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Productivity Growth of Vietnamese Commercial Banks: An Application of Non-Parametric Analysis*

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Abstract

The purpose of the research to evaluate the efficiency and productivity growth rate of some Vietnamese commercial banks in the period 2008–2020. Using input and output selection theory, the author selected 2 models, estimating the efficiency for model 1 and estimating the yield change for both the models. We have built a model to estimate the efficiency and calculate as well as decompose the productivity growth of Vietnamese commercial banks during the period of active mergers and acquisitions activities in the banking system. Based on the results of the efficiency estimation, TFP shows during mergers and acquisitions, efficiency fluctuates but in an inverted U-shape (increasing from 2008–2011 but decreasing from 2013 to 2020). The estimated results of the impact assessment model show that FDI reduces the efficiency of banks. Productivity analysis shows that 6 out of 23 banks in the study period had positive TFP growth (tfpch > 1) due to technical progress and management efficiency. The findings of this study suggest that Vietnam's commercial banking system has many opportunities to improve operational efficiency in many aspects. In which, there are opportunities to increase credit, improve governance as well as improve the technology level of each bank. In addition, along with traditional products such as deposits and loans, diversification with a wide range of products and services is an important factor to enhance customer experience and demand in commercial banks.

Keywords: Commercial Banks, TFP, Productivity Growth, Vietnam

JEL Classification Code: G20, G21, C25

1. Introduction

In the process of economic transformation, banks play a very important role in the economy. In Vietnam, in recent years, there have been tremendous changes in the banking system. In terms of the organization alone, mergers and acquisitions have taken place very actively in the past 10 years. Regarding technology, the banking sector, not only in Vietnam but also in the world, has undergone profound changes in regulation and technology. Advanced applications in technology 4.0 and communication along with the introduction of new financial tools have changed the way banking is done. Such changes significantly change the bank's production technology. In this respect, a frequently asked question is about how the impact of these changes on the performance of banks will be. Berger and Humphrey (1997a) give a complete overview of answering this question by proposing new methods of measuring the efficiency of the banking sector. The most widely used efficiency methods are non-parametric analysis and parametric method (random boundary approach). Below we briefly present some of the key points from the productivity and efficiency literature, focusing on the methodology used in this article.

The objective of this study is to use the model (non-parametric models) as well as the input and output choices in our previous study to calculate efficiency, technological progress, growth productivity of Vietnamese commercial banks from 2008–2020 - the period of mergers and acquisitions (M&A) in the Vietnamese commercial banking system.

2. Literature Review

Research on productivity growth in the banking sector is often based on cost ratio comparisons. There are several

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expense ratios used and each of them deals with a unique aspect of banking. Since the banking industry uses many inputs to produce many outputs, this has led to the study of appropriate pooling (Kim, 1986). Several studies have attempted to estimate average practice cost functions. While these approaches are successful in determining the average increase in performance, they do not consider the productivity of best practice banks. These problems associated with the "classical" approach to productivity have led to other approaches that include multiple inputs/outputs and consider the relative performance of banks.

A series of studies used frontier analysis to separate efficient banking units from underperforming ones, according to a specified set of standards. The focus of these studies is on changes in the efficiency frontier and how banks operate near the efficient frontier. The first method entails identifying efficient units of production and constructing a linear efficiency frontier using these units of efficiency. This method was first implemented by Charnes et al. (1978), who used linear programming methods to determine the efficiency units and coined the name Data Envelopment Analysis (DEA).

Outstanding studies in the productivity, efficiency, and regulation of the banking system include the studies of Humphrey (1990) and Berg et al. (1991) for Norwegian banks; Lang and Welzel (1996) for German banks; Resti (1997) for Italian banks; Drake and Hall (2000) for Japanese banks; Rebelo and Mendes (2000) for Portuguese banks; Gilbert and Wilson (1998) for Korean banks; Leong et al. (2002) for Singapore banks; Leightner and Lovell (1998) for Thai banks; Minh et al. (2013), Huynh & Nguyen (2019), Le and Diep (2020), and Pham (2021) for Vietnamese banks. It is possible to detail a few studies such as Leong et al. (2002) employed data on Singaporean banking for the period 1993 to 1999 to develop efficiency scores and rankings for Singapore banks. It then invokes the five consistency conditions developed by Bauer to examine these scores and rankings. Their approach allowed researchers to experiment with different models and select the most appropriate model for policy purposes. Sathye (2002) studied the change in productivity in Australian banks over the period 1995–1999 using the Malmquist index and found that the average total factor productivity in Australian banks was 1,013.

Pastor et al. (1997) analyzed the productivity, efficiency, and differences in technology of several banking systems. Using a non-parametric approach together with the Malmquist index, they compared the efficiency, productivity, and differences in technology of different European and US banking systems for the year 1992. Tran et al. (2020) examined the effect of corporate governance on corporate social responsibility disclosure of 155 samples of 31 Vietnamese commercial banks from 2015 to 2019. The data of this study employed time-series data and used the ordinary least squares to test the model. The results showed that three factors positively affect corporate social responsibility disclosure, namely, the board size, foreign members of the board, and audit committee. Thereby, the article proposed that the board of directors in Vietnamese commercial banks needs to raise awareness about corporate social responsibility, and the Central bank of Vietnam should monitor the disclosure of information regularly with severe sanctions on commercial banks that do not comply with the regulations of corporate social responsibility disclosure. This contributes to improving the information quality of the banking sector to meet the trend of international economic integration.

