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Reallocation and efficiency of Vietnamese commercial banks from 2008 to 2018

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ABSTRACT

This study applied DEA window analysis in combination with non-parametric testing to examine the efficiency and the stability of the efficiency ranking of Vietnamese commercial banks from 2008 to 2018, a very active period of M&A deals and resource reallocation. The estimation results of the window analysis model showed that the average efficiency under the assumption of constant returns to scale reached 80-88%, while the average efficiency under the assumption of variable returns to scale reached 86 - 91%. The non-parametric testing of the efficiency ranking showed that some banks had much lower efficiencies than other banks after carrying out M&A deals.

ملخص

طبقت هذه الدراسة نافذة تحليل مغلف البيانات (DEA) بالاقتران مع الاختبار غير المعياري لفحص كفاءة واستقرار تصنيف كفاءة البنوك التجارية الفيتنامية من 2008 حتى 2018، وهي فترة تعتبر نشطة للغاية من حيث صفقات الاندماج والاحتياز وإعادة تخصيص الموارد. وأظهرت نتائج عملية التقدير من خلال نموذج تحليل النافذة أن متوسط الكفاءة في ظل افتراض العوائد القياسية الثابتة بلغ 80-88%، بينما بلغ متوسط الكفاءة بافتراض العوائد القياسية المتغيرة 86-91%. كما أظهر الاختبار غير المعياري لتصنيف الكفاءة أن بعض البنوك تمتلك كفاءات أقل بكثير من البنوك الأخرى بعد تنفيذ صفقات الاندماج والاحتياز (M&A).

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ABSTRAITE

Cette étude a appliqué l'analyse de fenêtre DEA en combinaison avec des tests non paramétriques pour examiner l'efficacité et la stabilité du classement de l'efficacité des banques commerciales vietnamiennes de 2008 à 2018, une période très active d'opérations de fusion et d'acquisition (F&A) et de réaffectation des ressources. Les résultats de l'estimation du modèle d'analyse des fenêtres ont montré que l'efficacité moyenne sous l'hypothèse de rendements d'échelle constants atteignait 80-88%, tandis que l'efficacité moyenne sous l'hypothèse de rendements d'échelle variables atteignait 86 - 91%. Le test non paramétrique du classement de l'efficience a montré que certaines banques avaient une efficience beaucoup plus faible que d'autres banques après avoir réalisé des opérations de fusion et d'acquisition (F&A).

Keywords: DEA window analysis, banks, ranking statistics, mergers and acquisitions, Vietnam

JEL Classification: G21

1. Introduction

The Vietnamese banking sector has recently been under pressure from changes in legislation, the deepening and widening of the economy and a fiercely competitive trading environment. Therefore, each bank has needed to continuously improve its efficiency, especially compared to other banks, to remain competitive. Over the past ten years, Vietnam's commercial banking system has undergone a very thorough restructuring process. As a result, between 2012-2015, there were six successful M&A deals. The M&A activities have included 13 banks, causing the reduction of 7 joint-stock commercial banks.

Therefore, it is important to evaluate the efficiency of Vietnamese commercial banks, especially banks that have participated in mergers and acquisitions. Using panel data covering a sample of 26 Vietnamese commercial banks over the period from 2008-to 2018, the main contribution of this study was the use of DEA window analysis in combination with statistical tests to measure technical efficiency (TE), pure efficiency (PE) and scale efficiency (SE). Notably, this research examined the sampled banks' efficiency pre-and post-merger. It also evaluated the stability of the efficiency ranking of Vietnamese banks during M&A deals during the research period from 2008 to 2018.

The remainder of this paper is organised as follows: Section 2 reviews the related existing literature. Section 3 introduces this study's methodology, including DEA window analysis and the Kruskal-Wallis's test. Section 4 offers descriptive statistics concerning resource reallocation and commercial bank mergers in Vietnam. Additionally, it summarises the results of evaluating bank efficiency using the DEA window analysis model with a 3-year width, the results of the non-parametric test for the stability of efficiency ranking and other analyses. The last section contains the conclusion to this research.

2. Literature Review

Two common techniques measure banks' efficiency: (a) non-parametric and (b) parametric approaches. These techniques calculate banks' technical, scale, and cost efficiencies. The Stochastic Frontier Approach (SFA) is a non-parametric method often used to estimate efficiency (Berger and Humphrey, 1997; Fethi and Pasiouras, 2010; Mokhamad Anwa, 2018. In contrast, the most used parametric approach has been Data Envelopment Analysis (DEA) (Sathye, 2013, Sufian *et al.*, 2014; Basilio *et al.*, 2016; Rusydiana *et al.*, 2019; Azad *et al.*, 2021). Several studies have compared different estimation techniques (Rusydiana *et al.*, 2019; Thiago, 2017; Ikra *et al.*, 2021). DEA window analysis is another method that has been applied to analyse efficiency in many fields, such as energy, environment, finance, and banking. For example, Yue (1992) used DEA window analysis to evaluate relative efficiency in the banking industry. The author concluded that DEA window analysis helped indicate the best and worst banks relatively and the most stable and most variable banks, in terms of the average DEA in the research period. Asmild *et al.* (2004) used DEA window analysis, and the Malmquist index to examine the efficiency of Canadian banks. Řepková and Iveta (2014) applied DEA window analysis on Czech commercial banks' data and estimated the efficiency of the Czech banking industry between 2003 and 2012. Using panel data covering the period from 2005 to 2011 in Serbia, Savić *et al.* (2012) used extended DEA window analysis to evaluate the efficiency of banks.

