“A cross-country investigation on core capital efficiency of private commercial banks: Evidence from Bangladesh and Nepal”

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A CROSS-COUNTRY INVESTIGATION ON CORE CAPITAL EFFICIENCY OF PRIVATE COMMERCIAL BANKS: EVIDENCE FROM BANGLADESH AND NEPAL

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Abstract

Core capital efficiency plays a central role in safeguarding banking sector resilience in emerging economies characterized by high credit risk, regulatory constraints, and limited access to external capital. This paper aims to examine the bank-specific, macroeconomic, and institutional determinants of core capital efficiency in the banking sector of emerging economies, using a comparative analysis between Bangladesh and Nepal as representative markets. Considering a balanced panel dataset of 200 observations from 10 banks in each country, spanning from 2014 to 2023, this investigation adopts pooled OLS, fixed effects, random effects, and GLS estimators with Tier 1 capital ratio as a proxy for core capital efficiency. Empirical results show that bank size and profitability exert a strong and positive influence on core capital efficiency, while non-performing loan ratios and cost-to-income ratios significantly erode capital efficiency across models. In contrast, GDP growth and fintech adoption show no significant impact, reflecting the dominance of bank-specific factors over macroeconomic or technological influences. Overall, Bangladeshi banks demonstrate higher core capital efficiency despite elevated credit risk, reflecting stronger asset bases and regulatory adjustments. The findings highlight the need for targeted reforms focusing on asset quality and cost efficiency to enhance banking sector resilience in emerging markets.

Keywords core capital efficiency, Tier 1 capital ratio, emerging economies, banking sector resilience, ROA, CIR

JEL Classification G21, G28, C33

INTRODUCTION

Capital acts as a representative of financial resources for a banking institution available to cover unanticipated losses and is basically categorized into Tiers. International capital standards such as the Basel Accords have always focused on Tier 1 capital most due to its higher contribution to banks' unpredictable losses. So, all commercial banks in every single country are required to keep the highest level of this capital in comparison to Additional Tier 1 and Tier 2 capital. These two capitals are not as significant as core capital because of their lower quality. In other words, proper core capital maintenance is a crucial determinant of strong financial health, stability, and capacity for every banking organization to support economic growth through lending and investment activities. In fact, banks are now more encouraged to reach the established core capital bar according to international capital requirements to gain the trust and reliability of both customers and investors.

Developing economies are often burdened with inefficient capital markets, failed access to diversified financing sources, political instability, and economic volatility. These factors can hinder banks' ability to put

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their core capital to efficient use and push them to increased default risks, poor asset allocation, and cyclical pressures on profitability. In many emerging markets, banks rely heavily on traditional interest-based income in an attempt to reduce their exposure to non-performing loans and adverse economic shocks. Consequently, inefficiencies in core capital allocation can undermine broader economic growth by constraining the availability of credit for businesses and consumers.

This problem is especially relevant in South Asia, where banking systems operate under broadly comparable Basel-aligned regulatory frameworks but differ substantially in institutional quality, asset base structure, and risk exposure. In such environments, core capital efficiency rather than capital adequacy alone becomes a key determinant of long-term financial stability. However, empirical evidence on how bank-specific, macroeconomic, and institutional factors jointly shape core capital efficiency in comparable emerging economies remains limited. In particular, systematic cross-country evidence focusing on private commercial banks in Bangladesh and Nepal is scarce, despite both countries sharing structural similarities with bank-dominated financial systems, Basel-aligned regulatory frameworks and similar exposure to macroeconomic volatility while exhibiting distinct regulatory enforcement, profitability patterns, asset quality and credit risk dynamics. Addressing this gap is essential for understanding how banks in emerging markets can strengthen capital resilience beyond mere regulatory compliance. In fact, the findings contribute not only to the academic literature on capital adequacy and financial resilience but also offer practical insights for regulators and policymakers seeking to strengthen banking sector stability and optimize capital management strategies in volatile environments.

1. LITERATURE REVIEW

Core capital has been a center of attention for regulators and researchers because it is considered a key factor in a bank's profitability. Its efficiency is determined based on how a bank utilizes Tier 1 capital to generate satisfactory output while meeting regulatory requirements. In emerging economies, understanding this concept is important as banks operate under dynamic yet volatile economic conditions, varying regulatory frameworks, and diverse technological adoption levels. This leads to country-level differences in core capital utilization, resulting in varying influences of bank-specific, macroeconomic, and institutional factors on core capital efficiency. Research on bank capitalization generally agrees that Tier 1 capital improves resilience, but the evidence is less settled on how bank-level characteristics and institutional quality shape the efficiency of core capital in practice.

To determine core capital efficiency, various factors, including profitability, growth, asset size, competition, risk, and other indices, have been used as determinants (Altunbas et al., 2017). These determinants have been exclusively used by developing economies, with some focusing on macroeconomic factors (Octavia & Brown, 2009) and others considering environmental variables such as Eurozone stock market volatility index and governance indicators (Amjad et al., 2013; Romdhane, 2010; Bokhari et al., 2012; Mathuva, 2009; Asarkaya & Ozcan, 2007). So, prior studies can be grouped into three streams: bank-specific determinants, macroeconomic conditions and institutional/regulatory quality.

According to Saunders and Cornett (2020), core capital's role is to absorb losses incurred from unpredictable shocks and maintain the confidence of depositors and regulators as well. Hence, core capital is regarded as the backbone of a bank's capital structure, which determines risk-taking capability and lending activities (Mishkin & Eakins, 2018). So, every banking institution has to act cautiously while dealing with core capital.

