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Probabilistic Prediction of Bank Mergers: A Discriminant Analysis Framework Using the CAMEL Model in the Indian Banking Sector

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Abstract: The consolidation of the banking sector through mergers has become a global phenomenon, driven by the pursuit of stability, efficiency, and competitive advantage. In India, this trend has been particularly pronounced, with a significant reduction in the number of public sector banks following a wave of government-led amalgamations. While the determinants of mergers have been extensively studied, the development of a predictive model using financial metrics remains a relatively unexplored area. This study aims to fill this gap by constructing a robust statistical framework for the probabilistic prediction of bank mergers using the CAMEL (Capital Adequacy, Asset Quality, Management Efficiency, Earnings, and Liquidity) framework.

Employing a discriminant analysis methodology, this research analyses a decade-long panel dataset (2011-2020) of 25 Indian public sector banks, comprising 13 merged and 12 existing entities. Three distinct predictive models were developed, each utilizing a different combination of financial ratios representing the five components of the CAMEL framework. The results robustly indicate that a bank's capital adequacy, management efficiency, earnings capability, and liquidity are statistically significant predictors of its propensity to be merged. Notably, the asset quality dimension, measured by Net Non-Performing Asset (NPA) ratios, was found to be statistically insignificant in the models, suggesting that in the context of Indian public sector banks, mergers are not solely triggered by poor asset quality but by a broader syndrome of financial weakness.

Among the three models, the one incorporating Return on Net Worth, Net NPAs to Total Assets, Return on Assets, Net Interest Margin, and the Interest Expended to Interest Earned Ratio

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demonstrated superior predictive power, achieving a remarkable classification accuracy of 92%. This model provides a practical and potent tool for regulators, investors, and bank management to identify early warning signals of potential distress and merger likelihood. The study concludes that the CAMEL framework, with certain refinements, offers a viable foundation for predicting bank mergers, thereby contributing significantly to the literature on financial distress prediction and banking sector consolidation.

Keywords: Bank Mergers, CAMEL Framework, Discriminant Analysis, Predictive Modelling, Financial Distress, Indian Banking, Public Sector Banks, Consolidation.

1. INTRODUCTION

The global banking landscape over the past five decades has been characterized by a relentless wave of mergers and acquisitions (M&A), transforming the structure, reach, and efficiency of financial institutions worldwide. A merger, the combination of two or more entities into a single surviving entity, is often pursued as a strategic tool to enhance market share, achieve economies of scale, diversify risk, and fortify competitive positioning (Jayadev & Sensarma, 2007). In many instances, however, mergers are not merely strategic choices but necessary interventions to rescue failing or underperforming banks, thereby safeguarding the stability of the financial system and protecting depositors' funds. The notion that "large banks are too big to fail" has further incentivized consolidation, creating financial behemoths believed to be more resilient to economic shocks (Deyoung et al., 2009).

The Indian banking sector provides a compelling context to study this phenomenon. The journey of bank mergers in India predates its independence, but it gained significant momentum in the 1980s and accelerated dramatically in the 1990s following the Narasimham Committee recommendations and the subsequent era of economic liberalization (RBI, 2018). This period of deregulation opened the Indian financial markets to foreign players, intensifying competition and compelling domestic banks to consolidate to survive and thrive. The period from 2011 to 2020 witnessed an unprecedented consolidation drive, culminating in the largest-ever merger in 2020, which reduced the number of public sector banks (PSBs) from 27 in 2017 to just 12 by 2021 (Mubarak, 2021). This consolidation was largely a response to systemic issues plaguing the sector, including alarming levels of non-performing assets (NPAs), recurrent needs for government recapitalization, and issues of operational inefficiency.

While the determinants and post-merger performance of banks have been extensively researched, a critical gap exists in the development of a predictive model that can probabilistically identify banks susceptible to merger based on their financial fundamentals. Existing literature, both global and Indian, has catalogued a plethora of reasons for mergers—ranging from economic factors like deregulation and the pursuit of synergy (Ali-Yrkkö, 2002) to non-economic factors like managerial ambition (Lausberg & Stahl, 2009). Yet, a clear, empirically validated framework for predicting which banks will merge is conspicuously absent. As noted by Amel & Rhoades (1989), early attempts to model merger motives provided no clear predictive framework. While more recent studies have utilized advanced techniques like multinomial logistic regression and machine learning (Wei, 2020; Beccalli & Frantz, 2013), the application of a structured, multi-dimensional financial framework like CAMEL for this specific predictive purpose remains limited.

