A cross-country efficiency and productivity evaluation of commercial banks in South Asia: A meta-frontier and Malmquist productivity index approach

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Abstract

South Asia primarily consists of developing economies with diverse financial systems. The commercial banking industry plays a crucial role in each country’s financial development in the region. This research aims to evaluate commercial banking industries’ efficiency and productivity growth in the South Asian (SA) region over 6 years (2013–2018). In addition, the technology gap among the banking industries of all countries is also explored. Data envelopment analysis (DEA) Meta-frontier is employed to measure the technical efficiency (TE) and technology gap ratio (TGR) among the countries. Further Malmquist productivity index (MPI) is used for productivity change estimation. Results indicate that, on average, 147 commercial banks (CBs) have a technical efficiency score of 0.6208, while CBs in Nepal are the most efficient in the region with an average score of 0.7153. The Meta frontier analysis also confirms the presence of different production technologies in CBs. Nepal’s CBs group frontier is closer to meta-frontier (technology gap ratio, TGR = 0.9361) While, Bangladesh, Pakistan, India, and Sri Lanka rank second, third, fourth, and fifth, respectively. The results of productivity contend that the total factor productivity change of all 147 CBs decreases by 0.8 percent on average over the study period. CBs have enhanced their productivity growth in Sri Lanka, Nepal, and Pakistan, but declining trends have been witnessed in Indian and Bangladesh’s commercial banking industries.

1. Introduction

The financial sector is one of the most important aspects of a country’s economic system since sustainable economic development is mainly dependent on its financial sector development [1]. CBs play a critical role in achieving economic development goals through the necessary
fund supply [2]. A.L. Sobiech et al. [3], recognized that commercial banks are essential sources of long-term investment finance. CBs are also the backbone of the banking system since they lend capital to the private sector [4]. Indeed, these banks contribute widely to financial capital mobilization in any economy. However, the efficient growth of these banks is determined primarily by the aggressive marketing strategy in the banking sector and technological advances in the production of new products. Such factors increase the productivity and efficiency of the CBs. Consequently, the CBs’ performance assessment is essential in proposing policy outcomes to decision-makers. The fundamental intention is to assess the efficiency and productivity change of CBs in the markets where they operate and further compare their performance with their competitors. This paper analyzes the performance of South Asian CBs due to its virtual importance in the developing world. Indeed, the South Asian region has the potential to influence the world economy as it is a densely populated region with approximately 1.8 billion population. Commercial banking industries of South Asian countries are the driving force for the financial structure of these developing economies [5]. Though these countries have similar cultures, geography, and economic conditions to some extent, commercial banks’ production technologies still vary from country to country. Moreover, owing to heterogeneous technology, the performance of each country’s commercial banks may differ.

India’s commercial banking industry, for example, is one of the world’s leading and well-developed industries. The Indian banking sector continued to develop and was found to be efficient at 73.44 percent [6]. Nevertheless, CBs production technologies in Pakistan, Sri Lanka, Bangladesh, and Nepal differ from the massive Indian CB industry. However, these countries are reviving policies to strengthen the operations of the banking system, thereby banking efficiency and assets of the banks are expected to rise. Tables 1 & 2 show the financial indicators, average equity returns (AROE), and average asset returns (AROA) of South Asian banking industries, which explain the financial position of banking sectors. The Mean ROAE and ROAA of commercial banks for Nepal are the highest of sample countries.

