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Performance of Banks' Asset Liability Management Strategies: A Practical Approach with Machine Learning

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Abstract


This research examines the performance of banks' Asset Liability Management (ALM) strategies using Data Envelopment Analysis (DEA) to improve bank efficiency and estimate the efficiency scores of emerging banks. ALM is an essential process for financial institutions to manage their assets and obligations effectively, ensuring profitability, liquidity, and risk oversight, while DEA offers a comprehensive methodology for evaluating and comparing the efficiency of Decision-Making Units (DMUs). By utilizing DEA in the context of ALM, this research seeks to uncover inefficiencies and recommend optimization strategies. The results reveal considerable differences in efficiency levels, underscoring potential improvement areas and best practices. This study adds to the existing literature by illustrating the practical use of DEA in ALM and providing actionable insights for banks to boost their performance.

Keywords: Asset liability management, Machine learning, Performance evaluation, Profitability.

1 | Introduction

Asset Liability Management (ALM) is a pivotal function within financial institutions, focusing on the optimization of the balance between assets and liabilities. Effective ALM is crucial for maintaining financial stability, ensuring liquidity, and maximizing profitability. Banks employ various strategies and tools to manage and mitigate the risks associated with mismatches between assets and liabilities [1]. The primary goal of ALM is to manage the risks arising from the mismatch between assets and liabilities, ensuring profitability, liquidity, and solvency [2]. Data Envelopment Analysis (DEA) is a widely used non-parametric method in operations research and economics for measuring the efficiency of Decision-Making Units (DMUs) [3], [4]. DEA evaluates the relative efficiency of entities by comparing their input-output ratios, providing a comprehensive assessment of performance. DEA is used to measure the efficiency of DMUs, such as banks or financial

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portfolios, by comparing their performance relative to each other [5]. The integration of DEA into ALM offers a novel approach to identifying inefficiencies and enhancing resource allocation.

Despite the critical importance of ALM, many financial institutions struggle with inefficiencies and suboptimal performance [6]. Traditional methods for evaluating ALM practices often fall short of providing a holistic view of efficiency. This study addresses this gap by applying DEA to assess the efficiency of ALM strategies in financial institutions, aiming to identify areas for improvement and optimization [7].

The main objectives of this study are to:

- I. Evaluate the efficiency of ALM practices in financial institutions using DEA.
- II. Identify inefficiencies and provide actionable recommendations for improvement.
- III. Demonstrate the practical application of DEA in optimizing ALM practices.
- IV. Predict the efficiency score of new financial institutions by ML and ANN.

This study contributes to the existing literature by offering a comprehensive analysis of ALM efficiency through the lens of DEA. By highlighting best practices and areas for enhancement, the findings can help financial institutions achieve better financial stability and profitability. Furthermore, this study showcases the practical utility of DEA as a valuable tool for ALM optimization. Also, regression prediction [5], [9] and neural network of test set performance based on the training set under different classification combinations are performed.

The rest of this paper is structured as follows. The Problem formulation is explained in Section 2. Section 3 includes experimental testing of the methodology.

2 | Problem Formulation

In this section, we shall formulate the optimal investment problem based on the asset-liability ratio.

2.1 | The Dynamics of Assets and Liabilities

Suppose that an investor can allocate his/her wealth within the time horizon $[0, T]$ in banks. These assets are risk-free assets (cash) and a default-free zero-coupon bond (treasury bond). The price process of the risk-free asset is given by

$$dB_t = rB_t dt.$$

The price process of a default-free zero-coupon bond (treasury bond) is given by $dS(t) = S(t)(\mu dt + \sigma dW(t))$.

$W(t)$ is the Winner process or Brownian motion, where μ and σ are constants. geometric brownian motion is used to model the liability process [8]. To be specific, the accumulative liability process $L(t)$ is described by

$$dL(t) = L(t)(\alpha dt + \beta dW(t)).$$

2.2 | Performance of Banks' ALM Strategies

- I. Profitability:
 - *Interest spread: this is the difference between the interest earned on assets (like loans) and the interest paid on liabilities (like deposits). A higher interest spread indicates better profitability.*
 - *Net profit margin: this ratio measures the percentage of revenue left after all expenses, taxes, and stock dividends have been deducted.*

II. Liquidity:

- *Current ratio: this ratio measures a bank's ability to pay short-term obligations. A higher current ratio indicates better liquidity.*
- *Quick ratio: also known as the acid-test ratio, it measures a bank's ability to meet short-term liabilities with its most liquid assets.*

III. Risk management:

- *Capital adequacy ratio: this ratio measures a bank's capital in relation to its risk-weighted assets. A higher ratio indicates better risk management.*
- *Credit deposit ratio: this ratio indicates how much a bank lends out of the deposits it has mobilized. A higher ratio suggests better utilization of deposits for lending.*

IV. Efficiency:

- *Operating expenses to total income: this ratio measures the efficiency of a bank in managing its operating expenses relative to its total income.*

2.2.1 | Recommendations

Improve net profit margin: the bank should focus on curtailing expenses and enhancing value-added services to improve the net profit margin.