In Vietnam, there has been some research regarding the efficiency of the commercial banking system, such as Minh *et al.*, 2013; Turnell and Vu, 2010; Nguyen *et al.*, 2018. For example, Minh *et al.*, 2013 used the super-efficient model to estimate the efficiency of 32 Vietnamese commercial banks from 2001 to 2005. They then ranked the efficiencies to find the best and the worst banks in a relative sense. In general, these studies have only estimated efficiency based on DEA models, the Malmquist index or the Stochastic frontier production function and the window analysis approach, while the process of bank mergers and acquisitions was not examined.

Table 1: Sample Table

Subsample	Chi-Sq. Statistic	Chi-Sq. d.f.	Prob.
1	13.531	3	0.0036
2	25.488	2	0.0000

3. Methodology

The DEA approach was originally introduced by Charnes *et al.* (1978) based on the research of Farrell (1957). It can handle multiple inputs and outputs to estimate a firm's efficiency (Banker, 1984; Asmild *et al.*, 2004). The DEA approach measures the relative efficiency of a set of decision-making units (DMUs) using multiple inputs to create multiple outputs. However, the basic DEA model (CCR), introduced by Charnes et al., (1978), measures technical efficiency (TE) under the assumption of constant returns to scale efficiency. The basic DEA model (BCC) was modified by Banker, Charnes, and Cooper (1984) from the CCR model to measure pure technical efficiency (PTE), which evaluated technical efficiency without scale efficiency effect (SE). There are some limitations to the DEA approach. DEA results cannot be interpreted confidently when the integrity of the data has been violated. Besides, efficient analysis relies only on one period, which hampers the measurement of efficiency changes, especially in cases that study the impact of reallocation on efficiency. Therefore, it is necessary to incorporate the time factor into efficiency analysis.

Window analysis is a method used to determine productivity changes over time, based on the principle of moving averages (Charnes *et al.*, 1995;

Cooper *et al.*, 2007; Savić *et al.*, 2012). In window analysis, each DMU in a different period is treated as a different DMU (independent); however, it can still be compared in the same window. Therefore, a bank's efficiency in a period can be contrasted against itself and against that of other banks (Asmild *et al.*, 2004). And a certain DMU at a given time can compare its efficiency at different times and with other firms' efficiency at the same time and at different times (Yue, 1992).

3.1. The DEA model measuring the efficiency of commercial banks

The DEA approach comprises a non-parametric model without any prior assumption concerning the production function to process the observed data. Consider a set of N decision-making units (DMU) (n = 1,2, ... N) in periods T ($t = 1,2, ... T$) (T = 2008-2018) using m inputs to produce the output s. Set DMU_{tn} to represent DMUn for a period of t with the input vector m and the output vector s.
For DMU k (k^{th} bank). Suppose y_{rk} ($r = 1,2, s$) is an output r, and x_{ik} (i = 1,2, ..., m) is the i^{th} input. To measure the efficiency of the DMU k, Charnes *et al.* (1978) proposed the following model.

$$\begin{aligned} &\min_{\theta,\lambda} \theta \\ st.\quad &\theta x_{ik} - \sum_{j=1}^{N} \lambda_j x_{ij} \geq 0, \qquad i = 1,2,...,m \\ &\sum_{j=1}^{N} \lambda_j y_{rj} \geq y_{rk}, \qquad \mathrm{r} = 1,2,...,\mathrm{s} \\ &\lambda_j \geq 0, \qquad j = 1,2,...,\mathrm{N} \end{aligned} \tag{1}$$

Optimal θ, denoted by θ* satisfies the condition $0 \leq \theta^* \leq 1$. If θ*= 1, then the DMU is the technical efficiency (TE), and the DMU is on the efficiency frontier. The above model is often referred to as the input-oriented model with constant returns to scale efficiency of Charnes-Cooper-Rhodes (CCR). The value of the objective function of the CCR problem is called technical efficiency (TE). To consider the variable returns to scale efficiency, the CCR model is extended to the BCC model as follows:

$$\begin{aligned}
&\min_{\theta,\lambda} \theta \\
&st. \quad \theta x_{ik} - \sum_{j=1}^{N} \lambda_j x_{ij} \geq 0, \qquad i = 1,2,...,m \\
&\sum_{j=1}^{N} \lambda_j y_{rj} \geq y_{rk}, \qquad \mathrm{r} = 1,2,...,\mathrm{s} \\
&\sum_{j=1}^{N} \lambda_j = 1, \\
&\lambda_j \geq 0, \qquad j = 1,2,...,\mathrm{N}
\end{aligned} \tag{2}$$

The DMU operates under the assumption of variable returns to scale efficiency where an increase in inputs does not change outputs in the same proportion. The BCC model measures pure technical efficiency (PTE), ignoring the impact of scale, by only comparing the DMU with a unit of similar proportions. PTE measures how the DMU uses its resources in exogenous environments. *Low PTE implies that the DMU is inefficient in resource management*. Using the BCC model allows decomposition of the TE score into the pure technical efficiency score (PTE) and scale efficiency score (SE), where the relationship between them is shown as:

$$SE = TE / PTE \tag{3}$$

Scale efficiency (SE) measures how scale affects efficiency. SE also indicates management's ability to choose an optimal resource size, in other words, to select the production scale (bank activity in this study) that will achieve the expected level of production.

3.2. The DEA model measuring the efficiency of commercial banks

In this study, the window analysis model was used to analyse the efficiency for a sample of 26 Vietnamese commercial banks between 2008 and 2018.

