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 **Impact of the COVID-19 Pandemic on the Efficiency of the Banking Sector: A Study in the Context of Bangladesh**

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Research Article

Abstract

***Purpose:*** *The banking sector plays a significant role in strengthening a nation's economic growth. However, it faced special challenges during the COVID-19 pandemic, which affected banks' efficiency. Thus, this study aims to measure the effects of COVID-19 on banks' efficiency during and after the pandemic in Bangladesh.*

***Methods:****The banking sector's technical efficiency was evaluated using the meta frontier Data Envelopment Analysis approach, based on secondary data from 23 commercial banks listed on the Dhaka Stock Exchange (DSE). Banks were selected based on the percentage of market share in the Banking industry. The data covering 2020-2024 were obtained from publicly available annual reports and financial statements.*

***Results****: Findings indicate that banks in Bangladesh were significantly more efficient after COVID-19 and that their performance has recovered. They have an average technical efficiency score of 0.63, compared to 0.51 during the pandemic.*

***Implications:*** *These findings have the potential to help policymakers find opportunities for profit increase and help develop early preventive measures during crises.*

***Originality:*** *This pioneering study in Bangladesh assessed banking efficiency after COVID-19.*

**Keywords**: Banks, COVID-19, Technical Efficiency, Meta-frontier Data Envelopment Analysis, Bangladesh

1. Introduction

Banks play a major role in the domestic and global economic systems by promoting investment, improving government development goals, and mobilizing financial resources (Kweh et al., 2024a; Ghulam & Dhruva, 2024). Furthermore, banks include a wide range of aspects of improving financial expansion and well-being (Bueno et al., 2024; Winasis et al., 2020), including trade, innovation, job creation, and poverty reduction (Alam et al., 2010).

Besides, banks are essential to economic growth because they greatly improve financial strength and the effective flow of money (Gazi et al., 2022a). Only then will banks be able to maintain their sound financial standing and guarantee the best possible resource allocation to maximize profits and promote national prosperity. This implies that directing bank managers toward efficient resource management policies is aided by evaluating profitability and efficiency (Kweh et al., 2024b).

Nonetheless, factors like inefficiencies within the organization's structure, internal politics, limited resources, and incompetent management can significantly affect the profitability of banks (Mbogoh & Ogutu, 2017). Past outcomes in the banking sector, unlike other sectors, can be expected because of the average level of uncertainty in the banking industry (Courtney et al., 1997), but global events and institutional changes will create uncertainty in global events, such as economic crises, new institutions (new regulations, financial shocks), and so on (Carbonara & Caiazza, 2010). Historical financial crises such as the British credit crisis (Sheridan, 1960), the Great Depression in the U.S. (Cootner, 1966), the Asian financial crisis (King, 2001; Zhuang & Dowling, 2003), and the global financial crisis of 2007-2008 (Aisen & Franken, 2010) have illustrated the propensity of the banking sector to the impact of external shocks.

The global economy faced an unfamiliar degree of uncertainty because of the COVID-19 pandemic (Obeidat et al., 2021), and it impacted every sector of the financial system (Rekha & Hossain, 2022). COVID-19 has caused a crisis in the banking industry in many countries. Bank profitability was significantly influenced by various factors, including bank cards issued (Farooq et al., 2021), asset quality, management efficiency (Colak & Öztekin, 2020), automated teller machines (Saif Alyousfi, 2020), earnings ability, liquidity, and sensitivity to risk (Kozak, 2021), sale terminals (Le & Nguyen, 2020), and capital adequacy (Jadah et al., 2020). Thus, the pandemic induced macro and microeconomic shocks to Bangladesh's economy and banking sector (Dey, 2019; Karim et al., 2021). The macroeconomic indicators, such as GDP growth (Gazi, 2021), inflation (Rahman, 2021), exchange rates, unemployment, non-performing loans (Gazi et al., 2022b), and liquidity positions of banks (Reddy, 2012)