Fig 1 indicates the variability in South Asian banks’ total assets. The total assets of Indian commercial banks are 54.70%, followed by Bangladesh (17.60%), Pakistan (16.40%), Nepal (7.10%), and Sri Lanka (4.20%), respectively. In the extant literature, a variety of approaches such as financial ratio analysis [7], data envelopment analysis (DEA) [8], stochastic semi-non-parametric envelopment of data [9], and stochastic frontier analysis (SFA) [10], have been employed to assess the banking efficiency and productivity. However, data envelopment analysis is one of the most popular non-parametric linear programming techniques, extensively used to measure the efficiency and productivity change of banking industries [11–15]. Due to the production technology gap, limited research has been carried out on cross-country performance evaluation of commercial banking industries globally [16, 17]. For instance, many studies [18–24] have been conducted to measure the efficiency and productivity of South Asian

Table 1. Average of returns on equity (AROE) of 147 SA CBs.

| ROAE | 2013  | 2014  | 2015  | 2016  | 2017  | 2018  | 2013–2018 |
|------|-------|-------|-------|-------|-------|-------|-----------|
| Mean BD | 9.4718 | 11.5791 | 11.75 | 11.4971 | 11.8035 | 10.515 | 11.1028 |
| Mean IN | 8.2339 | 8.8361 | 2.2114 | 4.5303 | -4.8792 | -2.9186 | 2.669 |
| Mean LK | 9.338 | 15.344 | 15.1007 | 16.394 | 16.0227 | 12.198 | 14.0662 |
| Mean NP | 68.6666 | 22.4829 | 29.4369 | 23.4886 | 21.3897 | 15.474 | 30.1565 |
| Mean PK | 7.9116 | 12.5489 | 14.3305 | 14.0705 | 10.2168 | 12.9495 | 2.669 |
| Average All | 23.7208 | 14.1533 | 14.4515 | 13.6064 | 10.162 | 8.8282 | 14.1537 |

Note: BD stands for Bangladesh, IN for India, LK for Sri Lanka, NP for Nepal, and PK for Pakistan, respectively.

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commercial banks for individual countries. While the research conducted by [25] concentrated on pre- and post-regulatory reform efficiency of Indian and Pakistani CBs, none of the studies assessed regional performance on a combined basis and measured the technology gap ratio (TGR). To fill this void, we evaluate the efficiency and technology gap ratio of South Asian commercial banks through meta-frontier analysis, which is a significant approach to measure technological gaps between different production units or industries, [26, 27]. To best of our knowledge, this is the first study on the subject.

This research further contributes to the existing literature in the following ways. Using the data of 147 CBs from Bangladesh, India, Nepal, Pakistan, and Sri Lanka, efficiency and productivity change analysis were conducted through data envelopment analysis (DEA), first, it evaluates the annual operational efficiency of all DMUs for a specific period and shows the annual trend of average technical efficiency. Secondly, using Meta-frontier we measured the technology gap ratio (TGR) in CBs of sample countries, which has never been performed before for South Asia region. Finally Malmquist productivity index is employed to measure the productivity change in sampled CBs and differentiate the main factor (efficiency change or technological change) behind the total factor productivity change.

### Table 2. Average of returns on assets (AROA) of 147 SA CBs.

| ROAA   | 2013  | 2014  | 2015  | 2016  | 2017  | 2018  | 2013–2018 |
|--------|-------|-------|-------|-------|-------|-------|-----------|
| Mean BD| 1.0368| 1.125 | 1.3074| 1.1903| 1.0659| 0.9038| 1.1049    |
| Mean IN| 0.8131| 0.8575| 0.4692| 0.5706| 0.025 | 0.0725| 0.468     |
| Mean LK| 1.0267| 1.5087| 1.3887| 1.4713| 1.5173| 1.2473| 1.36      |
| Mean NP| 1.8131| 1.7457| 1.984 | 2.0994| 2.7563| 1.8457| 1.9424    |
| Mean PK| 0.9989| 1.2679| 1.2926| 1.2021| 0.8153| 0.9947| 1.0953    |
| Average All| 1.167 | 1.2739| 1.2681| 1.2687| 1.1114| 0.9765| 1.1776    |

**Note:** BD stands for Bangladesh, IN for India, LK for Sri Lanka, NP for Nepal, and PK for Pakistan, respectively.

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**Fig 1. Percentage of total assets of South Asian commercial banks (Bank focus).**

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The rest of the paper is designed as follows: section 2 includes all the relevant literature, while Section 3 methodology and data description. Section 4 presents the results evaluated through empirical analysis, while section 5 concludes the study and offers policy implications.