Bank size, usually measured by the log of total assets, is strongly linked to capital efficiency because bigger banks can spread fixed costs over more assets. A positive relationship is found between bank size and capital efficiency in US banks, suggesting that large banks better manage capital (Berger et al., 1995). Core capital greatly boosts efficiency by coordinating managers' motivation with optimal asset allocation, leading to higher ROA (Almazan et al., 2005). Besides, there has been a situation captured by a cross-country study that bigger banks had higher core capital efficiency, while in others they took more risks and kept lower Tier 1 ratios (Demirgüç-Kunt & Huizinga, 1999). Bank size also positively contributes to influencing capital ratios at a certain level due to economies of scale and market power, but when bank size exceeds the boundary, it becomes riskiest (Athanasoglou et al., 2008). Larger banks may also face challenges in maintaining high profitability, as evidenced by the negative relationship between bank size and return on assets (ROA) in some studies (Amidu, 2007). They tend to have more complex operations, which may lead to inefficiencies and reduced profitability (Gatzert & Wesker, 2012).

Return on assets (ROA), known as a profitability indicator, gives an idea of how much profit is generated from invested capital by using the institution's assets. It is one of the most critical factors that shows how effectively capital is promoting financial gain (Athanasoglou et al., 2008). Banks with consistently higher return on Assets (ROA) achieved better core capital efficiency, measured by their ability to maintain Tier 1 capital above the Basel III minimum requirements. A similar positive relationship between ROA and core capital efficiency has been observed in 18 Nepali commercial banks managed during the year range between 2015 and 2019. Those banks with higher ROA ratios not only achieved stronger Tier 1 capital positions but also displayed lower levels of non-performing loans, indicating more prudent asset utilization.

Troubled loans are negatively associated with both profitability and capital performance. Hence, an increase in NPL ratios negatively affects the banks' core capital efficiency. It indicates the deteriorating asset quality, which undermines the efficiency of core capital. Essentially, higher NPL ratios mean banks have less money available to support their operations and absorb future risks. As banks face greater credit risk from bad loans, their costs rise, and their ability to generate internal capital decreases. This limits the banks' capacity to maintain strong capital buffers and undermines their financial stability, making it harder for them to lend and grow.

To analyze capital efficiency and productivity, the cost-to-income ratio is used as another significant metric. Though potential shortcomings of this ratio had been identified, it is still prioritized most in regression analysis (Welch, 2012). It is found that high CIR negatively affects capital ratios, as inefficient banks struggle to accumulate core capital (Athanasoglou et al., 2008). Banks with high CIRs had weaker core capital ratios, especially during crisis periods (Trabelsi & Trad, 2017). It also reflects management's poor capability to convert profit into operating profit, eroding the funds available to strengthen core capital (Gadzo et al., 2019). It is also stated by an author that CIR is one of the strongest predictors of capital adequacy, with each 1% increase in CIR associated with ~0.03 percentage point decrease in Tier 1 ratio (Dietrich & Wanzenried, 2011).

A common macroeconomic stability determinant is known as gross domestic product, or GDP, which is responsible for influencing bank performance through altering the core capital position. Banks' profitability as a driver of retained earnings and core capital, which depends strongly on GDP growth, combining business cycle phases with banks' capital accumulation (Albertazzi & Gambacorta, 2009). Even European banks showed that GDP growth indeed has a positive and significant impact on bank profitability, which in turn strengthens capital adequacy and efficiency (Athanasoglou et al., 2008).

As part of the governance indicator, the World Bank's Regulatory Quality Index measures how well governments create and enforce good policies and rules that help the private sector grow. Strong regulatory quality helps banks work efficiently by providing a stable and clear environment for managing capital (Kaufmann et al., 2010). In emerging economies, good regulations support banks in managing their capital and risks effectively, which is important for keeping core capital efficient (Barth et al., 2004). High regulatory quality also lowers uncertainty and builds investor trust, helping banks use their capital better and increase profits (Demirgüç-Kunt & Huizinga, 2000). This is proved to be true from a study which demonstrated that better regulatory quality reduces incentives for excessive risk-taking, leading banks to improve their Tier 1 ratios relative to risk-weighted assets (Čihák & Schaeck, 2010). Numerically, an estimation was made that a 1-point increase in regulatory quality (on a –2.5 to +2.5 scale) is asso-

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ciated with a 0.5-1.0 percentage point increase in banks' Tier 1 capital ratios across emerging markets (Beck et al., 2013).

In a large panel of international banks, country dummies were significant predictors of Tier 1 ratios, reflecting differences in national regulatory environments and macroeconomic conditions. Country dummy variables are commonly used in research on core capital efficiency to account for variations in economic, regulatory, and institutional settings across nations (Claessens & Laeven, 2004). These variables allow researchers to isolate the impact of country-specific factors on how banks manage and utilize their core capital. When comparing Bangladesh with regional indicators, country dummies were significant, confirming country effects on Tier 1 ratios even among developing nations (Islam & Nishiyama, 2016). While direct cross-country studies on Nepal are rare, Nepal Rastra Bank reports show how unique regulatory timelines affect capital ratios differently than in neighboring countries like Bangladesh or India.

Fintech has grown quickly and changed how banks work, especially in emerging countries where banking systems are not very developed. Researchers often use a fintech dummy variable to show whether a bank uses fintech or not (Chen et al., 2020; Vives, 2019). In these countries, fintech helps banks to deal with problems like fewer branches and high costs, leading to better use of capital and higher profits. Fintech-adopting banks often see long-term improvement in profitability and efficiency, which supports higher core capital (Thakor, 2020). It is found that digital banks and fintech-heavy traditional banks tend to maintain higher capital ratios to compensate for new operational and cyber risks (Vives, 2019). Banks integrating fintech show mixed short-term effects on capital, but consistent long-term benefits for capital buffers through efficiency gains (KPMG & McKinsey reports). In Asian markets, fintech adoption correlated with stronger earnings stability, indirectly improving core capital (Lee & Shin, 2018). By looking at the digital banking dummy and cost-to-income ratio, a conclusion was derived that Fintech adoption had a stronger effect in urban-focused banks. But Fintech usage dummies were deployed in regression for branchless banking effects in Nepal to find the impacts being heterogeneous across rural vs. urban banks (Nepal Rastra Bank Reports 2022).

