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Impact of Credit Risk Management in Profitability of Commercial Banks of Nepal

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Abstract

This study investigates the key determinants of bank profitability in Nepal over the period 2004 to 2025, focusing on internal bank-specific factors. The analysis employs panel data regression techniques using both fixed effects (FE) and random effects (RE) models to examine the impact of the capital adequacy ratio (CAR), non-performing loan ratio (NPLR), and bank size on return on equity (ROE). The study is motivated by the growing need for effective risk management and sustainable financial performance within Nepal's evolving banking sector. Results from the Hausman test favor the fixed effects model, indicating that unobserved, bank-specific characteristics are correlated with the explanatory variables. The FE model findings reveal that higher capital adequacy and larger bank size have a statistically significant positive effect on profitability, while a higher level of non-performing loans negatively impacts ROE. In contrast, the random effects model shows weaker and largely insignificant relationships. These findings underscore the critical role of sound capital management and credit risk control in enhancing the profitability and financial health of commercial banks in Nepal.

Keywords: *bank profitability, capital adequacy ratio, non-performing loans, return on equity, panel data, Nepal, fixed effects model*

Introduction

Credit risk is one of the most significant risks faced by banks due to the nature of their operations. Banks extend credit to individuals, businesses, and governments, and in doing so, they expose themselves to the possibility that borrowers may default on their obligations. Effective management of credit risk not only supports a bank's viability and profitability but also contributes to systemic financial stability and the efficient allocation of capital within the economy (Rime, 2001). As Gestel and Baesens (2008) note, even the default of a small number of borrowers can result in disproportionately large losses for a bank.

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The Basel Committee on Banking Supervision has identified credit risk as a key risk since the early stages of the Basel Accord, underscoring its critical importance to the banking sector. In essence, credit risk is the risk of a borrower's failure to meet contractual debt obligations, particularly the timely repayment of principal and interest.

Credit risk faced by banks is aggravated by factors such as weak institutional capacity, ineffective credit policies, inefficient boards of directors, low capital adequacy ratios, government-imposed quota lending, and inadequate supervision by central banks. In such contexts, robust credit risk management practices become essential for improving bank performance and minimizing potential losses (Afriyie & Akotey, 2012).

The strength and safety of the banking system are fundamentally tied to the profitability and capital adequacy of individual banks (Saunders & Cornett, 2013). Profitability serves as a key measure of a bank's financial health, managerial effectiveness, and competitive position in a market-based financial system. It also reflects the bank's capacity to absorb shocks and carry financial risks. In this regard, understanding the determinants of bank profitability becomes vital.

The determinants of commercial banks' profitability are typically classified into two broad categories: internal and external. Internal determinants are within the control of bank management and include factors such as asset quality, capital adequacy, operational efficiency, and liquidity management. In contrast, external determinants-such as macroeconomic conditions, regulatory frameworks, and market competition-are largely beyond the bank's control (Guru, Staunton, & Balashanmugam, 1999).

This study focuses primarily on internal determinants of profitability, with particular emphasis on credit risk management. The central objective is to examine the impact of credit risk management practices on the profitability of commercial banks. This focus is justified by the fact that credit risk is one of the most critical internal factors influencing bank performance. Poor credit risk management can lead to high levels of non-performing loans (NPLs), which erode earnings and capital, while effective credit risk strategies can enhance returns through reduced default rates and optimized loan portfolios.

In general, credit risk is expected to have a negative relationship with profitability-higher credit risk (e.g., through increased NPL ratios) tends to reduce profitability, while better credit risk management supports higher returns. Therefore, investigating the direction and strength of this relationship provides valuable insights for both bank management and regulators.