Consider N DMU_s (banks) (n = 1,2, ... N) that use *m* inputs to produce *s* outputs in the period T (*t = 1,2, ... T*) (T = 2008-2018). Suppose that DMU^t_n represents observation *n* at period *t* with the input vector X^t_n and the output vector Y^t_n is given as:

$$X_n^t = \begin{bmatrix} x_n^{1t} \\ x_n^{2t} \\ . \\ . \\ x_n^{rt} \end{bmatrix}, \quad Y_n^t = \begin{bmatrix} y_n^{1t} \\ y_n^{2t} \\ . \\ . \\ y_n^{st} \end{bmatrix} \tag{4}$$

If the window starts at time k ($1 \le k \le T$) with window width w ($1 \le w \le T-k$), then the input and output matrices in the window analysis, respectively, are:

$$X_{kw} = \begin{bmatrix} x_1^k & x_2^k & . & x_N^k \\ x_1^{k+1} & x_2^{k+1} & . & x_N^{k+1} \\ . & . & . & . \\ x_1^{k+w} & x_2^{k+w} & . & x_N^{k+w} \end{bmatrix} \text{ and } Y_{kw} = \begin{bmatrix} y_1^k & y_2^k & . & y_N^k \\ y_1^{k+1} & y_2^{k+1} & . & y_N^{k+1} \\ . & . & . & . \\ y_1^{k+w} & y_2^{k+w} & . & y_N^{k+w} \end{bmatrix} \tag{5}$$

Adding these inputs and outputs to the above CCR and BCC models gives the window analysis problem as follows:
The CCR-DEA model of window analysis has the form:

$$\theta'_{k_w t} = \min_{\theta,\lambda} \theta, s.t: \left\{ -\lambda' X_{kw} + \theta' \mathrm{X}_t \ge 0; \quad \lambda' Y_{kw} - Y_t \ge 0; \quad \lambda_n \ge 0 \ (n = 1, ..., N \times w) \right\} \tag{6}$$

The BCC-DEA model for window analysis has the form:

$$\theta'_{k_w t} = \min_{\theta,\lambda} \theta, s.t: \left\{ -\lambda' X_{kw} + \theta' \mathrm{X}_t \ge 0; \quad \lambda' Y_{kw} - Y_t \ge 0; \quad \lambda_n \ge 0 \ (n = 1, ..., N \times w), \quad \sum_{n=1}^{N} \lambda_n = 1 \right\} \tag{7}$$

Note that the choice of the window length is important in determining efficiency. Charnes *et al.* (1995) found that w = 3 or 4 tended to provide the best balance of format and stability of efficiency scores. A narrow window width must be used to ensure reliable results. Thus, a 3-year window was selected in this study (w = 3).

3.3. Banking model

There are many different views concerning selecting bank inputs and outputs (see Berger and Humphrey, 1997). However, based on this study's sampled data collected from 26 Vietnamese commercial banks, a production model was used where the output consisted of; Y_1 total loans, Y_2: Securities and Y_3, operating income and the inputs included X_1: fixed assets; X_2: total deposits; X_3: operating expenses.

3.4. Testing the stability of the efficiency rankings to evaluate the operations of banks carrying out M&A deals

Brockett and Kemperman (1980) and Brockett et al. (1998) provided typical examples of matrix construction transforming efficient scores to rank statistics. Such rankings can then be used to test trends or test stability. The efficiency matrix was observed from the window analysis given in Table 1 to apply this methodology. The set of N.k efficiency scores was ranked in ascending order (the middle-rank replaced ties) and denoted R_j to be the sum of the ranks corresponding to the DMU j (bank j in this case) given in Table 2. The sums of the individual ranks for each DMU (Bank) are given in the last column in Table 2.

Table 1: Effective score matrix

Period (t)\DMU(j)	**1**	**…**	**k.**
1	te_{11}		te_{1k}
…	…….	…….	…..
N	te_{N1}		te_{Nk}

Table 2. Ranking of effective matrix

DMU	**1**	**…**	**k.**	**R_j**
DMU_1	r_{11}		r_{1k}	$R_1 = \sum_{j=1}^{N} r_{1j}$
…	….	…..	….	…
DMU_N	r_{N1}		r_{Nk}	$R_N = \sum_{j=1}^{k} r_{Nj}$

The efficiency scores in Table 1 (te_{tj}, $t = 1…, k; j = 1…, N$) were generated by running a window analysis model in which N.*k* DMU (bank) was assessed, each value corresponding to one of N DMU at a window in *k* windows. Using a single efficiency frontier to evaluate all *N.k* implicit observations assumed that no technical changes had affected production efficiency over *k* periods.

This study aimed to identify trends when observing relative rankings based on each DMU (bank) score over time. Based on the method of Brockett and Kemperman (1980) (called BK) shown, the actual efficiency score was replaced in each efficiency matrix column with a corresponding ranking statistic by approving the scores in that column in ascending order. Accordingly, the ranking value matrix in Table 2 was obtained. As in the BK model, when an equal efficiency appears, it will replace these ranking positions with the middle value. A thorough discussion of these hypotheses can be found in Brockett *et al.* (1998) and Brockett and Kemperman (1980).

This study tested the hypothesis that all banks (N DMU) maintained their relative positions despite M&A deals during the study period.