Minh et al. (2008) estimated and compared the efficiency performance of 32 commercial banks in Vietnam during 2001–2005, as well as identified possible factors determining such efficiency performance. Efficiency is measured by a data envelopment analysis (DEA) model and super-efficiency measure through a slacks-based model (SBM) under the assumption of variable returns to scale (VRS). They found that there were a small number of efficient banks, and there would be room for these banks to improve their production efficiency. Moreover, in comparison with small banks, large banks do not guarantee high super-efficiency scores. The results from a Tobit regression model provide such interesting findings as to the negative impact of state ownership, the positive influence of bank size and market share, but no impact of labor quality.

3. Research Methods

3.1. Performance Measurement Model

The model we consider for estimating the efficiency of banks is the DEA (data envelopment analysis) model with the assumption of variable returns-to-scale (VRS). We begin by presenting a DEA model with constant returns to scale (CRS) and then extend it to include variable efficiencies to scale. In the case of the technology under the assumption of constant efficiency to scale, through linear programming it is possible to establish decision units (DMUs) which in this case are banks, determining the envelopment, which is often called the efficient frontier. This benchmark is a linear combination of efficient banks in the sample. Decision units with no other decision units or a linear combination of units with all outputs equal to or greater than (when given a fixed number of inputs - for output-oriented models) or all inputs equal to or less than (when given a fixed number of outputs - for input-oriented models) are the best practice set or boundary observations. The DEA boundary is formed as a linear combination of this set of best practice observations, giving a convex production probability set. The DEA provides a computational analysis of relative efficiency for multiple input/output situations by evaluating each decision-

making unit and measuring its performance against a contour made up of the best practice unit. Units that do not lie on this surface are called inefficient. As such, this method provides a measure of relative efficiency.

Let us briefly describe this corresponding DEA (linear programming) model. We assume that each bank has K inputs and M outputs for each DMU. For the DMU, the inputs and outputs are represented by the vectors x_i and y_i, respectively. For each bank (DMU) we want to get a measure of the ratio of all outputs to all inputs, such as

$\frac{\sum_j u_{ij} y_{ij}}{\sum_j v_{ij} y_{ij}}$ where u_i and v_i are weight vectors. To choose the optimal weights, the following problem is proposed:

$$\max_{u_{ij}, v_{ij}} \frac{\sum_j u_{ij} y_{ij}}{\sum_j v_{ij} y_{ij}}$$

$$\text{with constraints } \frac{\sum_j u_{ij} y_{ij}}{\sum_j v_{ij} y_{ij}} \le 1$$

$$\begin{aligned} & u_{ik}, v_{im} \ge 0 \\ & i, j = 1.2, \ldots N \\ & k = 1.2, \ldots K \\ & m = 1.2, \ldots M \end{aligned} \tag{1}$$

As we have been with this performance of the model there are countless experiments. This can be avoided by inserting a constraint $\sum_j v_{ij} y_{ij} = 1$, and obtained the human form of the linear planning problem:

$$\max_{\mu_{ij}, Z_{ij}} \sum_j \mu_{ij} y_{ij}$$

$$\text{With constraints } \begin{aligned} & Z_i' x_i = 1 \\ & \mu_i' y_j - Z_i' x_j \le 0 \\ & \mu_{ik}, Z_{im} \ge 0 \\ & i, j = 1, 2, \ldots N \\ & k = 1, 2, \ldots K \\ & m = 1, 2, \ldots M \end{aligned} \tag{2}$$

Here the vectors u_i and v_i are replaced by μ_i and Z_i. Using the random attribute of this planning problem, Charnes et al. (1978) draw an equivalent form of packaging:

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

$$\text{with constraints } \begin{aligned} & -y_i + Y\lambda_i \ge 0 \\ & \theta_i x_i - X\lambda_i \ge 0 \\ & \lambda_{\text{print}} \ge 0 \end{aligned} \tag{3}$$

Here λ is a vector ($N \times 1$) dimensional; and θ navigation, is the effective score for the ith DMU. The λ combination λ (X_i, Y_i) can be explained as an effective DMU projection on the boundary line, with the constraints being explained accordingly. Note that $\theta_i \le 1$, with $\theta_i = 1$ implies a DMU located on the effective border. Because there are fewer constraints, this formula is often used for calculations.

However, the above approach is oversimplified because it assumes constant economies of scale. The assumption of constant efficiency to scale is only relevant when all banks operate at an optimal size. Factors that can keep banks from operating at an optimal scale include imperfect competition, leverage concerns, and certain requirements. The fact that banks face varying efficiencies with scale has been documented empirically by McAllister and McManus (1993), Wheelock and Wilson (1997), and many others. This phenomenon led Banker et al. (1984) to suggest an extension of the DEA model under the assumption of constant returns to scale to include variable efficiency to scale (VRS), adding a convex constraint $N1'\lambda = 1$ into problem 3 above (where $N1$ is a ($N \times 1$) dimensional vector of the number 1). This condition ensures that an inefficient bank is "benchmarked" against similarly sized banks. Therefore, the VRS technology encloses the data more closely than the CRS technology, and therefore the VRS technical efficiency scores are greater than or equal to the CRS technical efficiency scores. The advantages of the VRS model outweigh the increase in computational power required to solve the model, which allows VRS to be more universal than the CRS method (Fried et al., 1993; Coelli et al., 1998; Berger & Humphrey, 1997b). The model when adding constraints has the form:

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

$$\text{with constraints } \begin{aligned} & -y_i + Y\lambda_i \ge 0 \\ & \theta_i x_i - X\lambda_i \ge 0 \\ & N1'\lambda = 1 \\ & \lambda_{\text{in}} \ge 0 \end{aligned} \tag{4}$$

Data cover analysis has been widely used in research on the banking industry in developed and developing market economies. The above models have been applied very widely in the banking efficiency assessment (Hancock, 1991).