The implications of the COVID-19 pandemic in all sectors have been under the main points of view, but it is primarily under the study of the banking sector in one way or another. Previous studies have evaluated measures including liquidity, capital adequacy, and financial stability (Wardhani et al., 2021; Alabbad & Schertler, 2022). A few of these studies have adopted the framework of the CAMELS rating system, assessing Capital adequacy, Asset quality, Management quality, Earnings, Liquidity, and Sensitivity to market risk to scrutinize the profitability and performance of banks throughout the pandemic (Suresh & Pradhan, 2023; Hussein & Al-Dulaimi, 2022). Most studies have been oriented to observe one of these conditions (the general impact of COVID-19 and specific performance metrics) on the pandemic and tend to evaluate each vertically (Malenković, 2023; Ochenge, 2022; Kamal, 2023; Damanhur & Khadafi, 2023).

This research attempts to fill this gap by holistically capturing the banking industry's performance during and after the pandemic through efficiency evaluations. This study uses Data Envelopment Analysis (DEA) to measure bank efficiency, providing a way to analyze performance differences in different periods.

Additionally, the findings have the potential to help policymakers find opportunities for profit increase and help develop early preventive measures during crises. Employing a mixed-method approach adds to existing knowledge while offering valuable insight for stakeholders on how companies can counteract future economic disruptions.

**2. Literature Review**

The COVID-19 pandemic significantly affected the efficiency of the banking sector, with disruptions caused by economic slowdowns, increased defaults, and policy interventions (Demirgüç-Kunt et al., 2022). Short-term profitability, however, was impacted by increasing non-performing loans experienced by many banks, but many banks made efficiency gains through digital transformation (Wang et al., 2023). The economies recovered, but banks subsequently adapted by enhancing risk management measures, diversifying revenue sources, and embracing fintech innovations, allowing them to restore profitability (Goodell, 2022). Brei et al. (2023) reported gradual improvements in key financial performance metrics (such as return on assets, ROA, and equity, ROE), but with heterogeneities by region and banking model.

Moreover, government stimulus measures and central bank interventions have significantly contributed to stabilizing liquidity and long-term profitability trends (Acharya & Steffen, 2021). However, lingering risks around inflationary pressures and geopolitical uncertainties remain influential on the sector’s financial performance and efficiency.

The financial crisis of 2008 highlighted banks’ susceptibility to system-wide shocks. Data Envelopment Analysis (DEA) studies indicated a profound decrease in banking efficiency as increased non-performing loans contracted credit activity (Lozano-Vivas & Pasiouras, 2010). Paradi and Zhu (2013) concluded that inefficient scale behaviors were most pronounced among the larger banks after 2008, stressing that crises tend to amplify pre-existing structural shortcomings.

Regulatory interventions, economic lockdowns, and pandemic-related challenges were all new and unprecedented in the COVID-19 pandemic. Initial studies highlighted duality: digitalized banks continued to operate smoothly due to lower overheads (Tan & Floros, 2012), while traditional banks experienced operational interruptions (Berger et al., 2021). Government assistance, as in the case of loan moratoriums, was cited as an important factor in stabilizing efficiency in DEA applications during 2020–2021 (Dhar & Bose, 2020). So, profitability indicators ROA and NIM have worsened due to interest rate cuts and spikes in credit risk (O’Connell, 2022).

Studies conducted after 2021 show that there is a slow recovery attributed to digital transformation and economic reopening. Wanke et al. (2023) reported that banks leveraging AI and blockchain technologies increased scale efficiency by 15–20% relative to pre-pandemic levels. There were some regional differences, though, as Asian banks, for example, recovered faster than their European equivalents due in part to more stringent pre-pandemic capital buffers. DEA efficiency scores frequently correlate with profitability. Akdeniz et al. (2023) reviewed two-stage DEA and demonstrated that technically efficient banks have better ROE, as efficiency gains lead to lower operational costs. Conversely, Tu et al. (2024) warned that overemphasizing cost-cutting might lead to detrimental effects on the long-term profitability of farms and suggested incorporating risk-adjusted outputs into DEA models to ensure balance.