The Kruskal-Wallis non-parametric ANOVA test was applied to examine this stability hypothesis (Brockett and Levine (1984)). For this test, there were simultaneously N "overall" (banks) under review, and the original hypothesis (H0) was that all N totals had the same score distribution. To apply this statistical method, the set of $N.k$ points in ascending order were first ranked (equal positions were also taken in the middle-rank position), and the symbol Rj was the sum of the rank positions corresponding to the DMU (bank). The Kruskal-Wallis's test statistic was then calculated as follows:

a) $$H = \frac{12}{N \cdot k \cdot (N \cdot k + 1)} \cdot \left(\frac{R_1^2}{k} + \frac{R_2^2}{k} + ... + \frac{R_N^2}{k} \right) - 3 \cdot (N \cdot k + 1)$$

H ~ χ^2_{N-1} with N-*1* degrees of freedom. If χ^2_{N-1} larger than χ^2_{N-1} at the desired significance level, the null hypothesis of the distribution of efficiency ratings like all DMUs (banks) was rejected given the significance level.

4. Data and Empirical Results

Data on the outputs (Y) and inputs (X) of the six banks carrying out M&As during the 2008-2018 period were used to estimate the above models. However, to understand in general what happened to these banks during the research period, statistical analysis on data regarding the Vietnamese commercial banking system has been provided below:

4.1. Statistical analysis of the basic indicators of Vietnamese commercial banks carrying out M&A

Table 3: Change in the number of Vietnamese commercial banks over the years

Type of banks	1997	2010	2015	2018
State-owned Bank	5	5	7	7
Joint-stock commercial bank	51	37	28	31
Joint-venture bank	4	5	5	5
Foreign bank branch	24	50	50	48
Foreign bank		5	5	9

Source: Annual Report - State Bank of Vietnam

Table 3 shows the number of Vietnamese commercial banks over the years. In the 2012-2015 period, merger and acquisition activities took place quite actively, mainly under the mandatory restructuring program of the State Bank, to ensure the safety of the credit institution system and to stabilise the money market. As a result, 6 successful M&A deals occurred. 13 banks participated in M&A activities, contributing to a reduction of 7 joint-stock commercial banks.

From 2011-to 2018, the total assets of all types of banks increased sharply. State-owned banks gained the largest increase (2.56 times), followed by joint-venture and foreign banks (2.08 times). Joint-stock commercial banks, which participated heavily in the M&A process, had the lowest rate of asset increase in 2011-2018 (2.01 times).
From the statistical data of the 26 largest Vietnamese banks, which account for 80% of the assets of the Vietnamese banking system, there were six major M&A deals between 2012-2018. Table 4 below outlines these six M&As.

Table 4: Significant M&A deals between 2012-2018

No.	Time	Banks participating in M&As	Bank after M&As
1	2012	- SHB - Habubank	SHB
2	2012	- SCB - FicomBank - TinNghiaBank	SCB
3	2013	- HDBank - DaiABank	HDBank
4	2015	- Maritime Bank - MDBank	Maritime Bank
5	2015	- BIDV - MH Bank	BIDV
6	2015	- Sacombank - Southern Bank	Sacombank

Source: Compiled by the authors

The operations of the banks after mergers are specified in the table below. The values are expressed in Vietnamese Dong and deflated by the base year 2008. The most common point in the M&A deals pre-and post-merger is that the number of employees increased significantly, especially HDBank (up 203%). The bank with the lowest increase also reached 51% (SCB). The loan activities of the banks post-merger also saw significant growth, where, most notably, SHB increased by 346% and HDB increased by 279%.

However, the banks operating expenses also increased sharply after the merger and restructuring process, leading to fluctuations in the profits of the merged banks. Among the six banks that carried out M&A deals, three banks achieved positive net profit growth: HDBank, SHB and BIDV; the remaining three banks, Maritime Bank, Sacombank, SCB, saw sharp decreases in net profit. This outcome may also have been because some banks had to increase their expenses to handle bad debts, high human resource costs, and other expenses incurred after restructuring.

There was a decrease in net profits during the research period from 2008 to 2018. Declines in operating income were why banks not undertaking M&A activities suffered from decreased net profits. This group comprised the weakest banks with low lending, deposit, operating income, and net profit ratios regarding the merged banking group.

Table 5: Activities of the aquiring banks pre-and post-merger Unit: VND billion

Bank	Average share	Pre-merger			Post-merger			% Change (post/pre-merger)		
		Labour	Fixed Assets	Net Profit	Labour	Fixed Assets	Net Profit	Labour	Fixed Assets	Net Profit
Sacombank	4.6%	7662	2905	2528	16028	4543	1284	109%	56%	-49%
SHB	4.2%	2040	1410	833	5225	2382	1161	156%	69%	39%
HDBank	1.9%	1339	229	420	4062	657	1502	203%	187%	258%
BIDV	9.3%	12.301	3017	8833	23604	5755	12812	92%	91%	45%
SCB	2.8%	2619	877	793	3964	2028	100	51%	131%	-87%
Maritime bank	3.0%	2399	433	844	3840	292	505	60%	-33%	-40%

Source: GSO annual firm survey and banks' annual reports

Table 6: Operation of Vietnamese banks pre-and post-merger Unit: VND billion

Variable	Average 2008-2018	Banks without carrying out M&A		Acquired banks	Banks after aquiring other banks	
		2008-2012	2013-2018		Pre-merger	Post-merger
Labour	2,182	2,607	5,759	1,030	3,312	6,158
Customer loans	56,156.9	66,298.8	83,528.2	14,283.1	82,712.7	138,744.2
Investment securities	14,179.9	17,436.8	22,036.6	2,497.0	16,264.1	31,204.7
Operating income	3,342.8	5,110.5	4,645.3	964.2	5,152.5	5,231.0
Fixed assets	989.8	1,020.3	1,170.7	457.8	1,903.9	2,654.3
Customer deposits	62,480.4	72,151.9	96,734.2	11,902.6	83,675.4	150,667.5
Operating expenses	1,480.4	2,109.3	2,176.7	383.3	1,987.6	2,703.1
Net profit	1,862.4	3,001.2	2,468.6	580.9	3,164.9	2,528.0

Source: GSO's annual enterprise survey and the annual report of the Vietnamese banking system

4.2. Estimated results of the window analysis model

4.2.1. TE of the system of commercial banks through window analysis with a 3-year window length in the 2008-2018 period

An overview of banks' efficiency by window analysis is presented in the summary of the estimation results of Model (6) shown in Table 7. This table provides general information about the TE in nine windows of 26 banks.