Control operating expenses: the bank should implement better management practices to control operating expenses and improve the current ratio.

Monitor short-term liquidity: the bank should closely monitor and manage short-term liquidity to ensure financial stability.

By analyzing these performance metrics, banks can optimize their ALM strategies to achieve better profitability, liquidity, and risk management.

2.3 | Integration of DEA and ALM

DEA was employed to assess the efficiency of ALM practices in the selected financial institutions. The DEA model used in this study is the input-oriented Charnes, Cooper, and Rhodes (CCR) model. The input variables include total assets and total liabilities [10], while the output variables consist of net income, Return on Assets (ROA), and Return on Equity (ROE) [11]. The choice of inputs and outputs is based on their relevance to ALM and their ability to reflect the financial performance of the institutions.

The integration of DEA, ALM and ML might look like this:

Step 1. Define the study's objective, such as improving the efficiency of ALM in a set of banks and Predicting the Efficiency Score.

Step 2. Collect data on the bank's assets, liabilities, and other financial metrics.

Step 3. Select a DEA model, for example, a CCR or BCC model and define the inputs (e.g., risk measures) and outputs (e.g., returns).

Step 4. Calculate the efficiency scores for each bank using the DEA model.

Step 5. Analyze the efficiency scores to evaluate the performance of the banks' ALM strategies.

Step 6. Provide recommendations for improving the ALM practices based on the DEA results.

Step 7. Predict the efficiency score for a new financial institution.

By integrating DEA and ALM, the study can provide valuable insights into the efficiency of financial institutions' ALM practices and identify opportunities for optimization.

3 | Empirical Application

This section encompasses the presentation of the data, the execution of empirical analysis, and the subsequent interpretation of the results.

Step 1. Data collection.

Let's assume we have data from 12 banks over one year. The data includes the following variables: Assets (in millions), Liabilities (in millions), Net Interest Income (in millions), ROE (in millions).

Table 1. Asset liability management performance metrics of banks.

number	Assets(A)	Liabilities(L)	Net Interest Income (NII)	Return on Equity(ROE)	Efficiency_Score
1	200	190	90	43	1.0
2	190	231	87	50	1.0
3	250	160	67	55	1.0
4	270	168	70	34	0.7
5	220	158	94	50	1.0
6	550	255	69	38	0.47
7	330	235	85	23	0.61
8	310	206	79	45	0.68
9	300	244	93	40	0.71
10	500	268	88	50	0.55
11	530	306	82	45	0.46
12	380	284	90	45	0.56

Step 2. Calculate efficiency scores.

We use the CCR model in DEA to evaluate the efficiency of each bank. The inputs for DEA are Assets (A) and Liabilities (L), and the outputs are Net Interest Income (NII) and ROE.

Step 3. Machine learning integration.

We use Machine Learning (linear regression) to predict the efficiency of new banks based on their assets and liabilities.

I. Training data.

- Inputs: assets (A) and Liabilities (L).
- Output: efficiency Score.
- Train the model using the data from 10 banks.

Table 2. Efficiency assessment of banks based on asset-liability management.

Assets	Liabilities	Efficiency_Score
200	190	1.0
190	231	1.0
250	160	1.0

Table 2. Continued.

Assets	Liabilities	Efficiency_Score
270	168	0.7
220	158	1.0
550	255	0.47
330	235	0.61
310	206	0.68
300	244	0.71
500	268	0.55

II. Machine learning model.

- Use a regression model (e.g., Linear Regression) to predict efficiency scores.

III. Testing the model.

- Test the model using the data from 2 Bank.

Table 3. Predicted efficiency scores using linear regression.

Assets	Liabilities	Efficiency_Score	Linear Regression
530	306	0.46	0.44673652
380	284	0.5 [^]	0.60680667

IV. Evaluate Mean Square Error

Table 4. Model Performance Evaluation for Efficiency Prediction.

Method	Test Data (MSE)	Train Data (MSE)
Linear Regression	0.026273861200117307	0.009094697293406142

4 | Prediction

Using the trained model, predict the efficiency score for new Banks.

Table 5. Predicted efficiency scores for new banks.