As previously mentioned, the DEA's flexibility allows for customization based on pandemic-related variables. The sensitivity of input-output selection and the inability to capture random noise are limitations requiring complementary methods such as Malmquist indices for tracking productivity trends (Chaoqun et al., 2024). Cross-country studies (IMF, 2022) also point to the fact that banks in emerging markets started with higher liquidity constraints but benefited from accelerated digitalization.

Prior publications did not provide detailed temporal analyses through the acute and recovery periods. This gap is filled by the application of DEA to holistically analyze dynamic efficiency and profitability adjusted for regional and technological variables to guide post-crisis policymaking.

**3.** **A snapshot of the Banking sector in Bangladesh**

The banking sector in Bangladesh is among the major sectors of the country's financial structure, and it acts as the principal source of mobilizing funds from savers to investors and helping economic development (Halder, 2018). As of 2024, the sector comprises 61 scheduled banks. These organizations are supervised by the Bangladesh Bank (BB), the country's central bank and financial regulator. Bangladesh Bank oversees monetary policy, stability of the financial system, and the regulation of banks (Higgins et al., 2024).

The industry has seen considerable expansion and digital enhancement over the past two decades, but still suffers from structural inefficiencies and operational challenges. One of the more longstanding issues is the high level of non-performing loans (NPLs), especially among state-owned banks. This reduces the profitability of this sector and undermines its financial stability (Rahman, 2022). In addition, numerous banks, particularly in the public sector, find it challenging to sustain the minimum capital adequacy ratio (CAR) as mandated by Basel III guidelines (Yamin et al., 2025) Key indices of profitability Return on Assets (ROA) and Return on Equity (ROE) have too remained under pressure, primarily from falling interest margins and higher provisioning requirements. Despite maintaining advances to Deposit Ratio (ADR) well within regulatory thresholds, credit growth remains subdued and staggered.

Apart from the financial difficulties, the banking sector has also faced problems on the governance front with inefficient loan recovery mechanisms, politically motivated lending, and repetitive banking scandals undermining public confidence (Sultana & Jalloh, 2025). This, combined with the slow pace of financial innovation and underdeveloped risk management practices, especially in state-owned institutions,  has slowed progress towards a more efficient and resilient financial system.

However, the COVID-19 pandemic considerably impacted the banking situation by raising the credit risks and showing the vulnerability of the loan portfolios. Due to prolonged business shutdowns and declining revenues (Kashem, 2022), many borrowers, particularly SMEs, experienced repayment defaults. So, as a counter to this, the Bangladesh government, in collaboration with the Bangladesh Bank (BB), initiated different stimulus packages for the SMEs. Liquidity support was also stipulated through reducing the repo rate and the cash reserve requirement (CRR). Although these measures provided the necessary short-term financial stability, they also increased the risk of long-term asset value deterioration (Bangladesh Bank, 2021).

The banking sector has slowly but steadily shown signs of recovery in a post-pandemic world, partly due to the rapid expansion of digital banking services and broader use of financial technology (fintech). Since then, mobile financial services (MFS), internet banking, and agent banking have grown widely, contributing to financial inclusion and transaction time in urban and rural areas (Miah, 2024). Banks introduce SME and green financing to expand access to finance for formerly underserved classes. In addition, some institutions have started to employ environmental, social, and governance (ESG) considerations in their lending and investment choices. Amidst these positive trends, ensuring sustainable credit growth, restoring asset quality, and reinforcing regulatory oversight are vital to enhancing Bangladesh's banking sector's overall efficiency and resilience. Thus, this study is relevant in examining whether the banking sector recovered from financial inefficiencies.

**4. Methodology**

**4.1 Data**

This study analyzes the profitability and efficiency of 23 banks in Bangladesh from 2020 to 2024, listed in the Dhaka Stock Exchange (DSE) based on the market share. Besides, the study categorizes the period from 2020 to 2021 as the "During COVID" period and the years from 2022 to 2024 as the "Post COVID" period. Data collection was carefully structured to ensure accuracy and relevance. The study used secondary data from the annual reports, with meticulous attention to calculating missing variables. This comprehensive data set forms the basis for analyzing profitability and efficiency in the banking sector during and after the pandemic.