3.2. Model of Evaluating the Impact of Factors on Efficiency

While we can evaluate the relative effectiveness of DMU's by borders with linear planning problems and make recommendations to improve the efficiency of the unit based on estimated results in terms of efficiency, this may not help us detect factors that limit efficiency. Therefore, we will use a model that allows analysis to find the influential factors. Using the ordinary least squares (OLS) method to estimate unknown parameters will result in deflected and unsteady estimates. So, we look at the Tobit regression model, which is based on the principle of maximum reasonable estimates, to achieve a solid estimate of the parameters. The Tobit regression model was proposed by Tobin in 1958, and since then many scholars have continuously developed and improved the model. This regression model belongs to the type of econometric model with limited or amputated dependent variables, and the essence is that important explanatory variables can take real observations, but dependent variables can only be observed in a limited way, and the standard model is as follows:

$$\mathrm{TE}_i^* = \beta X_i + \mu_i, \mu_i \sim N(0, \sigma^2) \tag{5}$$

Here, I the ith DMU noted, i^* TE is a hidden variable (that is, impossible to observe), X_i is a 1-dimensional K matrix of × independent variable is a random error with distribution $N\ \mu\ (0,2\sigma)$. The limited sample value y_i is:

$$\mathrm{TE}_i = \begin{cases} \mathrm{TE}_i^* \text{ neu } \mathrm{TE}_i^* > 0 \\ T \quad \text{neu } \mathrm{TE}_i^* \le 0 \end{cases}$$

TE_i is the estimated efficiency from the model (4).
Output set from the boundary model:

$$\mathrm{TE} = \mathrm{TE}\{_i\text{: TE}i_{\text{is}} \text{ the test of the problem (4)}\}$$

The input consists of vector variables defined as follows:

Variables belonging to technology and enterprise-scale:

(i) Level of capital-to-labor equipment $\mathrm{KL}_i = \dfrac{K_i}{L_i}$

Variables belonging to corporate finance: (Berger et al., 1997)

(ii) ROA is the total asset sales rate; it is measured by net income divided by total assets that is:

$$\mathrm{ROA} = \frac{\text{Net income}}{\text{total asset}}$$

(iii) ROE is the equity turnover ratio; it is measured by net income divided by equity, that is:

$$\mathrm{ROE} = \frac{\text{Net income}}{\text{Equity}}$$

(iv) E/A self-funding ratio; it is measured as equity (vcsh) per total asset (TTS), that is:

$$\mathrm{E/A} = \frac{\text{Equity}}{\text{Total asset}} \text{ (Self-funding)}$$

3.3. Malmquist Index

Caves et al. (1982) developed Malmquist (output-based) thinking into a productivity index. The authors used the concept of a distance function, although no association was established with Farrel-type efficiency measures (see Farrel (1957)). Fare et al. (1994) used a nonparametric programming method (activity analysis) is used to compute Malmquist productivity indexes. These are decomposed into two component measures, namely, technical change and efficiency change. Further, Fare et al (1994) used DEA to calculate the component distance functions of the Malmquist index and build best practice (efficient) frontiers for banks. Many studies on the Malmquist index have followed the work of Fare et al. (1994) such as Grifell-Tatje and Lovell (1996), Ray and Desli (1997), Wheelock and Wilson (1997), and Rebelo and Mendes. (2000). We also use an advanced decomposition of the Malmquist index developed in Fare et al. (1994). It can be represented as follows:

$$\begin{aligned} m_0 &= \left(y_{t+1}, x_{t+1}, y_t, x_t\right) \\ &= \left[\frac{d_0^t\left(x_{t+1}, y_{t+1}\right)}{d_0^t\left(x_t, y_t\right)} \times \frac{d_0^{t+1}\left(x_{t+1}, y_{t+1}\right)}{d_0^{t+1}\left(x_t, y_t\right)}\right]^{1/2} \end{aligned} \tag{6}$$

This Malmquist index is decomposed into two factors: one that represents technological progress and the other that indicates technical change, which can be interpreted as a "catch-up" effect. We perform as follows:

$$\begin{aligned} m_0 &= \left(y_{t+1}, x_{t+1}, y_t, x_t\right) \\ &= \frac{d_0^{t+1}\left(x_{t+1}, y_{t+1}\right)}{d_0^t\left(x_t, y_t\right)}\left[\frac{d_0^t\left(x_{t+1}, y_{t+1}\right)}{d_0^{t+1}\left(x_{t+1}, y_{t+1}\right)} \times \frac{d_0^t\left(x_t, y_t\right)}{d_0^{t+1}\left(x_t, y_t\right)}\right]^{1/2} \end{aligned} \tag{7}$$

The first factor on the left side can be further decomposed into two factors. Efficiency changes are analyzed into two

components: one representing a pure effect change and the other a change of scale. We can also represent the above formula as follows:

$$\frac{d_0^{t+1}\left(x_{t+1},y_{t+1}\right)_{\text{CRS}}}{d_0^{t}\left(x_{t},y_{t}\right)_{\text{CRS}}}=\frac{d_0^{t+1}\left(x_{t+1},y_{t+1}\right)_{\text{VRS}}}{d_0^{t}\left(x_{t},y_{t}\right)_{\text{VRS}}}\left[\frac{d_0^{t}\left(x_{t},y_{t}\right)_{\text{VRS}}}{d_0^{t}\left(x_{t},y_{t}\right)_{\text{CRS}}}\times\frac{d_0^{t+1}\left(x_{t+1},y_{t+1}\right)_{\text{CRS}}}{d_0^{t+1}\left(x_{t+1},y_{t+1}\right)_{\text{VRS}}}\right] \quad (8)$$