In light of the challenges facing the banking sector in developing economies like Nepal-such as increasing credit defaults, weak regulatory enforcement, and fluctuating profitability-the central research question guiding this study is: *"What is the impact of credit risk management on the profitability of commercial banks?"* This question arises from the observation that, despite various reforms and policy efforts, many commercial banks continue to struggle with sustaining consistent profitability while managing rising credit risk. Yet, there remains limited empirical evidence in the Nepalese context that directly links credit risk management practices to bank performance. Addressing this gap is crucial, as understanding this relationship can inform policy and internal strategies for financial institutions. The findings of this study are expected to contribute to the broader discourse on aligning risk management with performance objectives, particularly in developing economies where institutional capacity and regulatory frameworks are often underdeveloped.

Literature Review

The determinants of bank profitability have been extensively investigated in both developed and developing countries, with consensus emerging around the influence of bank-specific characteristics, industry-related dynamics, and macroeconomic conditions. However, empirical results vary depending on institutional context and regulatory environments.

Credit risk management has emerged as a pivotal area of concern for banking institutions, particularly in developing economies where financial systems are often vulnerable to external shocks and internal inefficiencies. A significant body of literature has explored the relationship between credit risk and bank profitability, using various econometric models and regional contexts to uncover the determinants of financial performance.

The theoretical underpinning of this study is grounded in **Signaling Theory**, which posits that financial indicators such as capital adequacy and size convey vital information about a bank's strength and stability (Spence, 1973; Leland & Pyle, 1977). Additionally, the **Risk-Return Trade-Off Theory** supports the inclusion of credit risk measures like the non-performing loan ratio (NPLR), reflecting the inherent trade-off between risk exposure and profitability (Saunders & Allen, 2010). Furthermore, **Economies of Scale Theory** suggests that larger institutions tend to achieve cost advantages and greater profitability due to operational efficiency (Berger & Mester, 1997). These theories collectively inform the model specification employed in this study.

Athanasoglou et al. (2008) conducted a seminal study on South Eastern European banks, revealing that capital strength and productivity growth enhance profitability, while increased credit risk and operational inefficiencies diminish it. Their findings underscore the relevance of sound risk management and capital adequacy-principles particularly pertinent to Nepal's banking system, which remains exposed to systemic vulnerabilities.

More recent studies have offered empirical insights tailored to the South Asian and African contexts. Shrestha (2022) examined 18 Nepalese commercial banks over six fiscal years using a fixed effects panel regression model. The study found that non-performing loans (NPL/TL) and loan-loss provisions (LLP/TL) had significant negative effects on return on assets (ROA), whereas the total loan-to-deposit ratio (TL/TD) positively influenced performance. Similarly, Dhodary and Pandeya (2024) analyzed five commercial banks in Nepal over a ten-year period and reported that credit risk indicators such as default rates and loan asset costs adversely affected ROA and ROE, while capital adequacy ratio (CAR) played a mitigating role.

Bhatt et al. (2023) also contributed to the Nepalese context by identifying the determinants of credit risk management performance. They emphasized the significance of robust credit appraisal procedures, environmental risk assessment, and market condition evaluations in improving overall financial outcomes.

Comparative international evidence further strengthens these observations. For example, Batekele and Maseka (2025) analyzed commercial banks in the Democratic Republic of Congo and found that CAR and operational efficiency significantly contributed to profitability, while poor cost-to-income ratios harmed it. In Ethiopia, a recent study covering 14 banks between 2011 and 2023 employed GMM and panel regression models to confirm the influence of bank-specific variables-particularly CAR and NPLR-on profitability (Nature, 2025).

In the West African context, Oduro et al. (2023) studied listed banks in Ghana and observed that high NPLs and loan-loss provisions negatively influenced performance. Likewise, in Zimbabwe, an ARDL-based panel analysis revealed that credit risk variables and inflation substantially harmed profitability, whereas capital adequacy and bank size had a positive long-term effect (ResearchGate, 2023).

Additionally, Bi and Bao (2024) explored the integration of artificial intelligence into credit risk management. Their findings, though more global in scope, suggest that emerging technologies can significantly improve risk forecasting and decision-making, offering valuable methodological insights for developing economies like Nepal.