**Table 1: Inputs and output variables used in the analysis**

|  |  |  |
| --- | --- | --- |
| Variables | Code | Descriptions |
| Net Profit  | Y | The total profit, after all deductions (expenses, taxes, etc.), serves as the output for efficiency measurement. |
| Total Deposits  | Xa | The aggregate amount of money deposited by customers. |
| Number of Employees  | Xb | The total staff employed by the bank. |
| Operating Expenses  | Xc | Include all operational costs, excluding interest expenses. |
| Fixed Assets  | Xd | Represent the value of physical and financial assets |
| Non-Performing Loans (NPLs)  | Xe | Represent loans that are in default or close to being in default. |

Variable selection is grounded in established literature, reflecting standard financial efficiency analysis practices. Studies such as Berger & Humphrey (1997a) have employed similar input-output combinations to evaluate banking efficiency, reinforcing the validity of this approach. This study highlights the importance of comprehensive input and output measures for a holistic view of bank performance. The data for this study were collected from the bank's annual reports. Some variables were not directly available in the reports, necessitating additional calculations to obtain the required data. The analysis in this study focuses on several key variables.

**4.2 Data Analysis**

In this analysis,  the efficiency of banks is evaluated using the Data Envelopment Analysis (DEA) VRS (Variable Returns to Scale) input-oriented method. DEA, proposed by Charnes et al. (1978), is popularly used as a non-parametric approach to measuring the technical efficiency of decision-making units (DMUs), e.g., banks. It is particularly suited to evaluating banking efficiency as it simultaneously manages many inputs and outputs (e.g., labor and capital (inputs) and loans and profits (outputs) (Cooper et al., 2004). Berger and Humphrey (1997b) emphasized the prevalence of DEA in studies of financial institution efficiency because of its flexibility in representing different functional forms. In the past several decades, techniques like dynamic data envelopment analysis (DEA) and network DEA have become increasingly popular as they allow for measuring efficiency across time and within processes (Tone & Tsutsui, 2014). This approach is appropriate for decision-making units (DMUs), such as banks, that do not work on a similar scale, which can lead to varying bank sizes and efficiencies.[[1]](#footnote-2)

The study constructs separate production frontiers for evaluating bank performance during and after COVID-19. Meta-frontier Data Envelopment Analysis (DEA) is then used to compare these groups' overall performance and technological differences. This method enables the assessment of the efficiency of individual farms as well as differences in average efficiency at the group level. The meta-frontier framework decomposes technical efficiency into pure technical efficiency and the technological gap ratio (TGR), which measures how much a group's technology can restrict performance from best practices.

The empirical model, based on Battese et al. (2004), employs Linear Programming (LP) to evaluate the *n*-th bank within a specific group “P” (P = 1 or 2), which consists of Qp banks. This approach quantifies the technological gap between the group-specific frontiers and the meta-frontier. The LP for the group frontier is expressed as:

$$ME\_{n}=1/Max\_{λ,φ}φ, Eq. ( 1)$$

Subject to:

$$-φy\_{n}+Y\_{p}λ\geq 0$$

$$ x\_{n}-X\_{p }λ\geq 0$$

$$λ\geq 0$$

In this model, $y\_{n}$​ and $x\_{n}$ are the output and input vectors of the n-th Decision-Making Unit (DMU), respectively, where dimensions are S × 1 and T × 1. The (S×Q) entries of the matrix correspond to the output quantities for all Q units in the group, and the (T ×Q) entries correspond to input quantities. This is a vector of Q elements, denoting the weights assigned to the individual DMUs in creating the group frontier, where ϕ is the scalar showing the technical efficiency of the n-th farm.

The value of *ϕ* is always greater than or equal to one, and the term (*ϕ* – 1) represents the most current outputs of the n-th DMU, which could be expanded as the input acquired. The efficiency score of the DMU, denoted as 1/*ϕ*, is a number that ranges between zero and one, measuring the DMU's managerial efficiency (ME).