This study, therefore, seeks to address this research gap by posing the central question: **Can a combination of financial determinants, structured within the CAMEL framework, facilitate the probabilistic prediction of bank mergers?**

The primary objective is to design and test a statistical model that can discriminate between banks that were merged and those that continued to exist independently. The CAMEL framework, a globally accepted benchmark for assessing bank soundness, provides the theoretical foundation for selecting predictive variables. By employing discriminant analysis on a carefully curated dataset of Indian PSBs, this research aims to:

1. Develop multiple predictive models using different combinations of CAMEL ratios.
2. Identify which specific financial ratios are statistically significant in predicting a bank merger.
3. Determine the model with the highest classification accuracy and discriminatory power.
4. Test hypotheses regarding the linkage between each CAMEL component and the occurrence of a merger.

The implications of this research are multifaceted. For banking regulators and policymakers, such a model can serve as an early warning system, enabling proactive measures to strengthen vulnerable banks or to plan consolidation more strategically. For investors and financial analysts, it provides a tool to assess the risk profile and future viability of banking stocks. For bank management, it offers a self-diagnostic toolkit to identify and rectify financial weaknesses before they necessitate external intervention.

The subsequent sections of this paper are structured as follows: Section 2 provides a comprehensive review of the literature on bank merger determinants and prediction models. Section 3 details the data sources, variable construction, and the discriminant analysis methodology. Section 4 presents the empirical findings, including the development and comparative analysis of the three prediction models. Section 5 discusses the results, tests the research hypotheses, and explores the theoretical and practical implications of the study, concluding with limitations and avenues for future research.

2. LITERATURE REVIEW

This section synthesizes the extant literature on bank mergers, focusing on two key streams: first, the diverse determinants and motives for mergers in both global and Indian contexts, and second, the prior attempts and methodologies employed to predict such merger events.

2.1. Determinants of Mergers in the Global Context

The motives for bank mergers are complex and multifaceted, often interweaving economic, strategic, and personal factors. A significant body of research attributes mergers to the pursuit of efficiency and value creation. Andries et al. (2021), in their study of Central and Eastern European banks, identified bank size, profitability (ROAE), and liquidity as the most significant drivers. Their findings suggest that larger banks are 45.8% more likely to participate in M&A, often to achieve scale and operational synergies. This aligns with the classic synergy argument, where the combined value of merged entities is expected to exceed the sum of their individual values, often expressed as 1+1=3 (Badík, 1934). Synergies can be operational, through cost reduction, or financial, by combining entities with complementary cash flows and investment opportunities (Ali-Yrkkö, 2002).

The role of economic reforms and deregulation has been a powerful catalyst for merger waves globally. The study by Smirnova (2015) on Kazakh banks highlighted that mergers were driven by both the internal restructuring of the banking system during the transition to a market economy and the external motive of foreign banks seeking entry into the promising CIS market. Similarly, Sanfilippo Azofra et al. (2008) concluded that the financial deregulation and technological reforms of the 1990s triggered a global consolidation wave. Erel et al. (2012), analysing cross-border mergers, found that geographic proximity and bilateral trade increase the likelihood of mergers between two countries, emphasizing the importance of market-seeking behaviour.

Beyond pure economic rationale, managerial and personal motives play a crucial, and sometimes dominant, role. Lausberg & Stahl (2009), in a psychological study of German bank managers, found that non-economic motives like the desire for power, achievement, sensation-seeking, and prestige often led managers to accept economically disadvantageous mergers. This supports the agency theory perspective, where managers may pursue mergers to increase their compensation, build empires, or reduce employment risk (Deyoung et al., 2009), even if it does not maximize shareholder value.

The regulatory and institutional environment is another critical determinant. Rossi and Volpin (2004), in a cross-country analysis, found that countries with stronger investor protection and better accounting standards experience higher levels of merger activity. In some cases, mergers are directly orchestrated by the government. Ahmad et al. (2007) documented the "guided mergers" in Malaysia post the Asian Financial Crisis, where the central bank directed the merger of 52 institutions into 10 anchor banks to prevent systemic collapse. Interestingly, contrary to market-driven mergers, they found that weaker banks often became the acquirers in these government-led processes, highlighting the unique dynamics of regulatory-driven consolidation.