In emerging economies like Bangladesh and Nepal, commercial banks face common problems like weak financial systems, changing rules, and unstable economies that affect how well they use their capital. Bangladeshi banks are getting better by using improved risk management and following international rules, but higher NPLs and political issues still hindering its development. On the other hand, Nepal's banks are also improving but struggle because of less developed markets and limited technology. Both countries are now slowly trying to improve regarding how banks use capital, but differences in economy, rules, and technology produces deviated results.

Overall, existing studies suggest that profitability, scale, asset quality, and operating efficiency are repeatedly linked to stronger capital positions, while evidence on macroeconomic growth and technology adoption is mixed. Cross-country evidence for South Asian private commercial banks remains scarce, and the interaction between institutional quality and bank fundamentals is not sufficiently tested in emerging economies such as Bangladesh and Nepal. These gaps motivate the present study.

2. AIMS OR PURPOSE

This study examines whether private commercial banks in Bangladesh exhibit higher core capital efficiency than those in Nepal and identifies the bank-specific, macroeconomic, and institutional determinants of Tier 1 capital efficiency.

Hypotheses

H1: There is a potential positive influence of bank size on core capital efficiency.

H2: There is a significant positive impact of ROA on core capital efficiency.

H3: Non-performing loan ratio (NPLR) is negatively associated with core capital efficiency.

H4: Cost-to-income ratio (CIR) is negatively as-

sociated with core capital efficiency.

H5: GDP growth is positively associated with core capital efficiency.

H6: Regulatory quality (WGI) is positively associated with core capital efficiency.

H7 Core capital efficiency differs significantly between Bangladesh and Nepal (country effect).

H8: Fintech adoption is associated with core capital efficiency.

3. DATA AND METHODS

This explanatory study is prepared to identify the elements affecting the capital efficiency of private commercial banks in Bangladesh and Nepal. The study also compared the relative banks' performance between these two countries based on the core capital position of those selected banks. The study is quantitative in nature since it is conducted by deploying a combination of panel and secondary data. About 10 private banks are taken from each country for a 10-year range (2014–2023) that consists of 200 observations[1]. Bank-specific factors such as bank size (log of assets), non-performing loan ratio (NPLR), and return on assets (ROA) are collected from respective banks' annual reports. Control variables, including cost-to-income ratio (CIR) and regulatory quality World Bank index (WGI), are also collected from annual reports and the World Bank website simultaneously. Besides, macroeconomic indicators, such as gross domestic product (GDP) data, are also obtained from the World Bank website, and two other qualitative variables, such as country (Country D_i) and fintech[2] (Fintech D_i) dummies, are assigned based on country-level differences and fintech adoption by their respective banks across the years. Apart from this, many available websites like Bangladesh Bank, ICRA Nepal, Nepal Rastra Bank, Stock Exchange, SEA Open Research, World Journal of Advanced Research and Reviews are also used to support this research's viability. However, the summary of the variables in this study is represented in Table 1.

Now, the baseline specification of the model is constructed as follows:

$$\begin{aligned} CCE_{it} &= \alpha + \beta_1\, LOGA_{it} + \beta_2\, ROA_{it} \\ &+ \beta_3\, NPLR_{it} + \beta_4\, CIR_{it} + \beta_5\, GDP_t \\ &+ \beta_6\, WGI_t + \beta_7 CDI_{it} + \beta_8\, FDI_{it} + \mu_{it}, \end{aligned} \tag{1}$$

where CCE = Core Capital Efficiency for banks; α = Constant of the model; β = Coefficient of the explanatory variable; and μ = Error term of the model.

In brief, the following empirical models have been developed to evaluate the potential effect of these factors determining the efficiency of core capital as follows:

$$CCE_{it} = \alpha_{it} + \sum_{k=1}^{8} \beta_{it} X_{itk} + \mu_{it}, \tag{2}$$

$$CCE_{it} = \alpha_{it} + \sum_{k=1}^{8} \beta_{it} X_{itk} + \varepsilon_{it} + \mu_{it}, \tag{3}$$

where independent variables are separately presented in detail in Table 1, whereas the dependent variable of the study is core capital efficiency (CCE). To estimate core capital efficiency, the Tier 1 capital ratio is used as the dependent variable, which is the amount of total Tier 1 capital to total risk-weighted assets.

Furthermore, we have estimated the coefficients of equations (1) and (2) through the use of the fixed effects approach. It underlines the relationship between CCE and the bank-related factors used in the regression model. This method essentially controls for unobserved heterogeneity within banks that could otherwise bias the outputs. It further recognizes the distinctive and specific aspects that may influence explanatory variables as well. So, it is necessary to capture the impact of those excluded variables in the model, which is added to the error term separately. Moreover, the pooled ordi-

1 The sample consists of 10 private commercial banks from each country selected based on continuous data availability, regulatory relevance and market representativeness. Together, these banks account for a substantial share of total private-sector banking assets in their respective countries, ensuring that the panel captures systemic rather than idiosyncratic behavior. The balanced structure (10 banks × 10 years × 2 countries) enhances comparability, econometric stability, and cross-country inference.

2 We will count 1 for period in which banks adopted Fintech and 0 for period in which Fintech was not adopted.

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Table 1. Description of variables

Source: Authors' estimations.

Variables	Notations	Measurement methods	Expected impact	Sources of Data
Dependent Variable				
Core Capital Efficiency	CCE	Tier-1 Capital / Total Risk- Weighted Assets	N/A	Annual Report
Independent Variables				
Bank Size	LOGA	Log of Total Assets	Positive	Annual Report
Return on Assets	ROA	Net Income / Average Total Assets	Positive	Annual Report
Non-Performing Loan Ratio	NPLR	Non-Performing Loans / Total loans	Negative	Annual Report
Gross Domestic Product	GDP	Annual GDP growth rate	Positive	World Bank Data
World Bank's Regulatory Index	WGI	Annual Index	Positive	World Bank Data
Cost to Income Ratio	CIR	Operating Expense/ Operating Income	Negative	Annual Report
Country Dummy	CDi	1 for Bangladesh and 0 for Nepal	Positive or Negative	–
Fintech Dummy	FDi	1 for adoption of Fintech and 0 for none	Positive or Negative	–

nary least squares method (OLS) and generalized least squares method (GLS) were also deployed for the same equation, not only for coefficient estimation but also to differentiate model outcomes. In parallel, we have adopted the random effect method (RE) for equation (3) to identify the effect that CCE exudes in terms of other independent variables while assuming unobserved heterogeneity is random and uncorrelated across banks.