Table 7: Summary statistics of the TE from estimation model (6) comprising 26 banks with a 3-year window

Variable	Obs	Mean	Std.Dev	Min	Max
2008-2010	26	0.834	0.086	0.659	1.000
2009-2011	26	0.845	0.099	0.645	1.000
2010-2012	26	0.805	0.103	0.623	0.992
2011-2013	26	0.844	0.090	0.650	1.000
2012-2014	26	0.868	0.080	0.699	0.997
2013-2015	26	0.824	0.131	0.518	1.000
2014-2016	26	0.833	0.130	0.603	1.000
2015-2017	26	0.805	0.136	0.603	1.000
2016-2018	26	0.811	0.140	0.583	1.000

Source: Window estimation model analysis results model (6) from banks' annual reports

The results in Table 7 show that the TE scores in the windows were all greater than 80%. The highest average TE was 86.8% in the 2012, 2013 and 2014 windows. The second was the 2011, 2012, 2013 windows, where the average TE reached 84.4%. There were two windows with the lowest efficiency out of the nine, which were the windows of 2010, 2011, 2012 and 2015, 2016 and 2017.

4.2.2. Average efficiency (TE, PTE and SE) of commercial banks through window analysis with a 3-year window length in the 2008-2018 period

The estimation results of Models (6) and (7) are summarised in Table 8.
Table 8 presents the average TE, PTE and SE of commercial banks through window analysis with a 3-year window length between 2008-2018. The TE and PTE were estimated from the DEA model of window

analysis (Model (6) and (7)), respectively, with a 3-year window length and with three inputs and three outputs. Each of the TE or PTE average efficiency plots in the table is the average of nine windows. Each window had three efficiency scores from the window Models (6) or (7) (for example, see Table 9 for the results of the window analysis by Model (6) for the six banks participating in mergers and acquisitions).

Table 8: Average efficiency of the sampled commercial banks through window analysis with a 3-year length between 2008-2018

Name of Bank	**TE**	**PTE**	**SE**	**Name of Bank**	**TE**	**PTE**	**SE**
ACB Bank	0.736	0.765	0.961	Viet Capital Bank	0.732	0.867	0.844
AB Bank	0.671	0.686	0.978	MaritimeBank	0.854	0.924	0.923
Eximbank	0.787	0.806	0.976	NamA Bank	0.719	0.803	0.895
VietinBank	0.897	0.988	0.908	HDBank	0.755	0.779	0.969
AgriBank	0.872	0.992	0.879	SCB	0.930	0.945	0.985
National Citizen Bank	0.730	0.783	0.933	SaigonBank	0.801	0.919	0.871
Lienviet PostBank	0.787	0.843	0.934	VPBank	0.900	0.940	0.957
BIDV	0.976	0.999	0.977	PGBank	0.833	0.945	0.881
MBBank	0.811	0.826	0.982	OceanBank	0.856	0.881	0.972
VIB	0.917	0.934	0.982	Sacombank	0.681	0.741	0.919
SeaBank	0.842	0.860	0.979	Techcombank	0.847	0.921	0.920
VietABank	0.936	0.974	0.961	Tien Phong Bank	0.972	0.995	0.977
SHB	0.817	0.837	0.976	Vietcombank	0.921	0.977	0.942

Source: Estimated results from window analysis Models (6), (7) and banks' annual reports. Here: SE = TE / PTE

For the period 2008-2018, the average TE was calculated from the window analysis model under the assumption of constant returns to scale (CRS) (Model (6) presented in column 2 and 6. Table 8, ranging from 80% to 86%. This result shows that Vietnamese commercial banks were efficient. Therefore, the average level of inefficiency of Vietnam's commercial banking industry in the CCR model was in the range of 14-20%. The inefficiency of commercial banks was mainly due to the excess of customer deposits on the balance sheets and bad debts.

Estimating the TE of the banks showed that the banks which operated the most effectively, with average efficiency scores, according to nine windows in the research period, over 90% were: BIDV, VIB, VietABank, SCB, VP Bank, Tien Phong Bank and Vietcombank. On the other hand, the least effective banks with less than 70% efficiency scores were AB Bank and Sacombank.

The above shows the DEA efficiency score assuming constant returns to scale. However, this assumption cannot cover all cases in practice. Thus, this study also recalculated under variable returns to scale to solve this problem.

Columns 3 and 7 of Table 8 give the annual pure technical efficiency (PTE) scores of 26 banks in each window. The results show that the average efficiency calculated in Model (7) reached a value of 86 to 91%. Up to 50% of the banks had average PTE in the period over 90%. The number of banks with PTE under 70% only accounted for 3.8% of the sampled banks.

Other banks with efficiency scores of over 90% from the estimation results if Model (7) included VietinBank, AgriBank, TechcomBank, MaritimeBank, SaigonBank and PGBank. Also, in Model (7), the least efficient banks were AB Bank and Sacombank. PTE inefficiency was mainly due to management problems.

