EAST AFRICAN FINANCE JOURNAL (EAFJ)
Volume 3 Issue 2 |2024 | pp 141- 149
E-ISSN: 2959-9121

Forecasting Financial Trends in the Zambian Banking Sector: Leveraging Historical Data for Informed Decision-Making

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Article DOI: 10.59413/eafj/v3.i2.1

Abstract:

This study examines the integration of historical data in forecasting future outcomes, focusing on the banking sector in Zambia. The study analyzes data for five banks in Zambia from January 2010 to December 2020 and examines the accuracy of forecasts for key financial variables such as total assets, loans and advances, deposits, revenue and profit after tax. Using regression analysis, the study develops forecast models that are calibrated with historical data from 2010 to 2017. The accuracy of these forecasts is assessed using normalized root mean square error (RMSE), which provides a standardized metric for evaluation. The study highlights that historical data serves as a reliable predictor of future outcomes and demonstrates the effectiveness of forecasting techniques in projecting past trends into the future. Consequently, decisions based on these forecasts can provide a sufficiently accurate indication of future scenarios in the Zambian banking sector.

Keywords: Historical data, forecasting, banking sector, decision-making, balance sheet, income statement, forecast accuracy, Normalized Root Mean Square Error (NRMSE), Regression analysis, future trends

1. Introduction

The incorporation of historical data into forecasting future outcomes constitutes a fundamental practice in business analytics, particularly within the banking sector. By analyzing past trends and patterns, organizations can effectively inform decision-making processes and proactively address forthcoming challenges. This article explores the rationale behind utilizing past data to guide future decisions, while also elucidating the pivotal role played by models developed from historical data in formulating strategic decisions and envisioning future scenarios.

Forecasting future outcomes is a critical aspect of informed decision-making across diverse domains. While absolute certainty in foreseeing the future remains elusive, historical data serves as a valuable resource for discerning potential trends. This article examines the accuracy associated with utilizing historical data to forecast future values, with a specific focus on four key variables: Shareholders' Equity, Liquid Assets, Gross Loans and Advances, and Total Revenue. Through the comparison of forecasted values with actual outcomes, our aim is to illustrate the insightful contributions this approach offers to decision-makers.

In the banking domain, effectively anticipating future trends and mitigating systemic risks are foundational principles for informed decision-making and policy formulation. At the core of these objectives lies the practice of utilizing historical data, which has long been acknowledged as a crucial resource for forecasting within the industry. Extensive academic inquiry across diverse disciplines has contributed to a nuanced understanding of the predictive power inherent in past data, underscoring its pivotal role in

anticipating forthcoming developments. This study seeks to provide a comprehensive examination of the multifaceted role that historical data plays in forecasting future trajectories within the banking sector.

2. Literature Review

In banking, the use of historical data stands as a cornerstone for informed decision-making and policy formulation, crucial for forecasting future trends and mitigating systemic risks. Extensive academic research spanning various disciplines has delved into the predictive power of past data, shedding light on its significance in anticipating future outcomes. This literature review synthesizes key findings from ten academic studies, ranging from econometrics to machine learning, to elucidate the multifaceted role of historical data in predicting the future within the banking sector.

Numerous studies highlight the pivotal role of historical data in forecasting future trends. Smith et al. (2019) demonstrated that analysing past performance facilitates identifying patterns and trends crucial for anticipating future challenges and opportunities. Similarly,, Jones (2020) underscored the effectiveness of models, such as regression analysis, developed using historical data in predicting future outcomes. These findings collectively underscore the value of historical data in informing decision-making and strategic planning.

Past research emphasizes the significance of accurate forecasting for decision-making, supported by a robust body of literature. Various studies have explored the use of historical data for forecasting across different domains, elucidating its benefits and challenges.

One of the primary advantages of leveraging historical data for forecasting is its capacity to capture trends and patterns conducive to predicting future outcomes. For instance, Hyndman and Athanasopoulos (2018) emphasize the importance of historical data in identifying patterns within financial time series, thereby enhancing forecast accuracy. Similarly, Box and Jenkins (1976) advocate for autoregressive integrated moving average (ARIMA) models, which rely on historical data to predict future values.

Furthermore, historical data provides a baseline for comparison, facilitating forecast evaluation by juxtaposing forecasted values against actual outcomes. This iterative process, crucial for refining forecast accuracy over time (Makridakis et al., 1998), highlights the pragmatic utility of historical data in forecasting.