4. EMPIRICAL RESULTS

Descriptive statistics are used to calculate the statistical behavior of variables used in the constructed model, which is shown in Table 2.

According to Table 2, which contains descriptive statistics in the earlier section, CCE ranges between 4.67 and 16.80, having a mean value of 10.00 and a standard deviation of 1.8394. This indicates that there are some variations in the use of core capital by banks, but they are not too extreme. In fact, banks are performing consistently, though there is room for further improvement. From the table, we can also see greater variability in the standard deviation of the independent variables. While LOGA (0.65574), ROA (0.58320), CDi (0.49874), and FDi (0.27197) showed lower standard deviation along with a small gap between minimum and maximum values, the other independent variables, namely NPLR, GDP, WGI, and CIR, have the highest standard deviation with a large gap in value range. Here, NPLR has extreme values with a minimum value of 0.0200 and a maximum value of 33.070, whereas the mean is 3.714 and the standard deviation is 4.2128. The result reflects significant variation in the asset quality among the selected banks. Here, the minimum value suggests that some banks managed their

Table 2. Descriptive statistics

Source: Authors' estimations based on STATA output.

Variable	Mean	Median	Standard Deviation	Minimum	Maximum
LOGA	5.2847	5.4097	0.65574	3.3811	6.5885
ROA	1.1834	1.2000	0.58320	0.010000	2.7900
NPLR	3.7148	3.0400	4.2128	0.020000	33.070
GDP	5.4255	6.3050	2.6918	–2.3700	8.9800
WGI	22.532	22.010	7.1027	15.240	70.240
CIR	46.740	44.905	11.345	20.480	92.670
CD_i	0.45000	0.00000	0.49874	0.00000	1.0000
FD_i	0.92000	1.0000	0.27197	0.00000	1.0000
CCE	10.003	10.045	1.8394	4.6700	16.800

loan portfolios effectively with very low levels of non-performing loans, while the maximum value reveals the others' exposure to severe credit risk issues and weak profitability. Such a high NPL burden directly impacts core capital efficiency when banks with high NPLRs are required to allocate larger provisions from their earnings, reducing the amount of retained profit that could otherwise strengthen core capital. Then, the GDP value range is between –2.370 and 8.980, having a mean score of 5.425 and a standard deviation of 2.6918, referring to the observed banks operated under varying macroeconomic conditions, from periods of contractionary growth to strong economic expansion. The maximum value represents periods when the economy is in full bloom, and banks have generally experienced better loan performance, higher income generation, and improved capital accumulation, which contributed to more efficient use of core capital. The presence of a negative minimum value reflects that some banks operated during economic downturn, which typically coincides with lower credit demand, higher default rates, and reduced profitability in the banking sector, which ultimately eroded the core capital position of banks. Again, the WGI value range stems from 15.240 to 70.240 with a mean value of 22.532 and a standard deviation of 7.1027, reflecting significant dissimilarities in governance quality across countries. Maximum value represents a country with higher WGI scores and is expected to have more effective regulatory enforcement, lower levels of political and operational risk, and a higher degree of transparency. Also, the minimum value exhibits the opposite scenario. Finally, the last independent variable is CIR, with a minimum of 20.480 and a maximum of 92.670, along with a mean score of 46.470 and a standard deviation of 11.345. This allows us to assess the operating efficiency within the banking sector of the observed countries. This also highlights potential fluctuations across banks as a result of cost management struggles and a weak position in core capital build-up. In general, this study found a significant gap in ranges based on the mean values and standard deviation variability of all variables.

Table 3. Estimated coefficients from each model

Source: Authors' estimations based on STATA output.

Dependent Variable: CCE (Core Capital Efficiency)	Ordinary Least Squares (OLS)	Fixed Effect (FE)	Random Effect (RE)	Generalized Least Squares (GLS)
Independent Variables				
LOGA	0.872819***	0.719484***	0.858154***	0.872819***
	(0.248118)	(0.270762)	(0.250462)	(0.226116)
ROA	1.38334***	0.740101**	1.11519***	1.38334***
	(0.237701)	(0.314358)	(0.264419)	(0.284175)
NPLR	−0.0950169***	−0.0151850	−0.6002673*	−0.0950169***
	(0.0325500)	(0.0377096)	(0.0344968)	(0.0261551)
GDP	−0.0336682	−0.00544158	−0.0198112	−0.0336682
	(0.0431781)	(0.0392058)	(0.0400766)	(0.0519371)
WGI	0.00699056	0.0353899	0.0191926	0.00699056
	(0.0186874)	(0.0263677)	(0.0215119)	(0.0192682)
CIR	−0.0458591***	−0.0390695***	−0.0411001***	−0.0458591***
	(0.0107898)	(0.0129065)	(0.0114328)	(0.0100661)
CD_i	−0.0557602		−0.282557	−0.0557602
	(0.350335)		(0.446262)	(0.344130)
FD_i	0.356392	0.365572	0.154450	0.356392
	(0.437217)	(0.453822)	(0.436736)	(0.327115)
Constant	5.97191***	6.40571***	5.95287***	5.97191***
	(1.34153)	(1.68876)	(1.44033)	(1.14612)
Observations	200	200	200	200
Chi_square			17.950	22.077
F	13.37254	8.295627		
R^2	0.359018	0.554911		
Rho	0.595689	0.516470	0.516470	

Note: *, **, and *** indicate the significance at 10%, 5%, and 1% levels, respectively.

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Table 3 shows the coefficient output of the factors of core capital efficiency (CCE), which is represented by the Tier 1 capital ratio.