When comparing the results of Models (6) and (7), the model under variable returns to scale efficiency achieved a higher level of efficiency than the model under constant returns to scale efficiency. This result was due to Model (7) decomposing the inefficiency of production units into two components: the pure technical inefficiency and the inefficiency to scale and eliminate the part of the inefficiency caused by a lack of size of the production units. The mean scale efficiency of Vietnamese commercial banks was 94% between 2008-2018. Most banks were highly efficient.

The results of scale efficiency showed that the banking groups that were not as efficient as the other banks included large banks, such as Agribank and small banks, such as Viet Capital Bank and ABBank. This outcome confirmed that the choice of their scale of operations was not appropriate.

4.2.3. Window analysis for six banks carrying out M&As

Window analysis captured the efficiency of banks after the reallocation of resources. Table 9 presents the results of estimating the window analysis model under the assumption of constant returns to scale with a 3-year window of six banks pre-and post-merger. The differences in the DEA scores of each bank reflected the performance of each bank and other banks over time.

Table 9:TE of banks pre-and post- mergers from the window analysis model under the assumption of constant returns to scale and window length of 3-years

CCR	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Average
BIDV	0.920	1.000	0.945									0.955
		1.000	0.946	0.996								0.981
			0.977	1.000	1.000							0.992
				1.000	1.000	1.000						1.000
					1.000	1.000	0.991					0.997
						1.000	0.994	0.997				0.997
							1.000	0.967	0.964			0.977
								0.936	0.931	1.000		0.956
									0.863	0.927	1.000	0.930
SHB	0.577	0.739	0.758									0.691
		0.743	0.762	0.571								0.692
			0.791	0.573	0.616							0.660
				0.724	0.674	0.829						0.742
					0.678	0.784	1.000					0.821
						0.647	1.000	0.975				0.874
							0.975	0.949	0.985			0.970
								0.897	0.932	1.000		0.943
									0.902	0.973	1.000	0.958
Maritime Bank	0.734	1.000	0.960									0.898
		1.000	0.960	0.766								0.909
			0.968	0.795	0.535							0.766
				1.000	0.615	0.698						0.771
					0.754	0.771	1.000					0.841
						0.757	0.983	0.920				0.887

CCR	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**Average**
							0.970	0.965	0.655			0.863
								0.841	0.654	1.000		0.832
									0.745	1.000	1.000	0.915
HD Bank	0.990	0.762	0.825									0.859
		0.764	0.825	0.653								0.747
			0.838	0.660	0.633							0.710
				0.814	0.809	0.935						0.852
					0.833	0.909	0.773					0.838
						0.874	0.717	0.705				0.765
							0.712	0.681	0.666			0.686
								0.614	0.601	0.665		0.627
									0.650	0.721	0.764	0.712
SCB Bank	0.867	1.000	0.866									0.911
		1.000	0.866	0.859								0.908
			0.917	0.875	0.800							0.864
				0.920	0.860	1.000						0.927
					0.964	0.755	1.000					0.906
						0.695	1.000	1.000				0.898
							0.970	1.000	1.000			0.990
								1.000	1.000	0.999		1.000
									1.000	0.968	0.940	0.969
Sacom Bank	0.566	0.778	0.821									0.722
		0.778	0.823	0.579								0.727
			0.853	0.610	0.548							0.670
				0.774	0.614	0.630						0.672
					0.788	0.740	0.722					0.750
						0.724	0.725	0.665				0.704
							0.715	0.672	0.654			0.680
								0.639	0.637	0.592		0.623
									0.622	0.578	0.549	0.583

Source: Estimation of Model (6) using data from annual reports of banks

BIDV was a highly efficient bank before acquiring MH Bank. Its Technical efficiency (TE) through the 3 - year windows 2008-2010, 2009-2011, 2010-2012, 2011-2013, 2012-2014, 2013-2015 was 0.955; 0.981; 0.982; 1; 0.997 and 0.997, respectively. However, after the merger with MH Bank, the efficiency of the three consecutive windows was 0.977, 0.956 and 0.930. The results of the restructured banks show that all indicators on credit, income, deposits, and fixed assets had generally increased, showing tremendous growth in scale. Especially after the M&A deals, the number of employees increased significantly, especially BIDV (up 92%). However, BIDV also had to bear bad debts and weaknesses from MH Bank; the efficiency of BIDV after the merger was still quite stable. This outcome proved the ability of BIDV's in the condition of increasing scale.

HDBank was considered a bank with efficient reductions after merging. The first window had efficiency scores of 0.99 in 2008, 0.762 in 2009 and 0.825 in 2010. In the second window, HDBank had efficiency scores of 0.764 in 2009, 0.825 in 2010 and 0.653 in 2011. Although its efficiency scores fluctuated slightly in the remaining windows, they tended to decrease since the merger in 2013. After the merger, the average efficiency level of these windows is 0,838; 0,765; 0,686; 0,627. By the last window of 2016-2018, the efficiency had increased higher than the previous windows but only reached 0.712. The efficiency of its BCC showed a similar trend.

Regarding M&A deals, the deal of Sacombank acquiring Southern Bank was also worth analysing because the results of the window analysis showed that the bank's TE scores compared to other banks in the sample were low. For example, starting in the first window with an efficiency score of 0.566 in 2008, 0.778 in 2009, and 0.821 in 2010. The average efficiency score of the remaining windows until the M&A deal was 0.859; 0.747; 0.710, and 0.852. After the merger, the efficiency level continued to decrease.