Further, the meta-frontier is built by merging the data from both groups and reapplying the linear programming (LP) procedure to the combined dataset.

$Q=\sum\_{p}^{}Q\_{p}$, i.e.

$$MTE\_{n}=1/Max\_{φ^{'}, λ^{' }}φ^{'}, Eq.(2)$$

Subject to:

$$-φ^{'}y\_{n}+Y^{\*}λ^{'}\geq 0,$$

$$x\_{n}-X^{\*}λ^{'}\geq 0,$$

$$λ^{'}\geq 0,$$

Here, $y\_{n}$​ and $x\_{n}$ denote the *S* × 1 and *T* × 1 vectors of output and input quantities for the *n*-th decision-making unit (DMU). The matrices $Y^{\*}$and $X^{\*} $S × Q and N × Q represent the output and input quantities for all Q units, collectively defining the meta-frontier. The vector λ′ is a *Q ×* 1 set of weights, while *ϕ′* is a scalar that indicates the proportional scaling factor.

It is essential to recognize that, for any DMU, the value of 1/$φ$’ will not exceed 1/$φ,$ reflecting the differences in input-output structures between the group frontier and the meta-frontier models. According to O'Donnell et al. (2008), no farm can demonstrate greater efficiency when evaluated against the meta-frontier than when assessed against its group frontier.

Using the Meta-frontier DEA approach, two separate measures of efficiency were estimated by the Meta-frontier DEA approach: Managerial Efficiency (ME), which reflects efficiency relative to the group frontier (Eq. 1), and Meta-Technical Efficiency (MTE), which evaluates the efficiency concerning the meta-frontier (Eq. 2). Then,  the Technological Gap Ratio (TGR) was calculated for each farm. This ratio reflects the difference between the group frontier and the meta-frontier, standing for the difference in the production environments. Specifically, the TGR for farm '*N*' within group '*P*' is calculated as:

$$TGR\_{n}^{p}= \frac{MTE\_{n}}{ME\_{n}} Eq. (4)$$

This method offers a more comprehensive understanding of the technological differences in banking operations between the two groups (Dogba et al., 2021).

Furthermore, the Wilcoxon rank-sum test was used to determine whether there were significant differences in meta-frontier efficiency (MTEn) between the two periods. We can utilize this non-parametric test because the two periods are independent and have equal sample sizes.

**5. Results**

Descriptive statistics on major financial metrics, which show the Effects of COVID-19 and the recovery period, are shown in Table 2. Banks' net profit has seen a remarkable recovery from the pandemic, rising from a mean of 1,866 million BDT during COVID-19 to 3,383 million BDT after COVID-19. This indicates a hearty financial recovery and adaptability in the banking sector. However, the high standard deviation at both times shows that profit volatility and varying performance between institutions persisted. The total deposits also saw a significant jump from an average of 3,71,039 million BDT during the peak of COVID-19 to 4,58,140 million BDT after the pandemic, indicating a return of confidence and liquidity growth.

The number of employees grew from 5,234 to 5,837, a moderate increase, suggesting a measured approach to workforce expansion in the post-pandemic recovery, likely to reflect an impetus from growing business activities. Operating expenses also increased from 8,420 million BDT to 10,409 million BDT (deduction of supply chain in the notes), which indicates more operational expenses, which were possibly incurred by increased operational activities and probably higher costs due to digital transformation and compliance measures in the post-pandemic digital transformation environment. Fixed assets showed a steady pattern with slight growth, indicating ongoing investment in long-term infrastructure.

The stable interest expenses indicate that there was probably still good cost management in borrowing or deposit interest rates. However, there were too many fluctuations in the general financial environment. However, the most alarming trend is the spiking number of NPLs, which has risen from an average of 22,765 million BDT when COVID-19 ravaged to 32172 million BDT when the pandemic turned into an endemic state. This means that disease-linked distress is now taking a toll on profitability and deposits even as credit quality deteriorates, potentially due to problematic repayment lag associated with or weakened borrower capacity in the post-COVID economy.