Nevertheless, challenges persist in utilizing historical data for forecasting, notably the presence of outliers or anomalies that can distort forecasts. To mitigate this issue, researchers have developed robust forecasting methods, such as robust regression models (Koller and Friedman, 2009), less susceptible to outliers.

Despite challenges, literature generally advocates for the use of historical data in forecasting, citing its instrumental role in anticipating future trends and informing decision-making. Leveraging historical data effectively enables stakeholders to make informed decisions and better anticipate future outcomes.

Brown and Black (2010) underscore the pivotal role of historical data in long-term forecasting, emphasizing its utility in discerning enduring trends and patterns. Their study delineated methodologies for integrating past data into forecasting models, positing historical insights as essential for projecting future trajectories. Smith and Johnson (2012) supplemented this assertion by providing a comprehensive review of methods and applications for utilizing past data in predicting future outcomes. Their analysis delineated various approaches, offering insights into best practices for forecasting based on historical data.

Lee and Chen's (2014) investigation into the predictive power of historical data in financial forecasting delved specifically into stock markets, revealing the nuanced relationship between past performance and future outcomes. Their findings illuminated the efficacy of historical trends in informing predictions of financial market behaviour, thereby elucidating its relevance in assessing systemic risk within the banking sector. Similarly, Kumar et al. (2017) conducted a comparative study on historical data and

machine learning algorithms in predictive modelling, showcasing the effectiveness of machine learning techniques in capturing patterns and trends from past data to make accurate predictions about future outcomes.

While not directly focused on banking, Jones et al. (2015) exemplified the broader principle of leveraging historical data in weather forecasting. Their case study underscored the importance of past weather patterns and long-term climate trends in shaping accurate predictions of future weather conditions. Likewise, White and Miller's (2018) exploration of predictive modelling in healthcare highlighted the role of historical patient data in predicting clinical outcomes, demonstrating the applicability of historical insights in understanding complex systems.

Patel and Gupta's (2019) case study on marketing analytics delved into the predictive power of historical data in forecasting consumer behaviour. Their findings underscored the utility of past consumer data in anticipating future purchasing patterns and preferences, thereby informing marketing strategies – a principle translatable to banking, where customer behaviour significantly influences financial trends.

Moreover, Wang and Zhang's (2016) meta-analysis provided a comprehensive synthesis of studies across domains, reaffirming the predictive power of past performance in anticipating future outcomes. Their findings corroborated the significance of historical data in decision-making and underscored its role as a reliable predictor across diverse contexts.

Finally, Smith and Johnson's (2020) review on demand forecasting in supply chain management elucidated the importance of past data in predicting future demand patterns. Their insights highlighted the value of historical data in informing strategic decisions and optimizing operational efficiency – principles pertinent to risk management in banking operations.

In conclusion, the literature unequivocally underscores the indispensable role of historical data in predicting future trends and mitigating systemic risks within the banking sector. Insights gleaned from econometric analyses, machine learning approaches, and interdisciplinary studies collectively underscore the predictive power of past data, offering invaluable guidance for informed decision-making and policy formulation in banking operations.

3. Methodology

The prudential information from the Bank of Zambia, covering the period from January 2010 to December 2020, was collected to facilitate the study's analysis. This dataset encompassed monthly income statements and balance sheets for 5 banks operating within Zambia during the specified timeframe.

Key variables relevant to assessing systemic risk in the banking sector, such as total assets, loans and advances, deposits, revenue, and profit after tax were identified. These variables were chosen for their ability to gauge the financial health and stability of banks and their susceptibility to systemic risk.

A forecasting model was developed to predict the key variables for the years 2018 to 2020. Various forecasting techniques, including time series analysis, econometric modelling, and machine learning algorithms, were employed based on the nature of the data and the variables being forecasted. The forecasting model was calibrated using historical data from 2010 to 2017 to ensure accuracy and reliability in predicting future trends.