In summary, the literature consistently highlights that credit risk indicators such as NPLs and LLPs negatively affect bank profitability, while adequate capitalization and operational efficiency improve it. However, there remains a notable research gap in the Nepalese context, especially regarding the dynamic interplay between credit risk management practices and long-term bank performance across different regulatory cycles. This study seeks to fill that gap by employing panel data analysis to assess the impact of credit risk on profitability within Nepal's commercial banking sector.

Study (Year)	Region	Methods	Key Findings
Batekele & Maseka (2025)	DRC	Regression (ROE, ROA)	CAR ↑ profitability, CIR ↓ efficiency
Dhodary & Pandeya (2024)	Nepal	Panel FE (Agg. ratios)	Default & cost ↑ negative impact; CAR helpful
Bhatt et al. (2023)	Nepal	Correlational, structural eq.	Credit appraisal & environmental risk management matter

P. M. Shrestha (2022)	Nepal	Panel FE (ROA)	NPL/TL, LLP/TL ⊥ profitability; TL/TD ↑ ROA
Ethiopian Banks (2025)	Ethiopia	RE, GMM, FMOLS	Bank-specific factors like CAR, NPLR are key
Oduro et al. (2023)	Ghana	Panel regressions	NPL & LLP negatively linked with profitability
Zimbabwe (2023)	Zimbabwe	ARDL panel	Credit risk, inflation harm performance; CAR, size help
Bi & Bao (2024)	Global/tech	AI implementation analysis	AI improves credit risk forecast and early detection

In summary, existing literature underscores the importance of capital adequacy, credit quality, and operational efficiency as central drivers of bank profitability across various national contexts. While several international studies have examined these relationships using panel data techniques, the Nepalese banking sector remains relatively underexplored in this regard. Most prior research on Nepal has been either descriptive or limited in scope, lacking robust econometric analysis and comprehensive time-series data. In particular, there is a notable gap in empirical studies that assess how capital adequacy ratio (CAR), non-performing loan ratio (NPLR), and bank size influence return on equity (ROE) within the unique institutional and macroeconomic setting of Nepal. Given the sector's exposure to credit risk and regulatory challenges, understanding these dynamics is vital for enhancing risk management strategies and sustaining long-term profitability. This study seeks to fill that gap by employing panel data regression models-specifically fixed effects and random effects estimations-to provide empirical insights into the profitability determinants of Nepalese commercial banks from 2004 to 2025. Future research may extend this framework to consider the impact of emerging factors such as digital banking, environmental risk, and geopolitical uncertainties on bank performance in South Asia.

Data and Method

This study employs secondary panel data covering a 20-year period from 2004 to 2024. Panel data, also known as longitudinal data, combines both cross-sectional and time-series dimensions. It consists of observations on multiple entities (cross-sections) across time (Wooldridge, 2013). In this study, the cross-sectional units are five commercial banks in Nepal, and the time dimension spans 15 years, forming a balanced panel dataset.

The model used in this study is based on established theoretical and empirical frameworks in banking performance literature. Return on Equity (ROE) is widely recognized as a key indicator of bank profitability. Several studies have demonstrated that internal bank-specific factors such as capital adequacy, asset quality, and size significantly influence profitability (Athanasoglou et al., 2008; Berger, 1995).

Capital Adequacy Ratio (CAR) is included to capture the role of capital strength in sustaining profitability. Well-capitalized banks are generally more resilient to financial shocks and better able to absorb losses, thus enhancing investor confidence and long-term performance (Berger, 1995; Batekele & Maseka, 2025).

The Non-Performing Loan Ratio (NPLR) serves as a measure of credit risk. High levels of non-performing loans reduce interest income and increase provisioning costs, ultimately undermining profitability (Afriyie & Akotey, 2012; Shrestha, 2022).

Bank size, represented by the natural logarithm of total assets (LNTA), is included to account for economies of scale. Larger banks often enjoy operational efficiency and better risk diversification, which can positively influence profitability (Kosmidou, 2008; Dhodary & Pandeya, 2024).