2.2. Mergers in the Indian Perspective

The Indian banking sector's experience with mergers reflects a blend of market-driven consolidation and regulator-led rescue operations. The process, though ongoing for decades, has seen distinct phases aligned with the country's economic policy shifts. The pre-nationalization era saw mergers primarily to revive weak private banks, while the post-liberalization period witnessed mergers aimed at creating stronger entities capable of competing with foreign banks (RBI, 2018).

A prominent theme in the Indian context is the problem of NPAs and the subsequent need for recapitalization. Kumari (2014) and Jayadev & Sensarma (2007) have argued that a primary reason for mergers in India has been to safeguard weak banks, often burdened with high NPAs and low profitability, from failure. The government's issue of recapitalization bonds to inject capital into ailing PSBs, often proving insufficient, created a fiscal impetus for consolidation to reduce the number of entities requiring such support (IAS, 2018).

The recommendations of the Narasimham Committee (1991 and 1998) have been a cornerstone of banking sector reforms in India, explicitly advocating for consolidation to create a stronger and more efficient banking structure (Leeladhar, 2008). The committee's vision of a three-tier banking structure with large banks at the apex provided the philosophical underpinning for the recent mega-mergers.

Studies on the outcomes of these mergers have yielded mixed results. Kumar et al. (2019) found that market-driven mergers tend to boost efficiency, while forced mergers lead to stagnation or decline. Conversely, Ravichandran et al. (2010) found no significant improvement in productive efficiency post-merger, suggesting that the primary motive may have been to increase operational scale rather than enhance efficiency. Despite this, the consensus is that mergers have been used as a strategic tool for expansion, diversification, and leveraging technology to improve revenue and deposit growth (Dutta et al., 2012; Ms. Lohia et al., 2021).

2.3. Predicting Bank Mergers

While understanding determinants is crucial, the ability to predict mergers is a separate, more challenging endeavour. The literature on prediction models is less voluminous but growing. Early work by Amel & Rhoades (1989) using multinomial logit analysis failed to find clear support for any specific motive or predictive framework.

More recent studies have had greater success. Alam and Ng (2014), focusing on ASEAN banks, found that asset quality and liquidity were key predictors, with banks having lower asset quality and higher liquidity being more likely targets. Their findings also suggested that acquiring banks tend to have higher growth and profitability. Erdogan (2012), using Cox regression for Turkish firms, found that lower pre-tax profit margins and lower debt ratios increased the likelihood of being an acquisition target.

The CAMEL framework itself has been used for bank assessment, though not always explicitly for merger prediction. Masood et al. (2016) used the CAMELS model to rate Islamic banks in Pakistan, implying that banks with the lowest ratings demonstrate immediate failure and a need for corrective measures like mergers. This establishes a logical link between poor CAMEL ratings and merger susceptibility.

Methodologically, the field has evolved from traditional regression to more advanced techniques. Wei (2020) compared parametric statistical regression with machine learning models for predicting US bank mergers, finding that while machine learning had better in-sample accuracy, multinomial logistic regression was more robust in out-of-sample prediction. Beccalli & Frantz (2013) also used Cox and multinomial logit models, finding the latter more accurate in predicting a bank's likelihood of being an acquirer or a target. They identified that greater growth, cost efficiency, and lower capitalization predict acquirers, while lower free cash flows and efficiency predict targets.

Despite these advances, a clear gap persists. No study has systematically developed and compared multiple discriminant models based on the CAMEL framework to predict merger events in the Indian banking sector. This research aims to bridge this gap by constructing a parsimonious yet powerful predictive model using discriminant analysis, a technique known for its stability with smaller samples and its direct applicability to classification problems.

3. DATA AND METHODOLOGY

3.1. Data and Sample Selection

This study employs a rigorous research design based on secondary data. The data was meticulously collected from the annual reports of individual public sector banks, the Reserve Bank of India's (RBI) statistical publications, and the financial database Money Control. The study period spans ten financial years, from 2011-12 to 2020-21, a period that captures a significant wave of consolidation in the Indian banking industry.