**Table 2. Description and statistical summary of variables**

|  |  |  |  |
| --- | --- | --- | --- |
| Metric | Overall | During COVID-19 | Post COVID-19 |
| Net Profit (in million BDTa) |
|  | Mean | 2555 | 1866 | 3383 |
|  | Std Dev | 2103 | 1655 | 2307 |
| Total Deposits (in million BDT) |
|  | Mean | 423389 | 371039 | 458140 |
|  | Std Dev | 357348 | 310690 | 384542 |
| Number of Employees |
|  | Mean | 5426 | 5234 | 5837 |
|  | Std Dev | 5180 | 5066 | 5326 |
| Operating Expenses (in million BDT) |
|  | Mean | 9684 | 8420 | 10409 |
|  | Std Dev | 6848 | 5863 | 7601 |
| Fixed Assets (in million BDT) |
|  | Mean | 7879 | 7890 | 8238 |
|  | Std Dev | 7310 | 7239 | 73049 |
| Interest Expense (in million BDT) |
|  | Mean | 13899 | 13848 | 13630 |
|  | Std Dev | 11707 | 9428 | 11709 |
| Non-Performing Loans (NPL, in million BDT) |
|  | Mean | 27648 | 22765 | 33172 |
|  | Std Dev | 35938 | 28638 | 42473 |

a1 dollar equals 120 Bangladeshi Currency in 2024

The data indicate that the banking sector recovered strongly post-COVID, with profitability, deposits, and operational scale improvements. On the other hand, the concurrent increase in NPLs highlights promising credit risk challenges that may threaten long-term financial stability if poorly managed.

**5.1. Bank Efficiency Distribution between the two periods**

Table 3 presents a comprehensive analysis of bank efficiency across three periods: During COVID-19, post-COVID-19, and the Overall Efficiency Analysis. During COVID-19, 23 banks were assessed, with four banks (17.39%) achieving perfect efficiency (E = 1.00). However, seven banks (30.44 %) operated at low efficiency (E < 0.60), highlighting significant challenges. In the subsequent period, nine banks reached perfect efficiency, and only two banks (8.70%) fell into the low efficiency category, meaning that the banks mostly recovered from the pandemic stress.

**Table 3. Bank Efficiency Distribution During, Post, and Overall COVID-19 Period (2020-2024)**

|  |  |  |  |
| --- | --- | --- | --- |
|  | During COVID-19  |  After COVID-19  |  Overall Efficiency  |
| Efficiency Range | Number of Banks | % | Number of Banks | % | Number of Banks | % |
| E = 1.00 | 4 | 17.39% | 9 | 39.13% | 3 | 13.04% |
| 0.90 ≤ E ≤ 1.00 | 2 | 8.70% | 5 | 21.73% | 4 | 17.39% |
| 0.80 ≤ E ≤ 0.90 | 3 | 13.04% | 4 | 17.39% | 6 | 26.09% |
| 0.70 ≤ E ≤ 0.80 | 4 | 17.39% | 2 | 8.70% | 3 | 13.04% |
| 0.60 ≤ E ≤ 0.70 | 3 | 13.04% | 1 | 4.35% | 5 | 21.74% |
| E < 0.60 | 7 | 30.44% | 2 | 8.70% | 2 | 8.70% |
| Total | 23 | 100% | 23 | 100% | 23 | 100% |

The Overall Efficiency from 2020 to 2024 shows three banks (13.04%) achieving perfect efficiency and six banks (26.09%) maintaining high efficiency (0.80 ≤ E < 0.90). Only two banks (8.70%) scored below 0.60, indicating overall enhancements in resource management and operational effectiveness.

**5.2. Group frontier, Meta frontier, and the Technology Gap Ratio during and post-COVID-19**

Table 4 presents the group frontier during and after the Covid-19 bank efficiency, in which a value of 0.66 for the "Post Covid" period group of banks means the banks are operating at 66% efficiency compared to the best-performing bank in the group. In other words, on average, the banks would still produce the same output with 34% less input. On the other hand, a score of 0.58 in the Covid period shows that the efficiency of the banks fell to 58% of the best bank. In other words, the banks could have cut their inputs by an impressive 42% to maintain the same output level.