2. Literature review

Data envelopment analysis is widely used to assess banking performance using linear programming techniques despite various approaches to resolving banking efficiency problems. Several studies have been conducted to evaluate the efficiency and productivity change of banking industries around the world. Such as, [28] is the first who use DEA on different bank branches in the US. They found that six out of 14 bank branches are relatively inefficient. Halkos (2004) [11] measured the performance of the Greek banking sector by applying data envelopment analysis. They argued that the size of the total assets accompanies the efficiency of Greek banks. In contrast, the traditional DEA method [12] employed a slack-based measure network DEA model to assess the Japanese regional bank’s management efficiency. They mentioned that the medium-sized banks are incompetent. Therefore, it is a dire need to improve the management efficiency of these banks, particularly in the marketable securities division than in the lending division. Fukuyama (2013) [13] analyzed productivity change for 269 Japanese Shinkin banks by analyzing data envelopment and reported that in the case of a weak economy, the bank purposely abandoned some current lending opportunities to minimize non-performing loans reallocating capital when the economy could be expected to recover. Fukuyama (2015), [14] also conducted a study for Japanese commercial banks and developed a dynamic two-stage network production model. They examined that bank inefficiency affects the portfolio size of the assets. Recently Q. Phung et al. [29] employed the DEA on USA banking and found a negative relationship between non-performing loans and bank efficiency. Emrouznejad et al. [30] surveyed the DEA application in various industries and argued that a large part of the DEA literature had been published in connection with banking industries in different countries and regions.

Additionally, several studies are conducted to explore the same nexus for example [15] for East Virginia; [31] for Turkey; [32] for Canada; [33] for Korea; [34] and [35] for the US; [36] for the UK retail Banks; [37–39] for India; [40] for Vietnam [41–43] for China; and [44] for a panel of 17 Central and Eastern European countries. Onwards wide range of scholars applied the DEA for performance evaluation of Commercial banks. For example [45–54] applied basic CCR and BCC models of DEA in different countries around the globe to measure the operational efficiencies of CBs.

Some scholars considered undesirable outputs (non-performing loans) to evaluate the banking performance, for instance [33]; [43] and [55, 56]. Simultaneously, [34] and [57–62], followed the super-efficiency model in data envelopment analysis. However, heterogeneous factors are ignored while evaluating the banking performance. Indeed, each bank has its own production sets that might be different owing to physical and capital stocks, in conjunction with the economic and social structure [63]. The ignorance of heterogeneous factors leads to biased banking efficiency measures. Meta frontier analysis is a more suitable approach to account for the heterogeneous factors, which follows two steps. Firstly, banks are categorized according to their inner individualities (public CBs, joint-stock CBs, and foreign banks) to evaluate a group-specific production frontier for each cluster (pones). Secondly, the Meta frontier is measured by enveloping the group-particular frontiers [64, 65]. By employing the Meta-frontier analysis on Chinese commercial banking data, C. Lee et al. [66] found that fintech innovation improves the bank efficiency and enhances the technology used by particular commercial banks. Authors further decomposed the source of Meta frontier inefficiency for
various banks with undesirable outputs and suggested that foreign banks do not operate efficiently in developed countries due to technology gaps of commercial banks. Considering the facts mentioned above, we also used the Meta frontier approach to account for the heterogeneous factors in South Asian CBs. Moreover, we fail to find a comprehensive study on the South Asia region and its technological gaps. Therefore, this study would be a valuable addition to the existing literature in different directions.