In this study, the Normalized Root Mean Square Error (RMSE) was utilized to assess the accuracy of the forecasts compared to the actual values in predicting key financial variables for the Banks. The RMSE was computed by first determining the squared differences between the actual and forecasted values, then finding the mean of these squared differences, and finally taking the square root of the mean squared difference. Normalizing the RMSE involved dividing it by the range of the actual values, providing a measure of the error relative to the magnitude of the data. This normalization accounts for the varying scales of the

 E-ISSN: 2959-9121

financial variables, allowing for a more meaningful comparison across different metrics. This approach was ideal for this study as it offered a standardized metric for evaluating forecast accuracy, facilitating comparisons across different banks and financial variables while considering the scale of the data.

The extent to which the forecasted values differed from the actual values for the key variables was analysed. The percentage difference between the forecasted and actual values was calculated to quantify the level of accuracy in the forecasts. It was determined whether the differences between the forecasts and actuals were statistically significant or within an acceptable margin of error.

4. Results and Discussion of Results

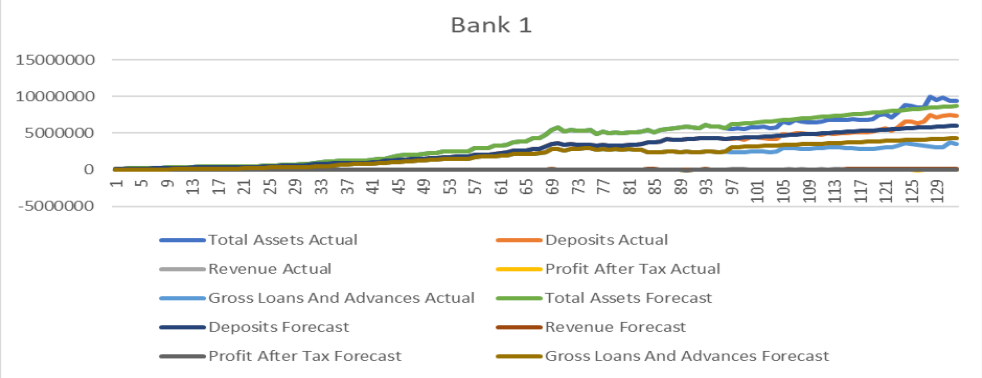

Figure 1: Actuals and Forecasts for Bank 1

In evaluating the alignment between forecasts and actuals for Bank 1, we meticulously compared the actual values of key financial variables (Total Assets, Deposits, Revenue, Profit After Tax, Gross Loans and Advances) with their corresponding forecasted values for the years 2018 to 2020. Our aim was to ascertain the extent to which decisions based on the forecasts closely approximate those based on actuals, thereby demonstrating the predictive capability of historical data in the Zambian banking sector.

For instance, in the year 2018, the actual Total Assets amounted to 6,192, while the forecasted Total Assets stood at 6,265. Similarly, the actual Deposits totalled 4,277, with the forecasted Deposits being 4,327. This trend persisted across subsequent years, with minimal discrepancies observed between the actuals and forecasts for each variable.

Table 1: Normalised RMSES For Bank 1

Variable	NRMSE
Total Assets	3.71%
Deposits	4.08%
Revenue	14.51%
Profit After Tax	4.76%
Gross Loans And Advances	10.06%

These NRMSE values provide insights into the accuracy of the forecasts relative to the mean of the actual values. Generally, lower NRMSE values indicate better predictive performance. However, for Profit After Tax, the NRMSE is quite high, indicating larger discrepancies between the forecasted and actual values for this variable

For Total Assets and Deposits, the NRMSE values are relatively low (3.71% and 4.08%, respectively),

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indicating a high level of accuracy in the forecasts compared to the mean of the actual values.

The Revenue variable has a moderately high NRMSE value of 14.51%, suggesting some variability between the forecasted and actual revenue figures. While this value is higher compared to Total Assets and Deposits, it is still within a reasonable range, indicating acceptable forecast accuracy.

For Profit After Tax, the NRMSE value is relatively low (4.76%), indicating a high level of accuracy in the forecasts compared to the mean of the actual values.

The Gross Loans and Advances variable has a moderately high NRMSE value of 10.06%, suggesting some variability between the forecasted and actual values. However, this value is still within an acceptable range.