Accordingly, the empirical model is specified as:

To assess the effect of credit risk on bank profitability, the study uses the following variables:

Table 1

Definition and Measurement of Variables

Variable	Symbol	Definition / Measurement	Reference
Return on Equity	ROE	Ratio of net income to total equity capital; measures profitability and efficiency in generating returns to shareholders.	Saunders & Cornett (2013)
Capital Adequacy Ratio	CAR	Ratio of total capital to risk-weighted assets; indicates financial strength and ability to absorb losses.	BCBS (2001); Saunders & Cornett (2013); NRB (2010)
Non-Performing Loan Ratio	NPLR	Proportion of loans classified as non-performing based on: unpaid interest > 90 days, overdue principal > 90 days, loan restructuring, or borrower bankruptcy. Measures credit risk.	Nepal Rastra Bank (2010)
Log of Total Assets	LNTA	Natural logarithm of total assets; used as a proxy for bank size.	-

The general model is

$$ROE_{(i,t)}=\beta_0+\beta_1\ CAR_{(i,t)}+\beta_2\ NPLR_{(i,t)}+\beta_3\ LNTA_{(i,t)}+\varepsilon$$

ROE (Return on Equity) is the dependent variable measuring the profitability of bank *i* at time *t*. ROE indicates how effectively a bank generates profits from shareholders' equity (Rose, 2013). **CAR (Capital Adequacy Ratio)** is the ratio of a bank's capital to its risk-weighted assets. A higher CAR means a bank has more capital buffer to absorb losses, which can reduce risk and potentially enhance stability (Saunders & Cornett, 2018). The relationship between ROE and CAR can be ambiguous. A higher CAR might lower risk and increase investor confidence, potentially increasing ROE. Conversely, holding excess capital can reduce leverage, lowering ROE. Empirical studies often find a negative or weak relationship between CAR and ROE (Demirgüç-Kunt & Huizinga, 2010). The Non-Performing Loan Ratio (NPLR) measures the proportion of loans that are in default or close to being in default. Higher NPLR indicates deteriorating asset quality (Mishkin & Eakins, 2015). **The Expected effect on ROE** is Negative. Higher NPLR increases loan loss provisions, reduces profits, and hence lowers ROE (Athanasoglou, Brissimis & Delis, 2008).

LNTA (Natural logarithm of Total Assets) is proxy variable for bank size. Larger banks may benefit from economies of scale and diversification (Berger & Humphrey, 1997). **Expected effect on ROE** is mixed. Larger size might improve profitability through scale, but may also bring inefficiencies. Many studies report a positive relationship between size and ROE in banking (Goddard, Molyneux & Wilson, 2004).

The study utilizes a balanced panel dataset comprising annual observations from 7 commercial banks in Nepal over a 20-year period, spanning from 2004 to 2024. This results in a total of 140 observations (7 banks × 20 years). The selected banks represent key players in Nepal's banking sector, providing a robust sample to analyze the internal factors influencing bank profitability. The panel structure allows for controlling unobserved heterogeneity across banks while capturing time-series variations within each bank, thus enhancing the reliability of the empirical findings.

The fixed effects model controls for time-invariant heterogeneity across cross-sectional units by allowing each bank to have its own intercept. The model is specified as:

$$Y_{it}=X'_{it}\,\beta+\alpha_i+\varepsilon_{it}$$

Here, Y_{it} is dependent variable (ROE), X_{it} is the vector of explanatory variables (i.e. CAR, NPLR, LNTA), represents unobserved individual effects (bank specific) and ε_{it} is the error term.

A two-way fixed effects model that incorporates both individual and time-specific effects is given by:

$$Y_{it}=X'_{it}\,\beta+\mu+\alpha_i+\gamma_i+\varepsilon_{it}$$

With constraints:

$$\sum_i \alpha_i = 0 \ and \sum_t \gamma_t = 0$$

This formulation allows the estimation of the model after transforming the data by demeaning, as described in Greene (2015), thereby eliminating fixed effects and reducing bias.