3. Research methodology

Parametric stochastic frontier analysis (SFA) and non-parametric data envelopment analysis are two renowned techniques to gauge the efficiency of homogeneous decision-making units (DMUs). Due to relaxed normality assumption, DEA is a more powerful tool in efficiency estimation [67]. We outline three steps procedures for empirical evaluation of South Asian commercial banks’ performance analysis (see Fig 2). First, data envelopment analysis (CCR, BCC) estimates the technical efficiency of CBs. Secondly, DEA-Meta frontier is applied to find the Meta frontier, group frontier, and technological gap ratio. Finally, we used the Malmquist Productivity Index for productivity analysis.

3.1. CCR model

Considering a set of $J$ DMUs with $n$ input and $m$ output in $T$ ($t = 1, \ldots, T$) periods. Suppose in time period $t$, decision-makers are using inputs $x^t \in R^n_+$ to produce outputs $y^t \in R^m_+$. Define

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**Fig 2.** Empirical evaluation outline of South Asian commercial banks’ performance analysis.

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the input requirement set in period $t$, which is:

$$L_t(y') = \{x' : x' \text{ can produce } y'\}.$$ 

Assume that $L_t(y')$ is non-empty, closed, convex, bounded and satisfies substantial disposability property of inputs and outputs $L_t(y')$ is bounded from below by the input isoquant (a constant returns to scale (CRS) production boundary), that is:

$$\text{Isoq} L_t(y') = \{x' : x' \in L_t(y'), \lambda x' \notin L_t(y') \text{ for } \lambda < 1\}.$$ 

Define the input distance function of period $t$ as follows:

$$D_t(y', x') = \sup_{\theta} \{\theta : (x'/\theta) \in L_t(y'), \theta > 0\}.$$ 

Thus, the following is the DEA-CCR model for measuring TE in time $t$:

$$TE_t(y', x') = 1/D_t(y', x').$$ 

Thus, the following is the DEA-CCR model for measuring TE in time $t$:

$$TE_t(y', x') = 1/D_t(y', x').$$ 

$$TE = 1\text{ means that a specific DMU is being evaluated compared to other DMUs, indicating that it is productively inefficient since it uses excessive inputs. In contrast, } TE = 1\text{ indicates that the DMU is entirely efficient.}$$

**3.2. BCC model**

In addition, Banker et al. [68] devised the DEA-BCC model, which provided that TE could be further decomposed into pure technical efficiency (PTE) and scale efficiency (SE). By generating the production possibility set from observed values set of input-output bundles without taking a functional form of the production technology:

$$TE = PTE \times SE.$$ 

The BCC model represents the PTE without including the SE and considers variable returns to scale (VRS). For the PTE, the BCC model is as follows:

$$\max h_k = \sum_{r=1}^{s} u_r Y_{rk} + \omega$$ 

Subject to:

$$\sum_{i=1}^{m} v_i X_{ik} = 1$$

$$\sum_{r=1}^{s} \mu_r Y_{rk} - \sum_{i=1}^{m} v_i X_{iq} + \omega \leq 0$$

$$u_r \geq 0; v_i \geq 0;\quad r = 1, \cdots, s; i = 1, \cdots, m; j = 1, \cdots, n;$$

$$\omega = \text{free.}$$

The DEA model becomes with increasing returns to scale when $w > 0$, it becomes decreasing returns to scale when $w < 0$, whereas DMU jb is Pareto-efficient in one condition, if and
only if \( q_b = 1 \), where \( q_b \) represents pure technical efficiency. When PTE or SE is below one, it implies that a DMU is inefficient compared to other DMUs being observed. We may infer a lack of skill in converting inputs to optimal output levels. Emrouznejad et al. [30] carried out a survey and reviewed existing research from 1978 to 2016, emphasizing the development of DEA models and their real-world applications. The DEA application is currently widespread in the banking and financial sector for performance evaluation.