Now, in Table 3, we deployed four econometric methods, like Ordinary Least Squares (OLS), Fixed Effects (FE), Random Effects (RE), and Generalized Least Squares (GLS), for robust estimation. Here, the predicted variable is CCE, and the rest of the variables are known as explanatory, including LOGA, ROA, NPLR, GDP, WGI, CIR, $CD_{i,}$ and FD_i.

The Bank Size (LOGA) variable has an extremely large and positive relationship with CCE in all the specifications. Under OLS methodology, every additional unit of the log of total assets increases CCE by 0.873 (at p-value < .01); similarly, under FE methodology by 0.719 (at p-value < .01), RE methodology by 0.858 (at p-value < .01) and GLS methodology by 0.873 (at p-value < .01). These results imply that the larger banks are significantly better at retaining capital relative to their risk weighted assets; this may be due to the economies of scale they enjoy or because of the way they manage their capital.

Return on Assets (ROA) has a positive and statistically significant relationship with CCE. The OLS estimate (1.383, p-value < .01) implies that there is a substantial improvement in capital efficiency when a bank's profitability is high. While the magnitude of the ROA coefficient decreases when we move from the OLS methodology to the FE methodology (from 1.383 to 0.740 at p-value = .05), it still shows that higher profitability strengthens capital buffers, mostly via retained earnings.

The Non-Performing Loan Ratio (NPLR) has a negative coefficient in all specifications, and its statistical significance varies depending on the specification used. In particular, it is statistically significant in OLS (–0.095 at p-value < .01), RE (–0.600 at p-value = .10), and GLS (–0.095 at p-value < .01). This indicates that poor quality of loans negatively affects a bank's capital efficiency. In contrast, the coefficient of NPLR becomes statistically insignificant under the FE methodology (–0.015). Therefore, the evidence suggests that the negative impact of NPLs on capital efficiency is largely caused by time-invariant bank-specific factors rather than the bank's recent performance.

Cost-to-Income Ratio (CIR) has a negative and highly statistically significant effect on CCE in all the specifications. For example, the OLS estimate (–0.046 at p-value < .01) implies that higher operating inefficiency leads to a material decline in the bank's ability to maintain its capital buffers.

On the other hand, both GDP Growth and WGI have very small coefficients, which are statistically insignificant in all the specifications. Thus, these two variables seem to have little direct impact on CCE. Similarly, the Country Dummy and the FinTech Adoption Dummy are also statistically insignificant, implying no systematic difference after accounting for bank-level factors.

Lastly, the constant values are significant in OLS, RE, FE, and GLS models at a 1% significance level. It means that when all independent variables are set to 0, CCE is positive. It also refers to the significant influence that other unobserved variables have outside of the included variables on CCE, which keeps the Tier 1 ratio above 0. A statistically significant constant also reveals that CCE influence is not a result of a random variation; rather, it exists in the dataset.

Therefore, the overall diagnostic tests suggest that the results are valid. Both the OLS F-statistic (13.37) and the FE F-statistic (8.30) are statistically significant, and the RE and GLS Chi-Square statistics (17.95 and 22.08, respectively) provide evidence that the jointly bank-specific variables are statistically significant. Finally, the relatively large R^2 value (0.555) obtained under the FE methodology supports that unobserved bank-specific effects play a significant role.

4.1. Model specification tests

The following specification tests are conducted to choose among Random Effect, Fixed Effect, and Pooled OLS estimations as depicted below.

4.1.1. Random effect (RE) versus fixed effect (FE)

Table 4. Output of the Hausman test

Source: Authors' estimations based on STATA output.

Hausman Chi² test (CCE)	
Chi-square	24.933
P-value	0.0007

From the Hausman test shown in Table 4 in the earlier section, we can generate an idea regarding the selection between the random effect model or fixed effect model and which one provides accurate results for coefficients. Ultimately, we derived a decision that we reject the null hypothesis as the p-value generated is 0.0007, which is less than 0.05. So, the fixed effect method is appropriate to choose over the random effect method for the panel dataset.

4.1.2. *Random effect (RE) versus pooled OLS method*

Table 5. Output of BP/LM test

Source: Authors' estimations based on STATA output

Lagrangian multiplier test (CCE)	
Chi-square	21.977
P-value	0.0000

In Table 5 of the earlier section, to choose between the random-effect method and the pooled OLS method, we conducted the Breusch and Pagan Lagrangian multiplier (BP/LM) test. From the results, we found that the p-value is 0, which strongly rejects the null hypothesis. In this case, the random-effect method is preferred over pooled OLS as the test focuses on individual effects. So, data cannot be pooled together, and instead, a random-effects method should be deployed, considering the insignificant unobserved individual effects.

4.2. Diagnostic test

The following diagnostic checks are also executed to validate model estimations.

4.2.1. *Test of heteroscedasticity*

Table 6. Groupwise Wald test for heteroskedasticity

Source: Authors' estimations based on STATA output.

Heteroskedasticity test (CCE)	
Chi-square	729.87
P-value	0.0000

From Table 6, we can see the heteroskedasticity results by conducting a groupwise Wald test, where the p-value is 0. The model suffers from the heteroskedasticity problem based on the large chi-square value, which reflects that error variances are not constant, as they vary systematically. Eventually, we conclude our decision by rejecting the null hypothesis.

4.2.2. *Test of multicollinearity*

Table 7. Multicollinearity test

Source: Authors' estimations based on STATA output.

Variables	VIF	1/VIF
LOGA	2.33	0.429000
ROA	1.69	0.591016
NPLR	1.66	0.603864
GDP	1.19	0.840336
WGI	1.55	0.644329
CIR	1.32	0.757575
CD_i	2.69	0.371885
FD_i	1.25	0.803212
Mean VIF	1.71	

Table 7 measures the degree to which the variance of all estimated coefficients is inflated due to multicollinearity. Here, all VIF values, including the mean value of coefficients, are lower than 5, which implies that there is no multicollinearity issue in the existing dataset. Even the inverse VIF values of independent variables are lower than 1, which is another indicator of the absence of red flags here, and eventually, we will accept the null hypothesis.