4. Bank's Input and Output Selection Facility

4.1. The Concept

Before analyzing bank-level productivity indicators, we begin by defining a bank's objectives and specifying its respective inputs and outputs. There is a long debate about what exactly constitutes bank output. In the view of Fixler and Zieschang (1992), this output includes "transaction services and portfolio management services that banks provide to depositors while acting as intermediaries". One could argue that the range of services, as defined above, can be quite broad and highly dependent on the level of financial development of the economy. It should not be surprising that both the breadth (diversity) and depth (complexity) of financial services available to the public change as the economy grows, so they can be assumed to be different between countries. The precise definition of inputs and outputs stems from the function the bank performs. This is the core to our model building.

The most presented approaches to bank production can perhaps be summarized under the following headings: asset approach, cost of use approach, and value-added approach. With the asset approach, banks are viewed only as financial intermediaries between the creditors and the beneficiaries of the capital (that is, the debtors). Loans and other assets are considered outputs by banks, while deposits and other payables are inputs to this intermediation process (Sealey & Lindley, 1977).

With the user cost approach, the net revenue generated by a particular asset or liability item determines whether the financial product is an input or an output. Hancock (1991) developed a model for banking products and was one of the first to apply the user cost approach to the banking industry. Hancock stated that it is not clear whether monetary goods are inputs or outputs in a production process. The author goes on to argue that if the financial return on an asset is greater than the opportunity cost of capital (or if the financial cost of debt is less than the opportunity cost), then the instrument is considered a financial output main. Otherwise, it is treated as an input. According to the Hancock rule, demand deposits are classified as outputs while time deposits are classified as inputs. However, there are problems with this approach. First, as interest rates fluctuate, so does the cost of use. An item that is considered an output in one period may become an input in the next period if the sign of the user cost changes. Furthermore, it is difficult to measure marginal revenue and costs for each liability item. Thus, the answer to the question of whether an item is an input, or output becomes the subject of significant measurement error and is sensitive to changes in the data over time.

Finally, the value-added approach assumes that both liabilities and assets have some output characteristic. However, only those with certain added value are considered outputs while the others are considered either inputs or intermediate products depending on the specific attributes of each group. The value-added approach differs from the user cost approach in that it is based on actual operating cost data rather than identifying these costs explicitly. This approach has been widely used in research on the banking industry by Berger et al. (1987) and Berger and Humphrey (1997a).

Considering the pros and cons of each method, a value-added approach is used, which allows classifying inputs and outputs based on observed value-added. This method becomes very attractive because it allows distinguishing between different functions performed by banks. What are they and why do we need to explain them? This also becomes very important for analysis. In analyzing the functions performed by commercial banks, Bergendahl (1998) mentioned five basic objectives of effective bank management: profit maximization, risk management, service provision, mediation, and provide utility. For simplicity, we argue that these five approaches can be subsumed into two broadly defined approaches: profit maximization (combining the return maximization and risk management aspects of Bergendhal) and service delivery (combining the elements of service provision, intermediation, and utility provision). In fact, any banking operation combines elements of these two functions since it is hard to imagine a mainstream bank that does not strive to generate (if not maximize) profits or establish a good relationship with customers. Notice that no weights are added to any function, but instead, the elements of both functions are included in the model. However, we specify two different sets of outputs to combine the elements of both functions, each time more emphasis is placed on either function being executed.

From the above analysis and the arguments presented in the previous study, and with limited data, we use an asset approach to select inputs and outputs for efficiency and Malmquist models (called model group 1). We add labor input to the Malmquist model called model 2 to compare the productivity index. Specifically in the 1 model.

Outputs include Y1: total loan amount; Y2: securities; Y3: operating income.

Input: X1: fixed assets; X2: total deposit; X3: operating expenses.

Specifically, in model 2, there is additional labor in the input set.

As one of the objectives of this article is to find potential links between the different policies and functions performed by the bank, especially the role of human capital in the management and production of banks and how they are affected by policy instruments will allow us to make useful recommendations.

4.2. Experimental Data

This study uses data collected from annual reports of 23 banks from 2008–2020 and includes the following criteria: total deposits, securities, operating income, fixed assets, and deposits. Operating expenses, labor. In which securities include available-for-sale investment securities plus hold-to-maturity investment securities - provision for diminution in value of investment securities and several other criteria but there are insufficient criteria for approach, so we only focus on the approach that can collect enough indicators.

5. Experimental Estimation Results

5.1. Statistics of the Collected Data Sets

The data we had collected includes 23 banks' annual reports from 2008–2020. Only 23 banks had basic data until 2020, while others that only had data until 2019 or lacked other basic indicators in previous years were excluded. Summary statistics of variables are given in Table 1.

5.2. Estimation Results of the DEA Model (1- Model with the Assumption that the Effect Varies with Scale*)*

In which: crste: technical efficiency
vrste: the net effect
scale: scale efficiency

During this period, technical efficiency increased from 0.84 in 2008 to 0.9 in 2011 and 0.91 in 2013 (Table 2a). An explanation of the difference in the performance of financial institutions can be found in Berger and Humphrey (1997b).