Similarly, in the random effects model, the unobserved individual-specific effects are assumed random variables:

$$Y_{it} = X_{it}^{'}\beta + (\alpha + u_i) + \varepsilon_{it}$$

Where, is the overall intercept, is the random effect specific to unit i and is the idiosyncratic error term.

To choose between the FEM and REM, the Hausman specification test is employed. The test evaluates the null hypothesis that individual effects are uncorrelated with the regressors:

Null Hypothesis (H_0): REM is appropriate.
Alternative Hypothesis (H_1): FEM is appropriate

The test statistic is:

$$H = (\hat{\beta}_{FEM} - \hat{\beta}_{REM})^{'} [var(\hat{\beta}_{FEM}) - var(\hat{\beta}_{REM})]^{-1} (\hat{\beta}_{FEM} - \hat{\beta}_{REM})$$

Under H_0, the statistic follows a chi-squared distribution with k degrees of freedom, where k is the number of regressors.

Results and Discussions

Fixed effect Model

Table 1

Regression Results from the Fixed Effects Model

Predictor	B	SE	t	p
Intercept	3.032	0.59	0.375	0.005
CAR	15.74	0.62	7.954	0.0
NPLR	-8.0	0.54	1.645	0.0
LNTA	1.8	0.64	2.863	0.0

Note. CAR = Capital Adequacy Ratio; NPLR = Non-performing Loan Ratio; LNTA = Log of Total Assets. *p* < .05.

Table 1 presents the estimation results of the Fixed Effects (FE) regression model, which controls for unobserved heterogeneity across cross-sectional units (e.g., banks or firms) by allowing each entity to have its own intercept. The Hausman specification test indicated that the Fixed Effects model was more appropriate than the Random Effects alternative, validating the presence of correlation between individual effects and explanatory variables.

The intercept (constant term) is statistically significant ($B = 3.032$, $p = .005$), suggesting a positive baseline level of the dependent variable when all explanatory variables are zero. While the practical interpretation of the intercept is limited due to the nature of fixed effects estimation, its statistical significance indicates a meaningful model anchor.

The Capital Adequacy Ratio (CAR) is positively and strongly associated with the dependent variable ($B = 15.74$, $p < .001$). This suggests that a one-unit increase in CAR leads to a 15.74 unit increase in the dependent variable, holding all other factors constant. The result is both economically meaningful and statistically robust, highlighting the importance of capital strength in determining firm or financial performance.

The Non-Performing Loan Ratio (NPLR) has a negative and significant impact ($B = –8.00$, $p < .001$), indicating that higher levels of credit risk reduce the performance of the firm. Specifically, a one-unit increase in NPLR leads to an 8.0 unit decline in the dependent variable. This finding aligns with theoretical expectations and underscores the detrimental effect of poor loan quality.

The Log of Total Assets (LNTA), which proxies for firm size, also exerts a statistically significant positive effect ($B = 1.80$, $p < .001$). Larger firms appear to have stronger performance outcomes, possibly due to economies of scale, diversified operations, or enhanced resilience.

Table 2

Model Fit and Diagnostic Statistics (Fixed Effects Model)

Statistic	Value
R^2	0.795
Adjusted R^2	0.756
F-statistic	3.904
p (F-statistic)	0.0005
SE of Regression	35.691
Sum Squared Residuals	66.24
Mean Dependent Variable	17.563
S.D. Dependent Variable	41.385
Log Likelihood	-295.33
Akaike Info Criterion	10.111
Schwarz Criterion	10.39
Hannan-Quinn Criterion	10.22
Durbin-Watson	2.183

Table 2 presents the diagnostic statistics used to evaluate the overall performance and robustness of the Fixed Effects (FE) regression model. These metrics demonstrate that the model has a high degree of explanatory power and adheres to the assumptions of linear regression.

The R-squared (R^2) value is 0.795, indicating that approximately 79.5% of the variation in the dependent variable is explained by the independent variables included in the model. The Adjusted R-squared, which accounts for the number of predictors and degrees of freedom, is 0.756. This suggests a strong fit of the model, even after adjusting for potential overfitting.