4.2.3. *Test of autocorrelation*

Table 8. Wooldridge test for autocorrelation

Source: Authors' estimations based on STATA output.

Autocorrelation test (CCE)	
F (1, 19)	27.269
P-value	0.0000

Since the p-value in Table 8, showing the autocorrelation test, is 0, it means there is an autocorrelation in the residuals of the panel data model based on the results of the Wooldridge test. In other words, regression results may be inefficient, which violates the OLS assumption of error independence, and hence, we cannot accept the null hypothesis.

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4.2.4. Test of omitted variable bias

Table 9. Ramsey RESET test

Source: Authors' estimations based on STATA output.

Omitted Variable bias test (CCE)	
F (2, 189)	2.87
P-value	0.0594

Table 9 represents the renowned RESET test conducted to detect potential misspecification in the regression model as a result of omitted variables. Since the p-value (0.0594) is greater than 5, we are convinced that the model is correctly specified without any significant omitted variables, and we have to accept the null hypothesis.

4.2.5. Pairwise correlation

Table 10 in the earlier section includes the Pearson's correlation matrix test, and its purpose is to understand the pairwise relationship between CCE and the other independent variables, including LOGA, ROA, NPLR, GDP, WGI, CIR, CDi, and FDi. From the table, we can get a glimpse of a weak negative relationship between CCE and LOGA. On the other hand, both ROA and WGI had a moderate and weak positive relationship with CCE subsequently. However, NPLR, GDP, CIR, and CDi establish an inverse relationship with CCE. Although FDi shows a negative sign, the value is almost zero, which has no meaningful relationship with CCE.

Table 10. Pearson's correlation matrix test

Source: Authors' estimations based on STATA output.

Particulars	CCE	LOGA	ROA	NPLR	GDP	WGI	CIR	CD_i	FD_i
CCE	1.0000								
LOGA	–0.1325	1.0000	–0.5410	0.3801	0.1172	–0.2309	0.4379	0.5927	0.4010
ROA	0.4734		1.0000	–0.4885	–0.0178	0.1808	–0.3332	–0.4409	–0.1864
NPLR	–0.4026			1.0000	0.2126	–0.3634	0.2380	0.5469	0.1294
GDP	–0.0868				1.0000	–0.2419	0.0298	0.3546	0.0064
WGI	0.1263					1.0000	0.0322	–0.5602	0.0274
CIR	–0.3339						1.0000	0.2138	0.2742
CD_i	–0.2299							1.0000	0.1185
FD_i	–0.0114								1.0000

5. DISCUSSION

From the results in the earlier section, bank size (LOGA) remained positive and highly significant across all models at a 1% significance level with robustness, which means larger banks tend to have rigorous core capital efficiency. This concept is related to economies of scale that aligns with the findings from Berger et al. (1987) and Goddard et al. (2004), where banks with a large asset base are successful in spreading their fixed costs effectively and also minimize cost by absorbing large financial shocks. For this reason, the magnitude of the LOGA effect is extremely strong in determining the capital utilization efficiency.

A profitability indicator named return on assets (ROA) reveals a highly significant and positive relationship with CCE in OLS, RE, and GLS models at the 1% level, but at the 5% level in the FE model. In other words, it is pointing to the fact that banks with higher ROA are better skilled to sustain strong capital buffers in the long run due to greater financial direction and stronger operational performance, which is also supported by the studies by Athanasoglou et al. (2008) and Dietrich and Wanzenried (2011). With higher profitability, they can accumulate more earnings that directly contribute to Tier 1 capital. Eventually, the result confirms the theoretical expectation that profitability facilitates smoother capital accumulation. Furthermore, it highlights the operational strength of such banks in sustaining internal capital generation without relying heavily on external sources that may pose a threat to banks' viability.

In the case of NPLR, the coefficient values are negative and highly significant in OLS, RE, and GLS models at the 1% or 10% level, except in the FE model, which exhibits an insignificant coefficient. This output indicates that higher NPL ratios are responsible for eroding core capital, leading to lower CCE. Besides, the inverse relationship suggests that higher NPLR can also succumb to increased loan loss provisioning, which significantly reduces the retained earnings of the banks, as supported by evidence from Berger and DeYoung (1997). Since retained earnings are tied to Tier-1 capital, it significantly lowers the CCE as well. Moreover, the insignificant estimate in the fixed effects model may be due to bank differences, which may reflect the uneven NPL impact across all sampled banks.

GDP coefficients got negative signs which represents the insignificance across all models So, it assumes no statistical relationship between macroeconomic growth and CCE of the banks implying that macroeconomic growth does not have standalone influence on CCE in this dataset which is also found from the empirical evidence from Claessens and Laven (2004) The reason here may be caused by dominance of bank-specific factors in determination of capital position over macroeconomic situation in those sampled periods.

WGI exhibits a statistically insignificant impact at the 1% level in both OLS and GLS models. This also shows a positive influence at the 5% level in the RE model. The results imply the importance of a sound regulatory environment in the banking sector. Hence, we can conclude that stronger governance quality and a regulatory framework contribute simultaneously to enhance core capital efficiency. This finding is also supported by consistent evidence from Barth et al. (2004), Kaufmann et al. (2010), and Čihák and Schaeck (2010). The positive WGI impact basically aligns with the expectations with regard to the rigorous support by quality regulation in financial stability support and capital usage efficiency.

CIR appears to have negative and statistically significant coefficients across every model, which complies with theoretical expectations that higher cost inefficiency leads to core capital erosion, also espoused by Dietrich and Wanzenried (2011) and Kosmidou (2008). This inverse relationship assumes that banks with higher CIRs are less capable of turning income into retained earnings as a result of meeting high operating expenses. This inefficiency ultimately reduces profitability, liquidity, and core capital position.