After their M&A deals, SHB, Maritime Bank and SCB Bank had good TE growth. For example, SHB's efficiency of windows was low before conducting M&A in 2012. SCB's average efficiency level in the three windows 2008-2010, 2009-2011, 2010-2012 was below 70%. However, after the merger, the average efficiency level increased significantly.

Although scale efficiency was expected to increase after the six bank's M&A deals, two banks had reduced scale efficiency, namely Sacombank and HDbank. Therefore, window analysis helped identify the best and worst banks in relative terms and the most stable and most variable banks in terms of their average DEA scores over the years.

4.2.4. Assessing the stability of banks

This section used a rank statistics approach to determine whether significant trends existed in each bank's performance patterns over time. With a certain level of statistical reliability, it was affirmed that the 26 banks maintained their relative efficiency rank positions over time.

The procedure was as follows: first, Model (6) was estimated with a window length of 3-years (9 windows). Each bank window had three efficiency scores, averaging an effective score. Thus, each bank had nine average efficiency scores. Thus, the twenty-six banks had 234 average efficiency scores.

After arranging the efficiency scores in a column in ascending order, the matrix of the ranking values shown in Table 10 was obtained. After conducting the efficiency matrix, Rj and Rj^2 were calculated according to the given formula in Table 2. As a result, Table 10 was completed.

Table 10: Efficiency rankings of the sampled 26 banks

N	Name of Bank/ window	2008-2010	2009-2011	2010-2012	2011-2013	2012-2014	2013-2015	2014-2016	2015-2017	2016-2018	R
1	ACB Bank	129	115	139	149	174	214	204	205	202	1531
2	AB Bank	199	197	219	210	185	215	186	193	184	1788
3	Eximbank	137	53	86	84	76	195	188	192	212	1223
4	VietinBank	127	62	46	35	31	80	67	73	114	635
5	AgriBank	90	79	120	82	49	66	74	128	131	819
6	National Citizen Bank	75	39	94	154	164	227	223	224	218	1418
7	LienViet Post Bank	124	179	177	152	93	100	123	173	178	1299
8	BIDV	24	11	6	4.5	3	4	13	23	42	131
9	MBBank	207	211	208	96	15	12	25	147	159	1080

N	Name of Bank/ window	2008-2010	2009-2011	2010-2012	2011-2013	2012-2014	2013-2015	2014-2016	2015-2017	2016-2018	R
10	VIB	99	33	40	37	18	88	91	89	19	514
11	SeaBank	121	143	165	145	135	56	102	59	77	1003
12	VietA Bank	72	45	110	48	92	32	4.5	4.5	4.5	413
13	SHB	190	189	206	166	133	95	16	34	22	1051
14	Viet Capital Bank	116	69	148	155	138	213	216	222	225	1502
15	Maritime Bank	71	60	157	156	117	81	106	122	54	924
16	NamA Bank	161	170	203	172	142	187	182	191	196	1604
17	HDBank	107	163	181	113	119	158	194	217	180	1432
18	SCB	58	61	104	44	63	70	9	2	17	428
19	SaigonBank	83	109	136	132	43	118	150	209	221	1201
20	VPBank	140	101	134	47	50	68	65	21	5	631
21	PGBank	141	111	105	38	85	171	160	144	108	1063
22	OceanBank	30	41	112	87	36	146	151	167	125	895
23	Sacombank	176	175	201	200	162	183	198	220	226	1741
24	Techcombank	169	153	168	130	126	78	20	51	27	922
25	Tien Phong Bank	4.5	4.5	7	57	52	4.5	4.5	10	29	173
26	Vietcomank	98	97	103	28	26	14	8	55	64	493

Source: Estimation based on the efficiency ranking matrix calculated from Model (6)

The value of Kruskal-Wallis H statistics was computed, using the information given in Table 10, resulting in:

$$H = \frac{12}{9*26(9*26+1)}\left(\frac{R_1^2}{9}+....+\frac{R_5^2}{9}\right)-3(9*26+1)=55.85$$

The value of H, when compared to $\chi^2_{25}(0.005)=46.93$ allowed the rejection of the H_0 hypothesis regarding the distribution of the same efficiency ranking of the 26 banks conducting M&As at a significance level of 0.005. Rejecting the H_0 hypothesis concluded that some banks exhibited better economic performance than others, measured by inputs and outputs and incorporated into the model. Thus, the results of statistical testing also confirmed that through the merger and acquisition deals, some of the banks still operated far worse than others.

From the calculated value of R, the least efficient bank was AB Bank, with an R value of 1788, followed by SacomBank, Nam A Bank, Viet Capital Bank and ACB Bank.

4.2.5. Sensitivity analysis

Two models were examined to see how banking efficiency through window analysis changes when using different input and output options. The original model, Model (6), used the asset approach, where three inputs and three outputs were selected and was called the M_0 model. The model to be compared was Model (6) using the production approach, comprising the four outputs: Y_1: total loans; Y_1: securities; Y_3: operating income and Y_4: operating expenses and two inputs: X_1: fixed assets and X_2: total deposits, this model was called the M_1 Model.

The method was conducted as follows:

Step 1: First, Model M_0 was estimated under the assumption of constant returns to scale efficiency (Model (6)) and variable returns to scale efficiency (Model (7)) to calculate TE, PTE, and SE according to nine windows and denoted TE_{33}, PTE_{33}, SE_{33}. Next, Model M_1 was estimated under the assumption of constant returns to scale efficiency (Model (6)) and variable returns to scale efficiency (Model (7)) to calculate the TE, PTE, and SE according to nine windows and denoted TE_{24}, PTE_{24}, SE_{24}. There were six banks and nine windows. Thus, there were 54 observations for each efficiency series.