### 3.3. Meta frontier analysis

Meta frontier analysis can measure the technology gap between different groups of DMUs. Consistent with [63], an output-oriented measurement of technical efficiency with relation to meta-technology for one observation (or one form) can be described as:

\[
TE^-(x, y) = D^-(x, y)
\]

For group A, the output-oriented measurement of technical efficiency about the technology of a group is described as:

\[
TE^A(x, y) = D^A(x, y)
\]

Hence, the output-oriented meta-technology ratio for group A can be written as:

\[
MRT^A(x, y) = \frac{D^-(x, y)}{D^A(x, y)} = \frac{TE^-(x, y)}{TE^A(x, y)}
\]

Or

\[
TE^-(x, y) = TE^A(x, y) * MRT^A(x, y)
\]

Where \( MRT^A(x, y) \) computes the variation between meta-frontier and the groups A frontiers, also known as the TGR.

Fig 3 depicts the meta-frontier function model and meta-technology ratio, where the meta-frontier envelopes the groups A 1, 2, 3 frontiers (or country frontiers), and the meta-technology ratio is calculated by dividing \( TE^-(x, y) \) which equals \( \frac{TE^-(x, y)}{TE^A(x, y)} \).

### 3.4. Malmquist productivity index

Fisher index, Malmquist productivity index (MPI, also known as Total Factor Productivity, or TFP), and Tomqvist index are widely used indices to calculate productivity change. We used MPI in this study because of its extensive use in banking literature for productivity analysis. The extensive use of MPI in banking is because it does not require cost minimization and profit maximization assumptions. In Färe & Grosskopf (1994) [69], an approach for the value of MPI is obtained as follows:

\[
M(y^{i+1}, x^{i+1}; y', x') = \left[ \frac{D'(y^{i+1}, x^{i+1})}{D'(y', x')} \times \frac{D'(y^{i+1}, x^{i+1})}{D'(y', x')} \right]^{1/2}
\]

To disintegrate productivity change into TE change and technical change, the MPI approach can be used:

\[
M(y^{i+1}, x^{i+1}; y', x') = \frac{D'(y^{i+1}, x^{i+1})}{D'(y', x')} \times \frac{D'(y^{i+1}, x^{i+1})}{D'(y', x')} \times \frac{D'(y', x')}{D'(y', x')}^{1/2}
\]

Where TE Change = \( \frac{D'(y^{i+1}, x^{i+1})}{D'(y', x')} \), Technical Change = \( \left[ \frac{D'(y^{i+1}, x^{i+1})}{D'(y', x')} \times \frac{D'(y', x')}{D'(y', x')} \right]^{1/2} \).
Some ratios beyond the brackets in Eq (5) indicate the measure of TE shift between time t and time t+1. While the ratios within the brackets reflect a shift in technology, as our studied industry is commercial banking, the above equation can further elaborate on how efficiency and technology change over time. MPI can be achieved by solving a series of linear programming equations; see [69], for more details. If MPI > 1 (MPI < 1), the Malmquist index progress (regress) between t and t+1 is inferred. There is no noticeable difference in efficiency from time t to time t+1 if the MPI value is 1. If TEC > 1, TEC < 1, or TEC = 1, the technical efficiency will increase, decrease, or remain constant between periods t and t+1, respectively. TC > 1 and TC < 1 reflect progress and regress in production technology between period t and t+1, respectively. The TEC can be further decomposed into the scale efficiency change (SEC) and pure technical efficiency change (PTEC): TEC = SEC×PTEC [70, 71]. The MPI technique is frequently used in banking studies [30]. Since its inception by [72], the MPI technique has been widely applied in banking research. For example, [73–78] conducted studies on commercial bank productivity change in various parts of the world.