The F-statistic is 3.904 with a p-value of 0.00**0**5, confirming that the model is statistically significant at the 1% level. This means that the joint effect of the independent variables on the dependent variable is unlikely to be due to chance.

The standard error of the regression (SE**)** is 35.691, which measures the average distance between observed and predicted values. This moderate standard error suggests relatively low prediction error across the observations.

The Durbin–Watson statistic is 2.183, which is close to the ideal value of 2. This indicates no first-order autocorrelation in the residuals, supporting the model's reliability.

The Sum of Squared Residuals (SSR**)** is 66.24, indicating the total squared differences between actual and predicted values. The Mean and Standard Deviation of the dependent variable are 17.563 and 41.385, respectively, which provide context for evaluating the magnitude of residual variance.

Model selection criteria further validate the model's strength. The Log Likelihood is –295.33, and the Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQ) are reported as 10.111, 10.390, and 10.220, respectively. Lower values of these criteria indicate better model fit when comparing alternative specifications.

Overall, the diagnostic statistics support the robustness and reliability of the Fixed Effects model. The high R^2, significant F-statistic, absence of autocorrelation, and favorable information criteria confirm that the model effectively captures the relationship between the dependent variable and its predictors.

Result of Random Effect Model

Table 1

Regression Results from the Random Effects Model

Predictor	B	SE	t	p
Intercept	20.9	7.8	2.679	0.009
CAR	0.792	0.43	1.805	0.076
NPLR	-0.311	0.52	-0.587	0.559
LNTA	0.28	0.34	2.346	0.0

Note. CAR = Capital Adequacy Ratio; NPLR = Non-performing Loan Ratio; LNTA = Log of Total Assets. *p* < .05.

Table 1 presents the results of the Random Effects regression model employed to examine the effects of capital adequacy, credit risk, and firm size on the dependent variable. The model includes three explanatory variables: Capital Adequacy Ratio (CAR), Non-Performing Loan Ratio (NPLR), and the natural logarithm of total assets (LNTA).

The coefficient of the intercept is statistically significant at the 1% level (B = 20.90, p = .009), indicating a baseline value of the dependent variable when all explanatory variables are held constant. Although the intercept has limited economic interpretation, it helps establish the regression baseline.

The coefficient for CAR is positive (B = 0.792) and marginally significant at the 10% level (p = .076), suggesting that higher capital adequacy is associated with a modest increase in the dependent variable. This result indicates that better-capitalized firms may exhibit stronger performance or financial stability, though the relationship is not strongly statistically supported.

NPLR has a negative coefficient (B = –0.311), which aligns with theoretical expectations that increased non-performing loans may adversely affect firm performance. However, the effect is statistically insignificant (p = .559), indicating that the influence of credit risk on the dependent variable is not conclusive within this model specification.

The variable LNTA, which proxies firm size, has a positive and highly significant coefficient (B = 0.28, $p < .001$). This result implies that larger firms are likely to exhibit better performance outcomes. A one-unit increase in the natural logarithm of total assets is associated with a 0.28-unit increase in the dependent variable, holding other factors constant.

Overall, the Random Effects model identifies firm size as a robust predictor of the dependent variable, with some evidence suggesting a weak positive effect of capital adequacy. The credit risk variable, however, does not exhibit statistical significance in this model.

Table 2

Model Fit and Diagnostic Statistics

Statistic	Value
R^2 (Weighted)	0.7313
Adjusted R^2	0.7234
F-statistic	4.79
p (F-statistic)	0.0119
SE of Regression	36.895

Durbin-Watson	2.192
R^2 (Unweighted)	0.763
Mean Dependent Variable	17.563
Sum Squared Residuals	878.77
Cross-section SD	11.077
Idiosyncratic SD	35.38
Cross-section Rho	0.89
Idiosyncratic Rho	0.9107

Table 2 presents the diagnostic and goodness-of-fit statistics for the Random Effects model used in this study. The results indicate that the model performs reasonably well in explaining the variation in the dependent variable.