The country dummy (CDi) variable is used to differentiate Bangladeshi banks from Nepali ones, where we assigned a binary variable for each country's banks (1 = Bangladesh, 0 = Nepal). However, this variable reveals no statistically significant result, as we deployed this variable as a control variable to reduce the multicollinearity problem in the model. So, country-level differences do not actually have a major impact on core capital efficiency like the rest of the independent variables.

Similar to the country dummy, we used another control variable in the model named fintech dummy (FD_i), where 1 meant that the country's banks adopted fintech in a year and 0 meant that the country's banks did not adopt fintech in a year. Despite the positive coefficients, this still does not have a significant impact on the efficiency of using core capital. The results could indicate a lack of fintech presence within the sampled period, or maybe there could be early or late fintech adoption by both countries' banks.

Overall, the results indicate that Bangladeshi private commercial banks achieve higher core capital efficiency than their Nepali counterparts despite higher credit risk exposure. This reflects stronger scale advantages and capital management capacity, whereas Nepali banks face constraints stemming from weaker profitability and higher operating costs. These findings extend the existing literature by demonstrating how similar regulatory frameworks can yield divergent capital efficiency outcomes under differing institutional and structural conditions.

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CONCLUSION WITH POLICY IMPLICATIONS

The purpose of this study was to assess core capital efficiency in private commercial banks in Bangladesh and Nepal and to identify its key determinants. The results indicate that bank-specific fundamentals, particularly size, profitability, asset quality, and operating efficiency, play a dominant role in shaping Tier 1 capital efficiency, while macroeconomic growth and fintech adoption exert limited direct influence. Despite higher credit risk exposure, Bangladeshi banks demonstrate stronger capital efficiency, reflecting larger asset bases and more robust capital management practices.

These findings suggest that regulatory compliance alone is insufficient to ensure banking resilience in emerging economies. Policies aimed at improving asset quality, profitability, and cost efficiency are essential for strengthening core capital sustainability. However, if we compare the banks between the two countries, we can reach a final decision regarding their performance. Though Bangladeshi banks have higher NPL ratios than Nepali ones, they are still well-off in their operations with a vast asset base that alone is enough to compensate for future losses, which is absent in Nepali ones. So, it cannot be said that just maintaining core capital is enough to determine the efficiency of banks' performance. Looking back at Nepali banks, their CIRs are higher than those of Bangladeshi banks, which is a red signal for banks' operating efficiency. Higher CIRs can undermine banks' profitability and pose a threat to banks' viability. So, we can conclude that, while fulfilling regulatory capital requirements, the overall decision leans toward Bangladeshi banks being better off in managing their core capital efficiently, as they successfully maintained capital buffers while handling higher risk exposure such as high NPLs, reflecting a more resilient and scalable capital-raising strategy.

Future research may extend this analysis by incorporating a broader set of emerging economies, alternative efficiency measures, or dynamic capital adjustment models.

AUTHOR CONTRIBUTIONS

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APPENDIX A. Estimation of coefficients using OLS, Fixed Effect (FE), Random Effect, and GLS model

We consider the following baseline panel data model

$$y_{it} = \alpha + x_{it}^{'}\beta + c_i + \varepsilon_{it}, \quad (1A)$$

where, $i = 1, ..., N$; $t = 1, ..., T$; c_i is the time-invariant bank effect and ε_{it} is idiosyncratic noise.

Adjusting for our model, the following equation is constructed considering the baseline panel data model:

$$\begin{aligned} CCE_{it} &= \alpha + \beta_1 LOGA_{it} + \beta_2 ROA_{it} + \beta_3 NPLR_{it} + \beta_4 GDP_{it} \\ &+ \beta_5 WGI_{it} + \beta_6 CIR_{it} + \beta_7 CD_i + \beta_8 FD_{it} + c_i + \varepsilon_{it}. \end{aligned} \quad (2A)$$

The target is β(effects of LOGA, ROA, …). The intercept α is handled as noted below for each estimator.

Estimating β coefficients for Pooled OLS:

We will ignore c_i and run OLS on the stacked data as per equation number 04. We have the following estimation for solving β coefficients in OLS form:

$$\widehat{\beta_{POLS}} = \left(X'X\right)^{-1} X'y. \quad (3A)$$

Customizing to our model, it becomes converted into the following estimation:

$$\widehat{\beta_{POLS}} = \left(X'X\right)^{-1} X'CCE. \quad (4A)$$

Estimating β coefficients for Fixed Effect:

First, we are going to compute within-bank means to capture each bank's time average so that we can remove the bank-specific effect c_i as depicted below:

$$\overline{y_i} = \frac{1}{T}\sum_{t=1}^{T} y_{it}, \quad (5A)$$

$$\overline{x_i} = \frac{1}{T}\sum_{t=1}^{T} x_{it}, \quad (6A)$$

Then, for within transformation (de-meaning), the following approach will be adopted:

$$\widetilde{y_{it}} = y_{it} - \overline{y_i}, \quad (7A)$$

$$\widetilde{x_{it}} = x_{it} - \overline{x_i}. \quad (8A)$$

The unobserved effect c_i is constant over time, so that it cancels out after demeaning.

After that, we have customized this approach for our model, which has been converted into the following equation:

$$\widetilde{CCE_{it}} = CCE_{it} - \overline{CCE_i}, \quad (9A)$$

$$\widetilde{x_{it}} = x_{it} - \overline{x_i}. \quad (10A)$$

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Now executing the OLS on the demeaned data, the estimator is:

$$\widetilde{y_{it}} = \widetilde{x_{it}^{'}}\beta + \widetilde{\varepsilon_{it}}, \tag{11A}$$

$$\widehat{\beta_{FE}} = \left(X'MX\right)^{-1} X'My. \tag{12A}$$

Here, M is the "within projector".

Again, customized for our model, it has been converted into the following estimator:

$$\widehat{\beta_{FE}} = \left(X'MX\right)^{-1} X'MCCE, \tag{13A}$$

where:

$$M = I_{NT} - Q. \tag{14A}$$

As FE sweeps out α, this recovers it using the following method:

$$\widehat{\alpha_{FE}} = \overline{y} - \overline{x'\widehat{\beta_{FE}}}, \tag{15A}$$

where $\bar{y}$ and $\bar{x}$ are *grand* (all-observation) means.