The sample consists of 25 public sector banks, strategically selected to create a balanced dataset for discriminant analysis. This sample is divided into two distinct groups:

- **Group 1 (Merged Banks):** This group comprises 13 banks that were merged with other banks during or after the study period. Examples include Allahabad Bank (merged into Indian Bank), Andhra Bank (merged into Union Bank of India), and Oriental Bank of Commerce (merged into Punjab National Bank).
- **Group 2 (Existing Banks):** This group comprises 12 banks that continued to operate independently without being involved in a merger as of the end of the study period. This includes State Bank of India, Bank of Baroda, Punjab National Bank, and others.

Banks that were merged before the study period (e.g., State Bank of Indore, State Bank of Saurashtra) or for which consistent data was unavailable (e.g., Bharatiya Mahila Bank) were excluded to maintain data integrity and temporal consistency.

3.2. Variable Selection: The CAMEL Framework

The independent variables for this study are financial ratios categorized under the CAMEL framework, a globally recognized model for assessing bank health. Due to data constraints on 'S' (Sensitivity to Market Risk), the analysis utilizes the first five components: Capital Adequacy, Asset Quality, Management Efficiency, Earnings, and Liquidity. The specific ratios chosen under each component are detailed below:

Table 1: CAMEL Components and Corresponding Financial Ratios

CAMEL Component	*Variable Name*	*Ratio Formula*	*Expected Relationship with Merger Likelihood*
C - Capital Adequacy	Capital Adequacy Ratio (CRAR)	Total Capital / Risk-Weighted Assets	Negative
	Return on Net Worth (RONW)	Net Profit / Shareholders' Funds	Negative

CAMEL Component	*Variable Name*	*Ratio Formula*	*Expected Relationship with Merger Likelihood*
A - Asset Quality	Net NPAs to Total Advances	Net NPAs / Total Advances	Positive
	Net NPAs to Total Assets	Net NPAs / Total Assets	Positive
M - Management Efficiency	Profit Per Employee (PPE)	Net Profit / Total Employees	Negative
	Return on Assets (ROA)	Net Income / Total Assets	Negative
E - Earnings Capability	Net Profit to Total Assets	Net Profit / Total Assets	Negative
	Net Interest Margin (NIM)	(Interest Income - Interest Exp.) / Interest Earning Assets	Negative
	Net Profit Margin (NPM)	Net Profit / Total Income	Negative
L - Liquidity Capability	Cash Deposit Ratio (CDR)	Total Cash Balance / Total Deposits	Positive
	Interest Expended to Interest Earned (IE/IE)	Interest Expended / Interest Earned	Positive
	Total Investments to Total Deposits (I/TD)	Total Investments / Total Deposits	Ambiguous

3.3. Research Design and Model Specification

The research design is explanatory, aiming to establish a causal-linkage between the financial predictors (CAMEL ratios) and the categorical outcome (merged vs. existing). To ensure robustness and identify the most potent combination of variables, three distinct prediction models were developed, each utilizing a different set of ratios from the CAMEL framework.

Table 2: Specification of the Three Prediction Models

Model	*Capital Adequacy*	*Asset Quality*	*Management Efficiency*	*Earnings*	*Liquidity*
Model 1	CRAR	Net NPAs/Total Advances	Profit Per Employee	Net Profit/Total Assets	Cash Deposit Ratio
Model 2	RONW	Net NPAs/Total Assets	Return on Assets (ROA)	Net Interest Margin	Int. Expended/Int. Earned
Model 3	CRAR	Net NPAs/Total Advances	Return on Assets (ROA)	Net Profit Margin	Total Inv./Total Deposits

3.4. Analytical Technique: Discriminant Analysis

Discriminant Analysis was chosen as the primary statistical technique for this study. It is particularly suited for classification problems where the dependent variable is categorical (here, Merged vs. Existing) and the independent variables are continuous (financial ratios). Its advantages over other methods like logistic regression include greater stability with smaller sample sizes and the provision of a clear classification function.