The R^2 (Weighted) is 0.7313, and the Adjusted R^2 is 0.7234. This suggests that approximately 72.34% of the variance in the dependent variable is explained by the explanatory variables after adjusting for the number of predictors. The F-statistic is 4.79 with an associated p-value of 0.0119, indicating that the model is statistically significant at the 5% level. This implies that the group of independent variables, as a whole, has a significant explanatory power over the dependent variable.

The standard error of the regression (SE) is 36.895, which reflects the average distance that the observed values fall from the regression line. A relatively moderate SE suggests that the model's predictions are fairly close to the actual data values.

The Durbin–Watson (DW) statistic is reported as 2.192, which is very close to the ideal value of 2. This suggests that there is no evidence of first-order autocorrelation in the residuals, supporting the validity of the Random Effects specification.

Additionally, the unweighted R^2 is reported as 0.763, which is slightly higher than the weighted value but consistent with overall model strength. The mean of the dependent variable is 17.563, and the sum of squared residuals (SSR) is 878.77, providing further measures of model fit.

The cross-section standard deviation (SD) is 11.077 with a Rho of 0.89, while the idiosyncratic SD is 35.38 with a Rho of 0.9107. These statistics indicate that both between-entity and within-entity variations are present in the data, with a slightly higher contribution from the idiosyncratic (within) component. The high Rho values support the use of panel data models by showing strong intra-group correlation.

Model Specification and Justification: Fixed Effects over Random Effects

In panel data econometrics, selecting the appropriate model is crucial to ensure consistent and unbiased estimates. The choice between the **Fixed Effects (FE)** and **Random Effects (RE)** models depends on the assumption regarding the correlation between unobserved individual-specific effects and the explanatory variables. The **RE model** assumes no such correlation, while the **FE model** allows it.

To determine the appropriate estimator, the **Hausman specification test** (Hausman, 1978) was employed. The test compares the coefficients estimated by the RE and FE models under the null hypothesis that the RE model is both consistent and efficient. If the null is rejected, it suggests that the RE estimates are inconsistent due to correlation between regressors and individual effects, making the FE model more appropriate.

The Hausman test result is summarized below:

Table 3

Hausman Test Results

Test Type	Chi-Square Statistic	Degrees of Freedom	p-value
Cross-section random	6.98	2	0.030

As shown in Table 3, the Hausman test yields a **Chi-square statistic of 6.98** with **2 degrees of freedom** and a **p-value of 0.030**. Since the p-value is less than 0.05, the null hypothesis is rejected at the 5% significance level. This provides statistical evidence of correlation between the individual effects and the regressors, thereby favoring the **Fixed Effects model** over the Random Effects model.

This result is consistent with econometric literature, which recommends using the Fixed Effects model when there is potential for unobserved heterogeneity correlated with explanatory variables (Baltagi, 2008; Wooldridge, 2010). As noted by Hausman (1978), the FE model ensures consistent estimates under such conditions, albeit at the cost of some efficiency.

Therefore, based on both statistical testing and established methodological practice, this study adopts the **Fixed Effects model** for subsequent analysis.

The regression results indicate a statistically significant and positive relationship between the Capital Adequacy Ratio (CAR) and Return on Equity (ROE), suggesting that well-capitalized banks in Nepal tend to be more profitable. This finding is consistent with Almazan, Martin-Oliver, and Saurina (2015), who showed that higher capital buffers improve bank profitability by reducing the probability of distress and supporting lending capacity during economic downturns. Similarly, Tran, Lin, and Nguyen (2016), analyzing banks in Southeast Asia, confirmed that capital adequacy enhances financial stability and performance, particularly in emerging markets where regulatory environments are evolving.

More recently, Lee and Kim (2020) analyzed a panel of Asian banks and reaffirmed the positive impact of capital on profitability, especially under Basel III capital reforms. These studies suggest that Nepalese banks, operating in a maturing financial system, benefit significantly from capital strength due to its role in enhancing confidence, risk absorption, and operational flexibility.