In the period from 2018 to 2020, the efficiency fluctuated sharply from 0.84 in 2018, 0.86 in 2019 but decreased to 0.84 in 2020 (Table 2b).

5.3. Estimation Results of Tobit Regression Model to Evaluate the Factors Affecting the Efficiency of Banks

In this section, we present all 3 estimated Tobit models where the dependent variables are technical efficiency (crste), net efficiency (vrste,) and scale efficiency (Table 3). The independent variables are factors that belong to the characteristics of the enterprise such as the level of capital equipment per worker (K/L), some financial indicators such as ROA, ROE, E/A as well as some other indicators that are important such as macroeconomic variables like FDI (inward FDI (ln FDI)), GDP growth, and inflation.

The estimated results show that in the case of factors of enterprise characteristics, K/L, ROE, and E/A have a positive influence on technical efficiency and net efficiency. Only E/A is positive and statistically significant in all 3 models. In macro variables, ln FDI has a negative impact and is statistically significant in all three models, specifically, FDI inflows pressure banks to reduce efficiency.

5.4. Estimation Results of Malmquist Index from 2 Models (M1 And M2)

The following section presents the Malmquist index estimation results from the 3-input model (model 1), the 3-output, and the 4-input model (model 2). As a result of the Malmquist index estimation, we get effch (change inefficiency), techch (change in technological progress),

Table 1: Summary Statistics of Variables

Variables	Obs	Mean	Std. Dev.	Minimum	Maximum
y1	299	1.42e+07	1.76e+07	563.57	1.01e+08
y2	299	1.25e+08	1.93e+08	275341	1.20e+09
y3	299	3.11e+07	3.40e+07	3000	1.68e+08
x1	299	2065047	2530461	45628	1.14e+07
x2	299	1390639	2039515	3109.6	1.23e+07
x3	299	3114260	3755977	52809	1.77e+07
x4	299	6933.502	6468.715	668	29460

Source: Author estimates from figures from 23 banks collected from annual mail reports.

Table 2a: Summary Statistics on the Performance of Banks Over a Number of Years (2008, 2011, and 2013)

	2008			2011			2013		
	Crste	**Vrste**	**Scale**	**Crste**	**Vrste**	**Scale**	**Crste**	**Vrste**	**Scale**
Mean	0.84	0.93	0.89	0.90	0.94	0.96	0.91	0.94	0.97
Median	0.95	1.00	1.00	0.98	1.00	0.99	0.95	1.00	0.99
Maximum	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Minimum	0.50	0.62	0.60	0.65	0.71	0.79	0.73	0.75	0.77
Std. Dev.	0.19	0.12	0.14	0.12	0.09	0.06	0.10	0.08	0.06
Skewness	−0.66	−1.71	−0.92	−0.83	−1.53	−1.41	−0.65	−1.12	−2.22
Kurtosis	1.83	4.45	2.47	2.27	4.57	3.99	1.91	2.93	7.61
Jarque-Bera	2.98	13.29	3.48	3.13	11.39	8.57	2.78	4.81	39.18
Probability	0.23	0.00	0.18	0.21	0.00	0.01	0.25	0.09	0.00
Sum	19.27	21.46	20.53	20.81	21.64	22.07	20.91	21.64	22.21
Sum Sq. Dev.	0.79	0.34	0.41	0.31	0.17	0.08	0.23	0.16	0.07
Observations	23.00	23.00	23.00	23.00	23.00	23.00	23.00	23.00	23.00

Source: Author estimates from data of 23 banks collected from annual reports.

Table 2b: Summary Statistics on the Performance of Banks Over a Number of Years (2018, 2019, and 2020)

	2018			2019			2020		
	Crste	**Vrste**	**Scale**	**Crste**	**Vrste**	**Scale**	**Crste**	**Vrste**	**Scale**
Mean	0.84	0.89	0.95	0.89	0.93	0.96	0.84	1.00	0.84
Median	0.81	0.89	0.98	0.93	0.98	1.00	0.84	1.00	0.84
Maximum	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Minimum	0.61	0.68	0.72	0.63	0.70	0.64	0.60	1.00	0.60
Std. Dev.	0.13	0.11	0.08	0.12	0.09	0.09	0.15	0.00	0.15
Skewness	−0.02	−0.38	−1.58	−0.70	−0.99	−2.71	−0.14	NA	−0.14
Kurtosis	1.59	1.78	4.81	2.21	2.84	9.41	1.52	NA	1.52
Jarque-Bera	1.90	1.97	12.72	2.49	3.78	67.53	2.19	NA	2.19
Probability	0.39	0.37	0.00	0.29	0.15	0.00	0.34	NA	0.34
Sum	19.32	20.41	21.75	20.49	21.35	22.08	19.38	23.00	19.38
Sum Sq. Dev.	0.40	0.28	0.13	0.33	0.18	0.18	0.46	0.00	0.46
Observations	23.00	23.00	23.00	23.00	23.00	23.00	23.00	23.00	23.00

Source: Author estimates from data of 23 banks collected from annual reports.

pech (change in net efficiency), sech (change in scale efficiency and change inefficiency), and tfpch (the change in tfp) pairwise in 2008–2009, 2009–2010 and 2019–2020. However, these findings are reported in the appendix, which decomposes the Malmquist index of model 1 and compares the indices of both models by common years and for 13 banks across the research period 2008–2020. In Table 4 Malmquist index decay summary statistics (from model 1) for the period 2008–2020. The results are presented in Tables 4 and 5 below.