### 3.5. Data and descriptive statistics

The choice of inputs and outputs variables in DEA is a major concern for researchers. Literature advocates that two different approaches are used to measure commercial bank efficiency: production and intermediate. Banks are considered service providers in the production approach, where they emphasize operating costs and count deposits as output without taking into account interest expenses paid on deposit collection. On the contrary, the intermediation approach used deposits as an input variable to produce more bank assets, while all operating costs and interest expenses were used as input. Production approaches are more applicable for branch-level data, while intermediation approaches are for bank-level data. Data for two inputs (Interest expenses, Non-interest Expenses) and two outputs (Net interest income, Non-interest income) were collected.
income) were collected from the Bank focus website. The data includes 147 commercial banks from five South Asian countries (Bangladesh, India, Sri Lanka, Nepal, and Pakistan) for the time 2013–2018. The panel includes 35 CBs from Bangladesh, 40 from India, 16 from Sri Lanka, 36 from Nepal, and 20 from Pakistan. DEA-Max software was used for efficiency and productivity analysis. Table 3 presents the descriptive statistics for the variables.

### 4. Results and discussions

DEA method is applied to measure the operating efficiency of South Asian region banks. All CBs’ operational efficiency scores are reported in Table 4. The results suggest that the average TE of all 147 CBs is 0.6208, which indicates that there is still 0.3792 percent technical inefficiency in these CBs’ operations. In other words, South Asian banks can improve their technical efficiency by reducing the input amount by 37.92 percent to generate the same output. Further mean PTE and SE scores are 0.7022 and 0.8917 for all CBs. TE and PTE scores of all CBs were higher in 2015, while SE scores were higher in 2013.

Table 5 ranks the CBs of all the countries on the performance based on TE. Mean OE scores (TE, PTE, and SE) indicate that 36 Nepalese CBs perform better than their counterparts in the 2013–18 period. These efficiency scores of Nepalese CBs are aligned with the study’s results of Gajurel et al. [79]. Fig 4 shows the average technical efficiency of CBs for each South Asian country over the study period.

Table 6 shows the results of DEA-MF, which indicate that average TEs of DEA-GF are higher than DEA-MF, where DEA-MF envelops all the CBs from 5 South Asian countries. Mean TEs DEA-MF declined from 61.85 percent in 2013 to 59.85 percent in 2018. Nepal’s average DEA-MF is about 71.50 percent, leading the region over a specific period. In contrast, TEs DEA-MF scores of CBs for India, Sri Lanka, Bangladesh, and Pakistan fluctuated from 54% to 62%. On the other hand, average TEs DEA-GF improved from 74.26 percent in 2013 to

| Variables | Interest expenses | Non-interest expenses | Net interest income | Non-interest income |
|-----------|-------------------|-----------------------|---------------------|---------------------|
| Max       | 7333797           | 3625484               | 6974456             | 2396662             |
| Min       | 240               | 157                   | 245                 | 80                  |
| Average   | 596569            | 251382                | 369409              | 155797              |
| SD        | 1188127           | 493071                | 819425              | 341387              |

**Note:** SD shows standard deviation; Max and Min designate maximum and minimum values, respectively. All input-output variables are presented in real values of thousand US dollars.

**Table 3.** Descriptive statistics of input-output variables (N = 147).

| Years | TE    | PTE    | SE     |
|-------|-------|--------|--------|
| 2013  | 0.6323| 0.6864 | 0.9300 |
| 2014  | 0.5271| 0.6492 | 0.8336 |
| 2015  | 0.6702| 0.7282 | 0.9250 |
| 2016  | 0.6654| 0.7392 | 0.9034 |
| 2017  | 0.6223| 0.7036 | 0.8901 |
| 2018  | 0.6077| 0.7068 | 0.8679 |
| Mean 2013–2018 | 0.6208 | 0.7022 | 0.8917 |