The objective of discriminant analysis is to find a linear combination of the independent variables that best separates the two groups. This linear combination, known as the discriminant function, takes the form:

$$\mathbf{Z = a + W_1X_1 + W_2X_2 + \dots + W_nX_n}$$

Where: **Z** is the discriminant Z-score; **a** is the constant (intercept); $\mathbf{W_i}$ are the unstandardized discriminant coefficients (weights); $\mathbf{X_i}$ are the independent variables (financial ratios).

The analysis proceeds through several key steps:

1. **Testing Assumptions:** The analysis assumes multivariate normality of the independent variables and homogeneity of variance-covariance matrices across groups, tested using Box's M test.
2. **Deriving the Function:** The discriminant function is derived, and its significance is assessed using Wilks' Lambda and a associated Chi-square test. An eigenvalue indicates the proportion of variance explained by the function.
3. **Determining the Cutting Score:** The group centroids (mean discriminant scores for each group) are calculated. The cutting score, which is the criterion for classification, is typically the midpoint between these centroids.
4. **Classification:** Each bank in the sample is classified into one of the two groups based on its discriminant score relative to the cutting score. The accuracy of this classification is summarized in a classification matrix, which provides the "hit ratio" – the percentage of correctly classified cases.

All analyses were conducted using the SPSS statistical software package.

3.5. Research Hypotheses

The study tests the following null hypotheses, each corresponding to a component of the CAMEL framework:

- **H1:** Capital Adequacy is not directly linked to the occurrence of bank mergers.
- **H2:** Asset Quality is not directly linked to the occurrence of bank mergers.
- **H3:** Management Efficiency is not directly linked to the occurrence of bank mergers.
- **H4:** Earnings Capability is not directly linked to the occurrence of bank mergers.
- **H5:** Liquidity Capability is not directly linked to the occurrence of bank mergers.

Rejection of a null hypothesis would imply that the respective CAMEL component is a significant predictor of bank mergers.

4. FINDINGS AND ANALYSIS

This section presents the empirical results of the discriminant analysis for the three specified models, followed by a comparative assessment to identify the most effective predictive framework.

4.1. Preliminary Analysis: Group Statistics

The group statistics for all models provided initial insights into the financial characteristics distinguishing merged banks from existing ones. For instance, in Model 1, the mean Capital Adequacy Ratio for existing banks (12.27) was higher than for merged banks (11.56), suggesting that weaker capital buffers are associated with a higher propensity to merge. Similarly, the mean Profit Per Employee was lower for merged banks (0.049) compared to existing banks (0.078), indicating potential inefficiencies in management. Interestingly, the mean Net NPAs to Total Advances ratio was lower for merged banks (4.42) than for existing banks (4.83), a counter-intuitive finding that warrants further investigation in the multivariate analysis.

4.2. Analysis of Model 1

Model 1 utilized CRAR, Net NPAs/Advances, Profit Per Employee, Net Profit/Assets, and the Cash Deposit Ratio.

- **Assumption Check:** Box's M test yielded a significance value of 0.370, which is greater than 0.05, failing to reject the null hypothesis of equal population covariance matrices. This satisfies a key assumption for discriminant analysis.
- **Model Significance:** The canonical correlation for the function was 0.775, indicating that the model explains 60.06% of the variance in the grouping variable. Wilks' Lambda was 0.399 with a significance level of 0.002 ($p < 0.05$), confirming that the model is statistically significant in discriminating between the two groups.
- **Discriminant Function:** Z = -37.469 + 2.800(CRAR) + 0.341(Net NPAs/Advances) - 0.007(Profit Per Employee) - 3.100(Net Profit/Assets) + 0.451(Cash Deposit Ratio)
- **Group Centroids:** The group centroid for merged banks was -1.131, and for existing banks, it was 1.226. The cutting score for classification is the midpoint between these values.

- **Classification Results:** The classification matrix showed that Model 1 correctly classified 10 out of 13 merged banks (76.9%) and 11 out of 12 existing banks (91.7%), yielding an overall hit ratio of **84.0%**.

4.3. Analysis of Model 2

Model 2, which used a different set of ratios (RONW, Net NPAs/Assets, ROA, NIM, and IE/IE), emerged as the most powerful model.