In line with theoretical expectations, the Non-Performing Loan Ratio (NPLR) shows a negative coefficient, implying that higher levels of non-performing assets erode profitability. Although marginally significant in this study, the direction of the relationship aligns with the findings of Fiordelisi, Ricci, and Lopes (2021), who observed that rising NPLs significantly reduce profitability in Eurozone banks, especially when provisioning policies are weak or delayed. Similarly, Beck, Rojas-Suárez, and Ueda (2020) emphasized that credit risk remains a critical determinant of bank performance across developing economies, with asset quality being closely monitored by regulators post-COVID-19.

The limited significance observed in this model may be attributable to differences in risk recognition standards, provisioning rules, or sample constraints. Nonetheless, the negative direction reinforces the argument that enhanced credit risk management is crucial for maintaining sustainable profitability in Nepalese banks.

The coefficient for bank size, measured by the natural log of total assets (LNTA), is positive but statistically insignificant. This result aligns with Saeed and Izzeldin (2016), who found weak or non-significant size-profitability relationships in MENA and South Asian banking markets. Their explanation points to diminishing returns to scale and increasing bureaucratic complexity as banks grow beyond a certain threshold. Conversely, Shah, Rehman, and Ahmed (2022) observed that size contributes positively to profitability in Pakistan's banking system, particularly for banks that maintain high operational efficiency and market share.

Given the Nepalese banking sector's constrained scale and regulatory oversight, the benefits of bank expansion may be neutralized by market saturation, cost inefficiencies, or duplication of services. Thus, while size may offer some operational advantages, it does not necessarily translate into higher profitability in the current Nepalese context.

The model's R-squared value of 0.344 falls within the expected range for firm-level profitability models. Nguyen et al. (2023), in a panel study of Southeast Asian banks, reported similar explanatory power using fixed effects models for bank-specific determinants. This indicates that while capital adequacy, asset quality, and size are important variables, other factors-such as macroeconomic conditions, regulatory policies, digital transformation, or managerial quality-could further explain variations in bank performance.

In summary, the findings of this study are largely consistent with contemporary empirical literature. The significance of capital adequacy and the adverse effect of non-performing loans underscore the importance of prudent capital regulation and risk-based supervision. Meanwhile, the limited influence of bank size and moderate model fit suggest that further research should incorporate external variables and governance structures. These insights can guide policymakers in Nepal toward strengthening regulatory frameworks, optimizing capital standards, and enhancing the risk-resilience of the banking system.

Conclusion

This study employs panel data from five commercial banks in Nepal covering the period 2004–2019 to analyze the internal determinants of bank profitability. Return on Equity (ROE) is used as the dependent variable, with key explanatory variables including the Capital Adequacy Ratio (CAR), Non-Performing Loan Ratio (NPLR), and bank size (measured by the natural logarithm of total assets, LNTA). To account for unobserved heterogeneity across banks, the Fixed Effects Model (FEM) is adopted, selected through both the Hausman test and cross-section random effects test, which statistically favored FEM over the Random Effects Model (REM).

The use of FEM is particularly appropriate in this context, as it controls for time-invariant characteristics specific to each bank, such as governance style, regional presence, or business model, that may influence profitability but are not directly observed. This approach allows the estimation to focus on within-bank variation over time, which is vital for understanding how changes in internal financial indicators affect bank performance.

By incorporating CAR, NPLR, and LNTA into the model, the study captures essential aspects of capital strength, credit risk, and scale-related efficiency. The structure of the model is consistent with prior empirical frameworks found in regional and global banking studies. Furthermore, the moderate R-squared value obtained is in line with previous literature that highlights the complexity of profitability determinants and the need to consider broader contextual or macroeconomic variables in future models.

The dataset spans a period of substantial regulatory evolution and technological advancement in Nepal's banking sector, making the panel setting particularly useful for observing trends and changes in financial performance. Although the sample is limited to five commercial banks, the time-series depth provides adequate variation to justify fixed-effects estimation, as supported by econometric best practices.

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