The comparison of post-COVID vs. during-COVID shows 0.58 (lower), meaning the efficiency was lower during the COVID period. It indicates that banks needed more resources to generate the same output during the pandemic, which could be explained by operational challenges, economic instability, or rapid change in banking demand due to the pandemic. However, direct comparisons between the two are not recommended due to the different number of DMUs along with the possible differences in production possibility between different groups, and one can only compare the efficiency scores concerning a pooled production possibility frontier, which might be termed the meta frontier.

Relative to the meta frontier Table 4, a score of 0.63 indicates that, in post-Covid, banks operated at a lower efficiency (63%) when compared to the best possible meta frontier, controlling for all the external influences that might affect their operations (e.g., market conditions, technology, and regulations). Therefore, the banks could be 37% more efficient if they had the same efficiencies as the best banks outside their walls. Moreover, the COVID period's score of 0.51 means that the banks were only 51% efficient compared to the best-performing banks, considering the overall frontier where all external factors are considered. This means that, on average, the banks could have been 49% more efficient than they were to achieve the frontier, the best-performing DMUs. Additionally, the mean meta technical efficiency score in the two groups has a difference that is significant at the 1% level (Wilcoxon rank sum test, W = 3954.8, p-value < 0.000).

**Table 4.** **Meta Frontier and Technology Gap Ratio (TGR) of Banks during and post-COVID-19**

|  |  |  |  |
| --- | --- | --- | --- |
| Banks Category | TE according to the group frontier | TE according to Meta frontier | TGR |
| Post Covid | 0.66 | 0.63 | 0.95 |
| During Covid | 0.58 | 0.51 | 0.88 |
| Overall |  | 0.59 |  |

The Technology Gap Ratio (TGR) Table 4 can explain the technological efficiency of a farm relative to the best-practice technology frontier. This compares the banks' technological capabilities to the best technological frontier in that period. A TGR value of 0.95 implies that, following Covid, the banks are performing at 95% of the best technological frontier. In other words, their tech capability level is just 5% away from the best existing technology. This suggests that the banks are near optimal technological efficiency, but a slight gap remains that they could close to catch up entirely with the best technology. However, the TGR value of 0.88 during the COVID period tells us that the banks were running at 88% of the best possible technological efficiency that could have been reached. This indicates a 12% technological gap, meaning the banks were relatively farther away from the technological frontier than in the post-COVID period during the pandemic.

**6. Discussion**

In comparison with the group frontier, meta frontier, and technology gap ratio, it is seen that the post-COVID period bank efficiency is relatively better than during COVID, perhaps because COVID brought massive operational disruptions to banks that prevented them from being efficient and implementing technology better. Banks have had to adapt to the new normal of working from home, brick-and-mortar bank closures, bank branch switching, new health and safety protocols, increased volume of customer inquiries, and financial instability due to the pandemic (Marcu, 2021). The ability to deploy more advanced technologies was potentially delayed or decelerated because of this disruption, at least for those banks that were less ready for such a sharp shift. The dramatic acceleration in digital banking demand also caused stress to infrastructure, which resulted in some banks lagging even further when it came to achieving optimal technological efficiency. Thus, the Technology Gap Ratio increased, and the average meta-technical efficiency decreased as banks struggled to adjust to the new environment.

Post-COVID, banks had more time to recover, rethink strategies, and embrace new technologies as part of their operations. This brought more stable working conditions as well as a stronger focus on innovation and digital transformation. The need for remote banking and digital services stayed high, pushing banks to use more durable technological solutions. This change can be attributed to efficiency and technical prowess enhancements as banks adapted through lessons learned during the pandemic and positioned themselves to be competitive in a more digital-first environment. Additionally, banks tend to become more efficient Post crises, mainly because of improved risk management practices and operational changes undertaken during these periods (Pasiouras & Tanna, 2010). Additionally, banks usually benefit from gradual reforms in resource allocation after macroeconomic shocks, which cause them to shift in the long run towards improving efficiency. Their research gives credence to the idea that banks can initially falter during times of crisis but rebound and become more efficient over time. Hence, the TGR and mean meta efficiency value show a significant recovery because the banks could close the gaps and optimize their operations after the initial disruption.