- **Assumption Check:** Box's M test was non-significant (Sig. = 0.314), satisfying the assumption.
- **Model Significance:** The model exhibited a slightly higher canonical correlation of 0.778 (Variance explained = 60.52%). The Wilks' Lambda of 0.395 was the lowest among the three models (p = 0.002), indicating the strongest discriminatory power.
- **Discriminant Function:** Z = -38.192 + 0.205(RONW) + 0.081(Net NPAs/Assets) - 1.651(ROA) + 2.842(NIM) + 0.448(IE/IE)
- **Group Centroids:** The centroid for merged banks was 1.140, and for existing banks, it was -1.235.
- **Classification Results:** Model 2 demonstrated exceptional predictive accuracy. It correctly classified all 13 merged banks (100%) and 10 out of 12 existing banks (83.3%), resulting in a superior overall hit ratio of **92.0%**.

4.4. Analysis of Model 3

Model 3, a hybrid of ratios from the previous models, also performed strongly.

- **Assumption Check:** Box's M test was non-significant (Sig. = 0.206).
- **Model Significance:** The canonical correlation was 0.736 (Variance explained = 54.16%). Wilks' Lambda was 0.458 (p = 0.007), confirming the model's statistical significance, though it was less powerful than Models 1 and 2.
- **Discriminant Function:** Z = -26.984 + 2.240(CRAR) + 0.342(Net NPAs/Advances) - 2.529(ROA) - 0.191(NPM) - 0.028(Investments/Deposits)
- **Group Centroids:** The centroid for merged banks was -1.003, and for existing banks, it was 1.087.
- **Classification Results:** Model 3 correctly classified 11 out of 13 merged banks (84.6%) and 11 out of 12 existing banks (91.7%), giving an overall hit ratio of **88.0%**.

4.5. Comparative Analysis of Model Significance

A direct comparison of the three models is essential to identify the most reliable predictive framework.

Table 3: Comparative Model Performance

Model	*Eigenvalue*	*Wilks' Lambda*	*Sig.*	*Canonical Correlation*	*Classification Accuracy*
1	1.508	0.399	0.002	0.775	84.0%
2	**1.530**	**0.395**	**0.002**	**0.778**	**92.0%**
3	1.185	0.458	0.007	0.736	88.0%

As evidenced in Table 3, **Model 2 is the unequivocal leader**. It possesses the highest eigenvalue (1.530) and the lowest Wilks' Lambda (0.395), signifying the greatest variance between groups and the strongest discriminatory ability. This is corroborated by its stellar classification accuracy of 92.0%, significantly outperforming the other two models. Therefore, Model 2 is established as the optimal model for predicting bank mergers in this context.

4.6. Hypothesis Testing

The results from the discriminant analysis, particularly from the optimal Model 2, allow for a conclusive test of the research hypotheses.

- **H1 (Capital Adequacy):** The variable representing capital adequacy (RONW) was part of the significant Model 2. The null hypothesis is **rejected**. Capital adequacy is directly linked to bank mergers.
- **H2 (Asset Quality):** The variables for asset quality (Net NPAs/Advances and Net NPAs/Assets) were not statistically significant drivers in the final models. The null hypothesis is **not rejected**. Asset quality, as measured, is not directly linked to the occurrence of bank mergers in this sample.
- **H3 (Management Efficiency):** The variables for management efficiency (Profit Per Employee and ROA) were significant in the models. The null hypothesis is **rejected**. Management efficiency is directly linked to bank mergers.
- **H4 (Earnings Capability):** The variables for earnings capability (Net Profit/Assets, NIM, NPM) were significant. The null hypothesis is **rejected**. Earnings capability is directly linked to bank mergers.
- **H5 (Liquidity Capability):** The variables for liquidity (Cash Deposit Ratio and IE/IE Ratio) were significant. The null hypothesis is **rejected**. Liquidity capability is directly linked to bank mergers.

5. DISCUSSION AND CONCLUSION

5.1. Discussion of Key Findings

This study successfully demonstrates that a bank's financial profile, as captured by the CAMEL framework, holds significant predictive power for its likelihood of being involved in a merger. The development of a discriminant model with 92% accuracy (Model 2) is a substantial contribution to the field.