Table 3: Estimation Results of Tobit Regression Model Assessing the Impact of Factors on Efficiency

Crste	Crste	Vrste	Scale
	Coef.	Coef.	Coef.
K/l	9.21E−07 (0.84)	3.22E−06*** (2.88)	−4.59E−07 (−0.51)
ROA	−0.2373 (−0.09)	−1.2853 (−0.55)	0.5382 (0.26)
ROE	0.2461** (2.03)	0.201 (1.55)	0.1681* (1.7)
E/A	1.4764*** (4.94)	0.9422*** (3.56)	1.1073*** (4.42)
LnFDI	−0.265*** (−4.3)	−0.3622*** (−5.35)	−0.1513*** (−2.97)
gGDP	0.0046 (0.27)	0.0512*** (2.89)	−0.0059 (−0.41)
Inflation	0.0010 (0.6)	0.0064*** (3.49)	−0.0013 (−0.93)
_cons	1.0678*** (10.29)	1.0215*** (10.77)	1.0961*** (12.7)
/sigma u	0.1125	0.1050	0.0946
/sigma_e	0.1477	0.1181	0.1216
Rho	0.3669	0.4415	0.3771
Log likelihood	10.245	−15.720	53.123
Wald chi2(7)	60.11	47.26	48.95
Prob>chi2	0.000	0.000	0.000
LR test			
Chibar2(01)	73.46	62.10	76.27
Prob>chibar2	0.000	0.000	0.000

Source: Author estimates from data of 23 banks collected from annual reports.

Table 4: Malmquist Index: Compare 2 Models by Year

Year	Model 1 (3-Input Model 3 Output)					Model 2 (4-Input Model 3 Output)				
	Effch	Techch	Pech	Sech	Tfpch	Effch	Techch	Pech	Sech	Tfpch
2008–2009	1.257	0.54	1.06	1.19	0.672	1.26	0.557	1.073	1.17	0.7
2009–2010	1.054	0.99	1.041	1.01	1.047	1.04	0.999	1.037	1.01	1.04
2010–2011	0.945	1.68	0.968	0.98	1.586	0.98	1.655	0.994	0.99	1.62
2011–2012	0.94	0.84	0.971	0.97	0.788	0.89	0.815	0.928	0.96	0.73
2012–2013	1.1	0.65	1.015	1.08	0.715	1.11	0.646	1.038	1.07	0.72
2013–2014	1.018	0.86	1.022	1	0.879	1.02	0.853	1.015	1.01	0.87
2014–2015	0.928	0.94	0.947	0.98	0.873	0.92	0.997	0.932	0.99	0.92
2015–2016	0.622	1.55	0.623	1	0.965	0.61	1.501	0.622	0.99	0.92
2016–2017	0.877	1.19	0.902	0.97	1.044	0.88	1.189	0.904	0.97	1.05
2017–2018	1.006	1.05	0.986	1.02	1.052	1	1.043	0.983	1.02	1.05
2018–2019	1.769	0.67	1.714	1.03	1.189	1.77	0.671	1.714	1.03	1.19
2019–2029	0.959	0.95	0.954	1.01	0.909	0.98	1.08	0.975	1.01	1.06
Mean	1.011	0.94	0.993	1.02	0.952	1.01	0.952	0.994	1.02	0.96

Source. Authors estimate from data collected from banks' Annual Reports.

Comment: the estimated results from Table 4 show that the components of the Malmquist index in model 2 are slightly better than those in model 1 but have the same trend.

The estimated change in the efficiency of commercial banks during the study period of both models is greater than 1, while the change in tfp in both the estimated models is less than 1, the root cause of the problem. This is mainly due to technological progress and net efficiency (management) not being able to respond to profound fluctuations in the past period. If we analyze each year in detail, we can see that there are unique features. For example, in 2010–2011, the change in tfp from model 1 is 1.585 and from model 2 is 1.62 which is mainly due to the technological change component.

Table 5 is a breakdown of the productivity growth of each bank during the study period from 2008–2020. Out of 23 banks, only 6 banks, namely banks 1, 2, 4, 5, 6, and 11 have productivity growth greater than 1 during the study period, which is mainly due to efficiency change components and net efficiency (management efficiency) is greater than 1.

Table 5: Comparison of Components of the Malmquist Index of 2 Estimated Models for 23 Banks in the Period 2008–2020

Firm	Model 1 (3 Inputs and 3 Outputs)					Model 2 (4 Inputs and 3 Outputs)				
	Effch	Techch	Pech	Sech	Tfpch	Effch	Techch	Pech	Sech	Tfpch
1	1.038	0.97	0.993	1.05	1.007	1.04	0.969	0.993	1.05	1.01
2	1.049	0.96	1.014	1.03	1.01	1.05	0.962	1.014	1.03	1.01
3	1.001	0.94	0.963	1.04	0.942	1	0.934	0.963	1.04	0.94
4	1.045	0.96	1	1.05	1.001	1.05	0.959	1	1.05	1
5	1.054	1.21	1.038	1.02	1.275	1.05	1.202	1.038	1.02	1.27
6	1.026	1.01	1	1.03	1.034	1.03	0.995	1	1.03	1.02
7	1.018	0.91	0.981	1.04	0.931	1.02	0.89	0.981	1.04	0.91
8	1.004	0.93	0.96	1.05	0.936	1	0.931	0.96	1.05	0.93
9	0.991	0.96	0.967	1.03	0.948	0.99	0.954	0.967	1.03	0.95
10	1.036	0.94	1.014	1.02	0.971	1.04	0.935	1.014	1.02	0.97
11	1.048	0.96	1.048	1	1.009	1.05	0.956	1.048	1	1
12	1.051	0.95	1.05	1	0.996	1.05	0.921	1.05	1	0.97
13	0.941	0.97	0.941	1	0.913	0.94	0.922	0.941	1	0.87
14	0.981	0.86	0.981	1	0.843	0.98	0.786	0.981	1	0.77
15	1.038	0.96	1.015	1.02	0.997	1.04	0.94	1.015	1.02	0.98
16	0.962	0.97	0.962	1	0.932	0.96	0.935	0.962	1	0.9
17	0.983	0.86	0.983	1	0.848	0.98	0.807	0.983	1	0.79
18	1	0.93	0.994	1.01	0.926	1	0.899	0.994	1.01	0.9
19	0.966	0.93	0.966	1	0.896	0.97	0.872	0.966	1	0.84
20	0.997	0.98	0.998	1	0.974	1	0.928	0.998	1	0.93
21	1.013	0.97	1.007	1.01	0.985	1.01	0.924	1.007	1.01	0.94
22	1	0.9	1	1	0.896	1	0.865	1	1	0.87
23	1	0.92	1	1	0.921	1	0.868	1	1	0.87
Mean	1.01	0.95	0.994	1.02	0.962	1.01	0.926	0.994	1.02	0.94