**Note:** TE shows technical efficiency, PTE Shows pure technical efficiency, and SE shows scale efficiency.
76 percent in 2018. Comparing the performance of CBs operating in all 5 SA countries, we found that TE’s DEA-GF performance of CBs improved in India, Bangladesh, and Sri Lanka, while CBs performance of Nepal and Pakistan gradually decreased over the period. DEA-TGR results indicate that maximum TGR is in Nepal and then in Bangladesh CBs, approximately 94 percent and 89 percent respectively. This portrays that CBs in Nepal are operating in the best level of production technology in the South Asian region. Our results are consistent with the study conducted by [80] They measured the cost efficiency and technology gap ratio of commercial banks in 9 low-income countries for 2011–2017, and found that CBs of Nepal are cost-efficient and TGR is highest among all 9 low-income countries. In addition, Pakistan, India, and Sri Lanka are ranked 3rd, 4th, and 5th, with an average TGR of 78 percent, 77 percent, and 70 percent, respectively, indicating greater technical gaps.

Table 7 reveals that the total factor productivity change of all 147 CBs decreases by 0.8 percent on average. Further decomposing the total factor productivity change into efficiency change and technological change, 0.6 percent and 0.2 percent decline were noticed respectively. The results of annual growth change show that except for the years 2014/2015 and 2015/2016, there has been a decline in total factor productivity change in all other years.

Table 8 outlines the separate productivity growth results of CBs in each South Asian country. Findings demonstrate that over the period 2013–2018, on average, CBs in Sri Lanka,
Nepal, and Pakistan increased their productivity growth by 1.37%, 0.99%, and 1.09%. Still, Bangladesh and Indian CBs observed a decline in growth by 0.8% and 2.8%. Results indicate clearly that growth in total factor productivity change in CBs in Pakistan is due to increased efficiency change, which opposes the results of Zhu et al. [22] for the different study periods. In comparison, CBs growth in Sri Lanka and Nepal was mainly due to technical changes. Hence, we conclude that there is a decrease in the overall productivity growth of South Asia’s 147 CBs on average, except a slight growth observed in 2014–15 and 2015–16. Sri Lankan CBs recorded most growth in TFPC, with Pakistani and Sri Lankan ranked 2nd and 3rd while Bangladeshi and Indian CBs noticed a decline in their average growth. Fig 5 demonstrates the total

Table 6. Technical efficiency and technology gap ratio of DEA-meta frontier in South Asian countries.

| Bank Group | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | average |
|------------|------|------|------|------|------|------|---------|
| Mean 35 BD | 0.6358 | 0.5519 | 0.6436 | 0.6477 | 0.6849 | 0.6157 | 0.6299 |
| Mean 40 IN | 0.6255 | 0.4727 | 0.6227 | 0.6138 | 0.5686 | 0.564 | 0.5779 |
| Mean 16 LK | 0.6008 | 0.5254 | 0.6492 | 0.6172 | 0.552 | 0.5732 | 0.5863 |
| Mean 36 NP | 0.7151 | 0.5897 | 0.771 | 0.7972 | 0.715 | 0.7034 | 0.7153 |
| Mean 20 PK | 0.5156 | 0.4809 | 0.6473 | 0.6007 | 0.5094 | 0.5362 | 0.5484 |
| All Countries | 0.6185 | 0.5241 | 0.6667 | 0.6553 | 0.6059 | 0.5985 | 0.6115 |

Table 7. Malmquist Productivity Index (MPI) results over time.

| years | effch | techch | pech | sech | tfpch |
|-------|-------|--------|------|------|-------|
| 2013–2014 | 0.833 | 1.195 | 0.943 | 0.884 | 0.996 |
| 2014–2015 | 1.283 | 0.798 | 1.139 | 1.126 | 1.024 |
| 2015–2016 | 0.993 | 1.014 | 1.017 | 0.976 | 1.006 |
| 2016–2017 | 0.933 | 1.049 | 0.95 | 0.982 | 0.979 |
| 2017–2018 | 0.979 | 0.977 | 1.004 | 0.975 | 0.956 |
| Mean 2013–18 | 0.994 | 0.998 | 1.008 | 0.986 | 0.992 |

Note: effch Show efficiency change, techch shows technology change, pech shows pure efficiency change, sech shows scale efficiency change, and tfpch shows total factor productivity change.
factor productivity charge and its component technology and technical efficiency change in
commercial banking industries for each South Asian country over the study period.