The findings reveal that the journey towards a merger is signalled by a confluence of weaknesses across multiple financial dimensions, rather than a single failing. Banks that were merged typically exhibited:

- **Lower Capital Buffers:** A lower Return on Net Worth suggests an inability to generate adequate returns for shareholders, weakening the bank's intrinsic financial strength and making it a more likely candidate for consolidation.
- **Management Inefficiency:** A lower Return on Assets indicates that the bank's management is not effectively utilizing its asset base to generate profits, a sign of operational inefficiency.
- **Poor Earnings Quality:** A lower Net Interest Margin points to weaknesses in the core lending business, where the spread between interest earned and interest expended is insufficient. This erodes the fundamental profitability of the bank.
- **Ineffective Liquidity Management:** A higher Interest Expended to Interest Earned ratio is a particularly telling indicator. It suggests that the bank is paying out more in interest on its borrowings and deposits than it is earning from its advances, a situation that is unsustainable in the long run and strongly signals financial distress.

The most intriguing finding is the **lack of statistical significance for asset quality** (H2 not rejected). This is counter to conventional wisdom, which often posits high NPAs as the primary reason for bank failures and mergers. This paradox can be interpreted in the context of the Indian public sector banking landscape. During the study period, the NPA crisis was widespread across most PSBs. Therefore, while high NPAs were a systemic problem, the decision to merge a particular bank may have been influenced more acutely by its performance in other areas, such as its core profitability (NIM), operational efficiency (ROA), and liquidity stress (IE/IE ratio). A bank might have high NPAs but still manage a reasonable profit margin and liquidity position, potentially allowing it to survive independently. Conversely, a bank with moderate NPAs but a collapsing interest margin and poor efficiency could be deemed unsustainable. This finding suggests that regulators and policymakers might prioritize operational sustainability over asset quality alone when making merger decisions.

5.2. Theoretical and Practical Implications

Theoretically, this study enriches the literature on bank distress and consolidation by validating the CAMEL framework as a robust predictive tool, while also refining it by highlighting that not all components carry equal weight in the context of merger prediction. It underscores the importance of a multi-dimensional assessment of bank health.

From a practical standpoint, the implications are profound:

- **For Regulators (RBI, Government):** Model 2 can be deployed as an early warning system. By calculating the discriminant Z-score for banks annually, regulators can identify institutions that are drifting towards the "merged bank" profile. This allows for timely corrective actions, such as targeted recapitalization, management overhaul, or structured consolidation planning, thereby minimizing systemic risk.
- **For Bank Management:** The model provides a clear diagnostic checklist. Banks can benchmark their ratios against the model's centroids to self-assess their vulnerability. A low Z-score would signal an urgent need to improve profitability, operational efficiency, and liquidity management to avoid being forced into a merger.
- **For Investors and Analysts:** The framework offers a powerful tool for fundamental analysis. Investors can use it to gauge the merger risk associated with a bank's stock, which has direct implications for its valuation and risk premium.

5.3. Limitations and Avenues for Future Research

Despite its robust findings, this study has certain limitations. First, the sample is restricted to Indian public sector banks. The model's generalizability to private sector banks, smaller cooperative banks, or banking sectors in other countries needs to be validated. Second, the study relies solely on financial ratios. The predictive power could be enhanced by incorporating non-financial variables such as the size of the bank, quality of corporate governance, regulatory changes, and macroeconomic factors. Third, the study uses a dichotomous classification (merged/existing). Future research could employ a multinomial approach to distinguish between acquiring banks, target banks, and standalone banks.

Future studies could replicate this model in different national contexts, incorporate dynamic panel data analysis to track the evolution of a bank's Z-score over time, and integrate machine learning algorithms like support vector machines or random forests to see if predictive accuracy can be further improved.

5.4. Conclusion

In conclusion, this research establishes that the probabilistic prediction of bank mergers is not only feasible but can be achieved with a high degree of accuracy using a well-specified discriminant model based on the CAMEL framework. The findings confirm that bank mergers are precipitated by a syndrome of financial weaknesses, particularly in capital adequacy, management efficiency, earnings, and liquidity, rather than by poor asset quality alone. The developed model, with its 92% classification accuracy, provides a valuable decision-support tool for a wide range of stakeholders in the banking ecosystem. As the global banking industry continues to consolidate, the ability to foresee such structural changes becomes ever more critical, and this study offers a significant step forward in that direction.

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