Source. Authors estimate from data collected from banks' Annual Reports.

6. Conclusion

This study applies the DEA approach to estimate efficiency and measure composite factor productivity, technical change, and technological efficiency in the banking industry (commercial banks) from 2008 to 2020.

We have built a model to estimate the efficiency and calculate as well as decompose the productivity growth of Vietnamese commercial banks during the period of active mergers and acquisitions activities in the banking system. The efficiency models are built based on the traditional DEA models of Charnes et al. (1978) and Banker et al. (1984). The TFP growth decomposition is based on the Malmquist index model.

The efficiency model estimation results show that from 2008 to 2013 the average technical efficiency of 23 banks increased from 0.84 to 0.9 1, however, in the later period from 2018 to 2020 the efficiency fluctuated around 0.84.

The results of estimating the 3 Tobit models to assess the impact show that of the factors belonging to the characteristics of enterprises, only K/L, ROE and E/A have a positive influence on technical efficiency and net efficiency in which only E/A is positive and statistically significant in all 3 models. In the macro variables, ln FDI has a negative influence and has high statistical significance in all 3 models. That is, inward FDI puts pressure on banks, thereby reducing efficiency.

Malmquist productivity index was used to measure productivity growth in this study, with the data envelopment analysis (DEA) approach, yield growth can be decomposed into two components: technical change and effective change. This decomposition allows us to identify the contributions of technical progress and improvements in technical efficiency to productivity growth in the Vietnamese banking industry. We use DEA to calculate the component distance functions of the Malmquist index and build best practice (efficient) frontiers for Vietnamese commercial banks. The technical change index and the efficiency change index are obtained by comparing each bank with a best practice frontier with the same production technology. The Malmquist productivity index is then calculated as the product of these two indices.

Estimating results of Malmquist indexes from models 1 and 2 show that the change in the efficiency of commercial banks is positive (greater than 1), while the estimated change in tfp is less than 1, the root cause of the problem. This is mainly due to technological progress and net efficiency (management) not being able to respond to profound fluctuations in the past period. This makes us think about how to have a high-quality workforce that can keep up with the current technological changes in the world.

References

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

Berg, S. A., Forsund, F., & Jansen, E. (1991). Technical efficiency of Norwegian banks: A nonparametric approach to efficiency measurement. *Journal of Productivity Analysis*, *2*(2), 127–142. https://doi.org/10.1007/BF00156343

Bergendahl, G. (1998). DEA and benchmarks: An application to Nordic banks. *Annals of Operations Research, 82*, 233–249.

Berger, A. N., & Humphrey, D. B. (1997a). The efficiency of financial institutions: International survey and directions for future research. *European Journal of Operational Research*, *98*(2), 175–212. https://doi.org/10.1016/S0377-2217(96)00342-6

Berger, A. N., & Humphrey, D. B. (1997b). *The efficiency of financial institutions: International survey and directions for future research* (Finance and Economics Discussion Series Paper). Washington DC: Federal Reserve Board of Governors. https://www.federalreserve.gov/pubs/feds/1997/199711/199711pap.pdf

Berger, A. N., Hanweck, G. A., Humphrey, D. B. (1987). Competitive viability in banking: Scale, scope and product mix economies. *Journal of Monetary Economics*, *20*, 501–520. https://doi.org/10.1016/0304-3932(87)90039-0

Berger, A. N., Leusner J. H., & Mingo, J. (1997). The efficiency of bank branches. *Journal of Monetary Economics, 40*, 141–162. https://doi.org/10.1016/S0304-3932(97)00035-4

Caves, D. W., Christensen, L. R., & Diewert, W. E. (1982). The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica 50*(6), 1393–1414. https://doi.org/10.2307/1913388

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

Christensen, R., & Diewert, W. E. (1982). The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica, 50*(6), 1393–1414. https://doi.org/10.2307/1913388

Coelli, T. J., Prasada Rao, D. S., & Battese, G. (1998). *An introduction to efficiency and productivity analysis*. Norwell: Kluwer.