5. Conclusion

This paper investigates the efficiency, production technology gap, and productivity growth
among 147 CBs of South Asian countries from 2013–2018. Starting with financial indicators of
CBs, various techniques such as DEA (CCR, BCC), DEA meta-frontier and MPI are employed
for the empirical analysis. The financial indicators AROE and AROA reveal that, on average,
the performance of CBs gradually decreased from 2013 to 2018. CBs in Nepal performed
exceptionally well, while CBs recorded a declining trend in India. In the rest of the three sam-
ple countries (Pakistan, Sri Lanka & Bangladesh), CBs observed fluctuations in their financial
performance. The DEA (CCR, BCC) results indicate that on average TE of all 147 CBs is
0.6208, depicting that there is still 0.3792 percent technical inefficiency in these CBs’ opera-
tions. In other words, South Asian banks can improve their technical efficiency by reducing

Table 8. Productivity change of each country’s CBs (2013–2018).

|         | effch | techch | pech | sech | tfpch |
|---------|-------|--------|------|------|-------|
| Mean All| 0.994 | 0.998  | 1.008| 0.986| 0.992 |
| Mean BD | 0.9948| 0.9766 | 1.0129| 0.982| 0.9714|
| Mean IN | 0.9791| 0.9967 | 1.0078| 0.9715| 0.9757|
| Mean LK | 0.9955| 1.0183 | 1.0098| 0.9858| 1.0137|
| Mean NP | 0.9983| 1.0115 | 1.0003| 0.998 | 1.0099|
| Mean PK | 1.0128| 0.9982 | 1.0152| 0.9977| 1.0109|

Note: BD stands for Bangladesh, IN for India, LK for Sri Lanka, NP for Nepal, and PK for Pakistan respectively.

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![Fig 5. Mean productivity change in all 5 countries.](https://doi.org/10.1371/journal.pone.0265349.g005)
input by 37.92 percent to generate the same output. Mean PTE and SE scores of all CBs are recorded as 0.7022 and 0.8917. Among the sample countries, CBs in Nepal were most efficient among with an average TE score of 0.7153. The country-wise analysis of TGR reveals that CBs of Nepal utilized the best technology (TGR, 0.9361). At the same time, Bangladesh, Pakistan, India, and Sri Lanka are ranked 2nd, 3rd, 4th, and 5th, respectively, as the gaps between group frontier and meta-frontier are larger.

According to the MPI results, the total productivity change showed a declining trend on average in all observed years for 147 CBs. While further decomposing the tfpch into tech and tecch, it was observed that the decline in tfpch was mainly due to the decline both in tech and tecch, however, TE change plays a significant role. CBs in Sri Lanka, Pakistan, and Nepal gained productivity growth. In Pakistan tfpch was due to tech growth, while in Sri Lanka and Nepal, CBs productivity growth was due to the technology change. CBs in the rest of two countries (Bangladesh, India) had a decline in tfpch over the observed period. Based on the obtained results this study offers valuable policy implications. Policymakers in the South Asian region must strive to develop strategies, follow CB regulations in Nepal, and seek to use the best technology available to enhance their ability to compete with other CBs in the region.

Furthermore, CBs in Bangladesh and India need to improve technical efficiency and technological change to improve productivity. In contrast, CBs in Nepal and Sri Lanka need to focus on improving their technical efficiency, similarly tfpch in Pakistani CBs was mainly due to tech, so there is always a deficiency in tecch, which could be improved to foster the change in productivity. As data were collected for 2013–2018, data availability is a limitation of our study. In the case of data availability, the impact of the 2009 financial crisis on efficiency and productivity growth could be estimated, which is an additional contribution to banking literature.

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