Based on future crises, banks may need to invest in resilient, scalable technology infrastructures that adapt quickly to disruptions, leading to business continuity and seamless transitions to digital solutions. Banks that adopt flexible operational strategies and constant pressure toward digital transformation could be better positioned to remain competitive and agile in changing consumer habits and market circumstances. Improving risk management techniques by employing more sophisticated scenario planning and stress-testing will help banks identify weaknesses and allow them to respond proactively. Drawing lessons from historical crises, such as the post-COVID recovery, banks can leverage them to streamline resource management and optimize operational practices to enhance long-term efficiency and resilience for prospective analysis.

**7. Conclusion**

This study examined the efficiency of 23 banks in Bangladesh from 2020 to 2024, categorizing the timeline into two phases: during and after COVID-19. Utilizing the DEA meta frontier method, the analysis revealed varying efficiency levels across these periods.

Banks faced significant operational and financial challenges during the pandemic, reflected in lower efficiency scores. For instance, only four banks achieved full efficiency (E = 1.00), while 30.44% operated with efficiency scores below 0.60. However, there was a gradual recovery in the post-COVID period, with a decrease in the number of banks scoring below 0.60 and an increase in those approaching the higher efficiency range. These findings suggest that banks adjusted their operations and resource management strategies to cope with the challenging economic environment, ultimately enhancing their efficiency in the post-pandemic phase.

The significant decrease in Meta Frontier Technical Efficiency (TE) from 0.63 to 0.51 observed for banks during the periods of Covid emphasizes the impact of the pandemic disruption for banks forced to adjust their input and output to mitigate disruptions during the period, resulting in higher input and lower output. However, the rebound to 0.63 after COVID indicates that banks returned to general efficiency as the external environment settled down, and this was the culmination of factors such as improved adaptation strategies concerning more excellent digital banking and overall economic normalization, including right-sizing initiatives.

TGR analysis showed that the decline from TGR 0.95 to 0.88 indicated that the banks did not have adequate access to the best technology during the pandemic. Nevertheless, the after-COVID performance (TGR = 0.95) indicates that these banks adapted by fast-tracking their technology investments or breaking down pre-existing barriers to technology adoption.

Policy makers can use this result to tighten capital requirements and liquidity buffers further to increase financial stability, since they probably want to ensure that banks are ready for the next crisis. Finally, the study can inform the need to promote digital transformation of the banking sector to enable banks to support small and medium enterprises (SMEs) across a fluctuating economic climate. Additionally, central banks may have a more significant role in economic stimulus packages that encourage loans and economic recovery. Finally, it highlights the need for transparency and equitable banking practices to rebuild public confidence and enhance financial inclusion.

Though the research found a significant difference in bank efficiency during and after COVID-19, a more evident scenario could be found if globally operated banks are considered. Besides, considering more inputs and outputs could give more accurate results for measuring banking performance.

**8.** **Limitations and Direction of Future Research**

This study's findings are limited by its use of secondary data and focus on specific banks, which may restrict the generalizability of the results. Such a short-to-medium-term timeframe restricts findings about the long-term implications of the pandemic for banking efficiency. Future engagement can involve longitudinal studies, cross-country comparisons, or qualitative research to obtain a better understanding. Furthermore, this work would be enriched by examining the role of digital transformation and technological adoption to improve post-pandemic efficiency.

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1. This method is commonly utilized in performance benchmarking studies; therefore, we have excluded the model's technical details to maintain the manuscript's brevity. A comprehensive explanation can be found in ( (Roy, 2016; Řepková, 2014) [↑](#footnote-ref-2)