Drake, L., & Hall, M. (2003). Efficiency in Japanese banking: An empirical analysis. *Journal of Banking and Finance, 27*(5), 891–917. https://doi.org/10.1016/S0378-4266(02)00240-6

Fare, R., S., Grosskopf, M. N., & Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *American Economic Review, 84*(1), 66–83. https://www.jstor.org/stable/2117971

Farrell, M. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society*, *120*, 253–281. https://doi.org/10.2307/2343100

Fixler, D. J., & Zieschang, K. D. (1992). An index number approach to measuring bank efficiency: An application to mergers. *Journal of Banking & Finance*, *17*(2–3), 437–450. https://doi.org/10.1016/0378-4266(93)90043-D

Fried, H., Lovell, C. A. K., & Schmidt, S. (1993). *The measurement of productive efficiency*. New York: Oxford University Press.

Gilbert, R. A., & Wilson, P. W. (1998). Effects of deregulation on the productivity of Korean banks. *Journal of Economics and Business, 50*(2), 133–155. https://doi.org/10.1016/S0148-6195(97)00074-X

Grifell-Tatjé, E., & Lovell, C. A. K. (1996). Deregulation and productivity decline: The case of Spanish savings banks. *European Economic Review, 40*(6), 1281–1303. https://doi.org/10.1016/0014-2921(95)00024-0

Hancock, D. (1991). *A theory of production for the financial firm*. The Netherlands: Kluwer Academic.

Humphrey, D. B. (1990), Productivity in banking and effects from deregulation. *FRB Richmond Economic Review, 77*(2), 16–28. https://ssrn.com/abstract=2126223

Huynh, Q. L., & Nguyen, N. V. (2019). The effect of prior financial performance on organizational reputation and earnings management. *Journal of Asian Finance, Economics, and Business*, *6*(4), 75–81. https://doi.org/10.13106/jafeb.2019.vol6.no4.75

Kim, H. Y. (1986). Economies of scale and economies of scope in multiproduct financial institutions: Further evidence from credit unions: A note. *Journal of Money, Credit, and Banking*, *18*(2), 220–26. https://doi.org/10.2307/1992205

Lang, G., & Welzel, P. (1996). Efficiency and the technical progress in banking: empirical results for a panel of German cooperative banks. *Journal of Banking and Finance*, *20*(6), 1003–1023. https://doi.org/10.1016/0378-4266(95)00040-2

Le, T. T. D., & Diep, T. T. (2020). The effect of lending structure concentration on credit risk: The evidence of Vietnamese commercial banks. *Journal of Asian Finance, Economics, and Business, 7*(7), 59–72. https://doi.org/10.13106/jafeb.2020.vol7.no7.059

Leightner, J. E., & Lovell, C. A. K. (1998). The impact of financial liberalization on the performance of Thai banks. *Journal of Economics and Business*, *50*(2), 115–131. https://doi.org/10.1016/s0148-6195(97)00073-8

Leong, W. H, Dollery, B., & Coell, T. (2002). *Measuring the technical efficiency of banks in Singapore for the period 1993 To 1999: An application and extension of the Bauer Et Al (1997) technique*. (Economics Working Paper Series No. 2002–10). UK: University of New England. https://doi.org/10.1355/AE20-3A

McAllister, P. H., & McManus, D. (1993). Resolving the scale efficiency puzzle in banking. *Journal of Banking and Finance, 17*(2-3), 389–405. https://doi.org/10.1016/0378-4266(93)90039-G

Minh, N. K, Dragon, G. T., & Hung, N. V. (2013). Efficiency and super: Efficiency of commercial banks in Vietnam: Performance and determinants. *Asia-Pacific Journal of Operational Research, 30*(1), 1250047. https://doi.org/10.1142/S0217595912500479

Pastor, J. M., Perez, F., & Quesada, J. (1997). Efficiency analysis in banking firms: An international comparison. *European Journal of Operational Research*, *98*(2), 395–407. https://doi.org/10.1016/S0377-2217(96)00355-4

Pham, H. N. (2021). How does internal control affect bank credit risk in Vietnam? A Bayesian analysis. *Journal of Asian Finance, Economics, and Business, 8*(1), 873–880. https://doi.org/10.13106/jafeb.2021.vol8.no1.873

Ray, S. C., & Desli, E. (1997). Productivity growth, technical progress, and efficiency change in industrialized countries: Comment. *American Economic Review, 87*(5), 1033–1039. https://www.jstor.org/stable/2951340

Rebelo, J., & Mendes, V. (2000). Malmquist indices of productivity change in Portuguese banking: The deregulation period. *International Advances in Economic Research*, *6*(3), 531–543.

Resti, A. (1997). Evaluating the cost efficiency of the Italian banking system: What can be learned from the joint application of parametric and nonparametric techniques? *Journal Banking and Finance*, *21*(2), 221–250. https://doi.org/10.1016/S0378-4266(96)00036-2

Sathye, M. (2002). Measuring productivity changes in Australian banking: An application of Malmquist indices. *Managerial Finance*, *28*(9), 48–59. https://doi.org/10.1108/03074350210768068

Sealey, C. W., & Lindley, J. T. (1977). Inputs, outputs, and a theory of production and cost at depository financial institutions. *Journal of Finance*, *32*(4), 1251–66. https://doi.org/10.2307/2326527

Tran, Q. T., Lam, T. T., & Luu, C. D. (2020). Effect of corporate governance on corporate social responsibility disclosure: Empirical evidence from Vietnamese commercial banks. *Journal of Asian Finance, Economics, and Business, 7*(11), 327–333. https://doi.org/10.13106/jafeb.2020.vol7.no11.327

Wheelock, D. C., & and Wilson, P. W. (1997). Technical progress, inefficiency, and productivity change in U.S. banking, 1984–1993. *Journal of Money Credit and Banking, 31*(2), 212–34. https://doi.org/10.2307/2601230