Step 2: The basic statistics for the TE, PTE and SE series were calculated and then transferred to Table 11 corresponding to the efficiency columns. Autocorrelation of the series $\{TE_{33}, TE_{24}\}$, $\{PTE_{33}, PTE_{24}\}$ and $\{SE_{33}, SE_{24}\}$ was tested.

$$H_0 : \rho = 0$$
$$H_1 : \rho \neq 0$$

Step 3: The Spearman rank correlation for each pair of series {TE_{33}, TE_{24}}, {PTE_{33}, PTE_{24}}, {SE_{33}, SE_{24}} was calculated and recorded in the table. For example, the Spearman correlation of PTE_{24} and PTE_{33} of 0.620 was listed in the first row in the common column for these two series.

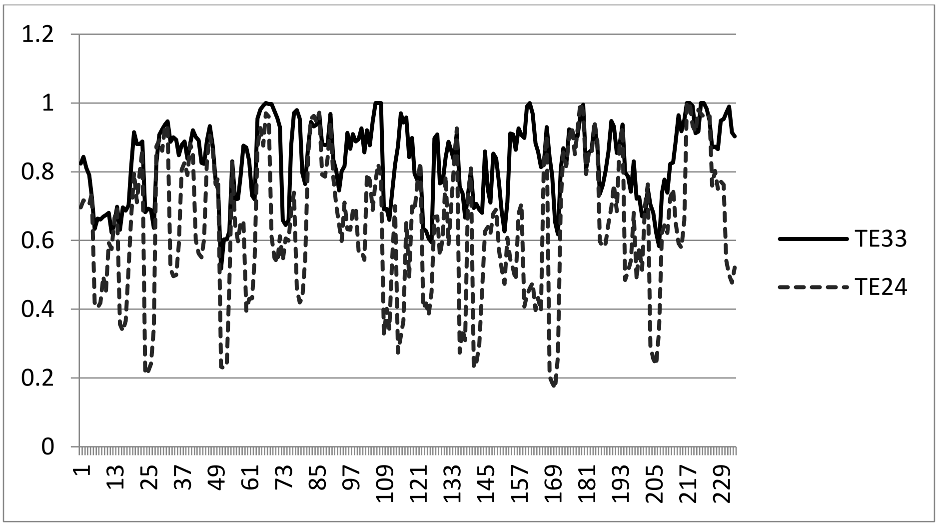
Table 11: Sensitivity analysis to determine the correlation between efficiencies from different input and output options

Variable	PET33	PET24	TE33	TE24	SE33	SE24
Spearman's ρ		0.740		0.570		0.376
Pror>|t|		0.000		0.000		0.000
Mean	0.882	0.764	0.830	0.637	0.942	0.833
Std.Dev	0.109	0.205	0.113	0.208	0.060	0.142
Min	0.614	0.240	0.518	0.170	0.620	0.274
Max	1	1	1	1	1	1
Obs	234	234	234	234	234	234

Source: Author calculated from the estimation results for models (6) and (7) with different input and output options.

The 5^{th} row from the bottom of Table 11 shows the average of each efficiency series. The average value of TE estimated from Model (6) with a choice of three inputs and three outputs (M_1) was 0.83. In contrast, the TE from Model (6) with two inputs and four outputs was 0.637, the correlation coefficient of these efficiency series was 0.57, the probability of rejecting hypothesis H_0 was 0.000. This result proved that the window analysis model for the TE results from M_0 and M_1 was highly correlated. The correlation between PTE from M_0 and M_1 was higher than the correlation of the TE series from M_0 and $M_{1;}$ this situation was because the two series correlation coefficient was 0.74, higher than 0.57. In particular, the scale efficiency derived from the two models with SE = PTE / TE had the lowest Spearman correlation coefficient (0.376). However, hypothesis H_0 ($\rho = 0$) was also strongly rejected.

Figure 1: Movement trend of the TE scores from estimation from M_0 and M_1



Source: Estimation of the Model (6) using data from annual reports of banks

Thus, using the window analysis approach, whether the asset or the production approach to analyse the efficiency of banks carrying out M&A deals, the TE, PTE, and SE were derived from the models having very high correlations.

The TE scores of the movement trend from the estimation of M0 and M1 can be seen in Figure 3 below. The figure clearly shows the correlation between the two efficiency chains from the two different input and output selection approaches.

The movement of efficiency was estimated from two different input and output options. Although the absolute values differed, they had a similar trend, which was the expected result.

5. Conclusion

This study applied the window analysis and non-parametric test approaches to estimate the TE, PTE, and SE of 26 Vietnamese commercial banks between 2008 and 2018. In addition, it tested the stability of the efficiency rankings. Window analysis helped to identify the best and worst banks in relative terms and the most stable and most variable banks in terms of their average DEA efficiency scores when compared to other banks and themselves over time. The integration of window analysis into the M&A process offered a better understanding of banks' ongoing competition and acquisition processes. The non-parametric testing showed that not all M&A deals gave banks better management and a more appropriate scale. The sensitivity analysis further strengthened these results because even if different input and output options were used, the analytical rank was still preserved.

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APPENDIX

Table 1. Describe the lengths of windows

Window 1	2008	2009	2010								
Window 2		2009	2010	2011							
Window 3			2010	2011	2012						
Window 4				2011	2012	2013					
Window 5					2012	2013	2014				
Window 6						2013	2014	2015			
Window 7							2014	2015	2016		
Window 8								2015	2016	2017	
Window 9									2016	2017	2018