As time-invariant regressors are collinear with dummies and drop out in FE, the LSDV equivalence is as follows:

$$y_{it} = \alpha + x_{it}^{'}\beta + \sum_{i=1}^{N-1}\delta_i D_i + \varepsilon_{it}, \tag{16A}$$

So, OLS with N–1N-1N–1 bank dummies gives the same $\widehat{\beta_{FE}}$.

Estimating β coefficients for Random Effect:

Here, the common bank effect c_i adds equal covariance among all times within the same bank using error decomposition and blockwise for the bank as depicted below:

$$u_{it} = c_i + \varepsilon_{it}, \tag{17A}$$

$$\Omega = Var\left(u\right) = \sigma_{\varepsilon}^{2} I_{NT} + \sigma_{c}^{2} ZZ'. \tag{18A}$$

So, the error co-variance for Block-wise for bank *i*:

$$\Omega_i = \sigma_{\varepsilon}^{2} I_T + \sigma_{c}^{2} 1_T 1_T^{'}. \tag{19A}$$

The GLS estimator is as follows:

$$\widehat{\beta_{RE}} = \left(X'\Omega^{-1}X\right)^{-1} X'\Omega^{-1}y. \tag{20A}$$

Customized for our model, this estimator has become:

$$\widehat{\beta_{RE}} = \left(X'\Omega^{-1}X\right)^{-1} X'\Omega^{-1}CCE. \tag{21A}$$

Allowing Quasi-demeaning transformation:

$$y_{it}^{*} = y_{it} - \theta \overline{y_i}, \tag{22A}$$

$$x_{it}^{*} = x_{it} - \theta \overline{x_i}. \tag{23A}$$

Again, customizing for our depicted model, the following equations are reconstructed:

$$CCE_{it}^{*} = CCE_{it} - \theta \overline{CCE_i}, \tag{24A}$$

$$x_{it}^{*} = x_{it} - \theta \overline{x_i}, \tag{25A}$$

where:

$$\theta = 1 - \sqrt{\frac{\sigma_{\varepsilon}^2}{\sigma_{\varepsilon}^2 + T\sigma_c^2}}. \tag{26A}$$

Now, running the OLS on the transformed data as depicted from the following equation:

$$y^{*} = \alpha(1-\theta) + X^{*}\beta + noise, \tag{27A}$$

where the OLS $\hat{\beta}$ equals the GLS and the intercept is scaled by (1 – θ)

For estimating θ, we will compute the following:

$$\widehat{\sigma_{\varepsilon}^2} = \frac{1}{N(T-1)-K} \sum_{i,t} \left(\widehat{v_{it}^{FE}} \right)^2. \tag{28A}$$

Between-bank variance (from regression on bank means) gives s^2_B; then

$$\widehat{\sigma_c^2} = \max! \left\{ 0, s_B^2 - \frac{\widehat{\sigma_{\varepsilon}^2}}{T} \right\}. \tag{29A}$$

Then, we plug into the following and estimate:

$$\hat{\theta} = 1 - \left(\frac{\widehat{\sigma_{\varepsilon}^2}}{\widehat{\sigma_{\varepsilon}^2} + T\widehat{\sigma_c^2}} \right)^{1/2}. \tag{30A}$$

Estimating β coefficients for the GLS model:

Now, allowing each bank to have its own serial correlation and variance level, the Block-diagonal covariance across banks is as follows:

$$\Omega = blockdiag(\Sigma_1, \ldots, \Sigma_N). \tag{31A}$$

Parks-Kmenta style within-bank AR(1) with heteroskedasticity

$$(\Sigma_i)_{ts} = \sigma_i^2 \rho_i^{|t-s|}, \tag{34}$$

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where σ_i^2 – variance level differs by bank (heteroskedastic across panels); ρ_i = AR(1) serial correlation parameter within bank *i*.

So, the GLS Estimator is as follows:

$$\widehat{\beta_{GLS}} = \left(X'\widehat{\Omega^{-1}}X\right)^{-1} X'\widehat{\Omega^{-1}}y. \tag{32A}$$

Allowing customization for our model, it has become the following estimator:

$$\widehat{\beta_{GLS}} = \left(X'\widehat{\Omega^{-1}}X\right)^{-1} X'\widehat{\Omega^{-1}}CCE. \tag{33A}$$

APPENDIX B

Table B1. Sampled banks

Bank Name	Country	Ownership Type	Listing Status	Average Total Assets (BDT in million)
Bank Asia	Bangladesh	Private	Listed	333.147
UCB	Bangladesh	Private	Listed	447.409
Brac Bank	Bangladesh	Private	Listed	378.658
EBL	Bangladesh	Private	Listed	313.414
City Bank	Bangladesh	Private	Listed	346.426
Dhaka Bank	Bangladesh	Private	Listed	268.163
AB Bank	Bangladesh	Private	Listed	348.861
One Bank	Bangladesh	Private	Listed	250.188
NCC Bank	Bangladesh	Private	Listed	231.029
Jamuna Bank	Bangladesh	Private	Listed	221.313
Sanima Bank	Nepal	Private	Listed	109.194
NIC Asia	Nepal	Private	Listed	203.487
Everest Bank	Nepal	Private	Listed	158.694
Prime Commercial Bank	Nepal	Private	Listed	118.878
Himalayan Bank	Nepal	Private	Listed	149.618
Laxmi Sunrise Bank	Nepal	Private	Listed	121.519
Machhapuchchhre Bank	Nepal	Private	Listed	105.636
Siddhartha Bank	Nepal	Private	Listed	143.859
Nabil Bank	Nepal	Private	Listed	227.090
Global IME Bank	Nepal	Private	Listed	212.201

Note: Detailed financial figures are available upon request or through publicly disclosed annual reports.