New Banks	Assets	Liabilities	Linear Regression
1	400	390	0.6557029284
2	350	340	0.87683615

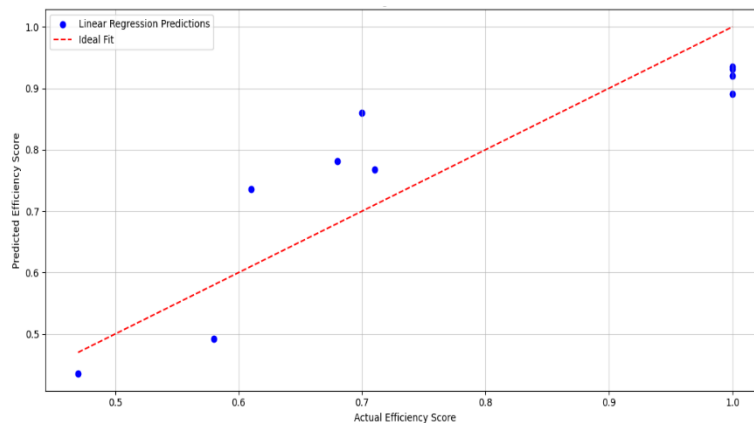


Fig. 1. Linear regression predictions vs actual efficiency scores.

6 | Conclusion

This study demonstrates the synergy of ALM, DEA and ML in evaluating and optimizing the efficiency of banks. By integrating DEA to assess and benchmark ALM strategies, actionable recommendations were provided to enhance financial performance. The inclusion of ML offers an innovative approach to predicting efficiency scores for new banks, further emphasizing the practical applications of this methodology. The findings underscore the importance of efficient resource allocation, risk mitigation, and strategic optimization within the banking sector. By addressing inefficiencies and leveraging predictive analytics, financial institutions can achieve greater stability, profitability, and competitiveness in an ever-evolving market. This study not only contributes to the existing literature but also opens avenues for future research in expanding these methodologies to other financial domains.

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Author Contributions

Shokoofeh Banihashemi: conceptualization, methodology, data analysis, writing – original draft.

Reza Kazemi: supervision, review & editing, validation, funding acquisition.

All authors have reviewed and approved the final version of the manuscript.

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Data Availability

The data utilized in this study can be obtained upon reasonable request from the corresponding author.

References

- [1] Peykani, P., Sargolzaei, M., Botshekan, M. H., Oprean-Stan, C., & Takaloo, A. (2023). Optimization of asset and liability management of banks with minimum possible changes. *Mathematics*, 11(12), 2761. <https://doi.org/10.3390/math11122761>
- [2] Aahmadyan, A. (2018). The effect of macroeconomic variables on asset and liability management. *Quarterly studies in banking management and islamic banking*, 4(2), 141-172. (In Persian). https://jifb.ibi.ac.ir/article_85166.html?lang=en
- [3] Basso, A., & Funari, S. (2001). A data envelopment analysis approach to measure the mutual fund performance. *European journal of operational research*, 135(3), 477-492. [https://doi.org/10.1016/S0377-2217\(00\)00311-8](https://doi.org/10.1016/S0377-2217(00)00311-8)
- [4] Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European journal of operational research*, 2(6), 429-444. [https://doi.org/10.1016/0377-2217\(78\)90138-8](https://doi.org/10.1016/0377-2217(78)90138-8)
- [5] Zahedi-Seresht, M., Khosravi, S., Jablonsky, J., & Zykova, P. (2021). A data envelopment analysis model for performance evaluation and ranking of DMUs with alternative scenarios. *Computers & industrial engineering*, 152, 107002. <https://doi.org/10.1016/j.cie.2020.107002>
- [6] Berger, A., Hunter, W., & Timme, S. (1993). The efficiency of financial institutions: a review and preview of research past, present and future. *Journal of banking & finance-j bank finan*, 17, 221-249. [http://dx.doi.org/10.1016/0378-4266\(93\)90030-H](http://dx.doi.org/10.1016/0378-4266(93)90030-H)

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- [7] Willa, K., Zawadzka, D., & Strzelecka, A. (2022). Examples of the use of data envelopment analysis (DEA) to assess the financial effectiveness of insurance companies. *Procedia computer science*, 207, 3924–3930. DOI:10.1016/j.procs.2022.09.454
- [8] Zhang, Z., Xiao, Y., & Niu, H. (2022). DEA and machine learning for performance prediction. *Mathematics*, 10, 1776. <http://dx.doi.org/10.3390/math10101776>
- [9] Michaud, R. O., & Ma, T. (2001). Efficient asset management: a practical guide to stock portfolio optimization and asset allocation. *The review of financial studies*, 14(3), 901–904. <https://doi.org/10.1093/rfs/14.3.901>
- [10] Indeed editorial team. (2025). *How to calculate total assets (with examples)*. <https://B2n.ir/ny1081>
- [11] Mohd Heikal, Muammar Khaddafi, A. U. (2014). Influence analysis of return on assets (ROA), return on equity (ROE), net profit margin (NPM), debt to equity ratio (DER), and current ratio (CR), against corporate profit growth in automotive in indonesia stock exchange. *International journal of academic research in business and social sciences*, 4(12), 101–114. <http://dx.doi.org/10.6007/IJARBS/v4-i12/1331>