innovation capacity building in improving operational efficiency. The study provides important empirical evidence to support policy making and development strategies for the Vietnamese banking sector in the context of financial integration and digitalization.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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