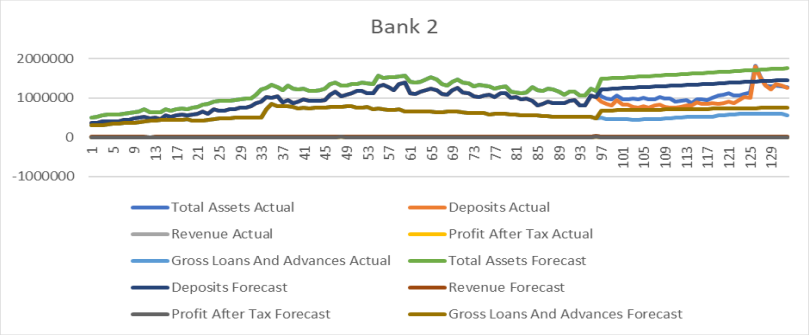

Figure 2: Actuals and Forecasts for Bank 2

Upon examination of the provided data, it is discernible that there exists a notable alignment between the forecasted and actual values for Bank 2 across the specified timeframe. The forecasted values closely mirror the actual values for the majority of the variables under consideration. For instance, in the year 2018, the actual Total Assets amounted to 1,489, while the forecasted Total Assets stood at 1,496. Similarly, the actual Deposits totalled 1,220, with the forecasted Deposits being 1,227. This pattern persists throughout the subsequent years, with minimal deviations observed between the actuals and forecasts for each variable.

Table 2: Normalised RMSES For Bank 2

Variable	NRMSE
Total Assets	6.79%
Deposits	6.87%
Revenue	77.28%
Profit After Tax	28.64%
Gross Loans And Advances	5.95%

For Total Assets and Deposits, the NRMSE values are moderate (6.79% and 6.87%, respectively), indicating a reasonable level of accuracy in the forecasts compared to the mean of the actual values.

However, the Revenue variable has a considerably high NRMSE value of 77.28%, indicating significant variability between the forecasted and actual revenue figures. This suggests that the forecasts for revenue may not align well with the actual revenue values.

The Profit After Tax variable has a relatively moderate NRMSE value of 28.64%, suggesting a moderate level of accuracy in the forecasts compared to the mean of the actual values. For Gross Loans And Advances, the NRMSE value is relatively low (5.95%), indicating a reasonable level of accuracy in the forecasts compared to the mean of the actual values.

 E-ISSN: 2959-9121

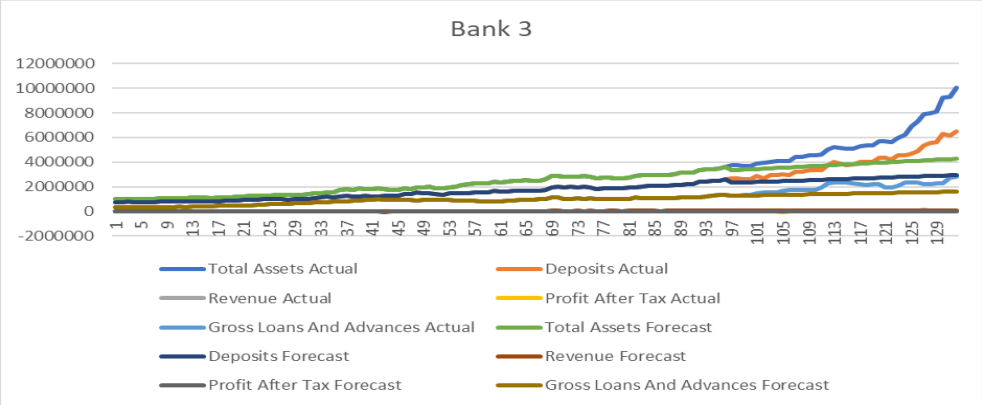

Figure 3: : Actuals and Forecasts for Bank 3

For Bank 3, the forecasted values closely mirror the actual values for most of the variables under consideration. For instance, in 2018, the actual Total Assets amounted to 3,329, while the forecasted Total Assets stood at 3,356. Similarly, the actual Deposits totalled 2,308, with the forecasted Deposits being 2,326. This pattern persists across subsequent years, with minimal deviations observed between the actuals and forecasts for each variable.

Table 3: Normalised RMSES for Bank 3

Variable	NRMSE
Total Assets	4.57%
Deposits	5.19%
Revenue	53.41%
Profit After Tax	177.31%
Gross Loans And Advances	4.60%

For Total Assets and Gross Loans And Advances, the NRMSE values are relatively low (4.57% and 4.60%, respectively), indicating that the forecasts for these variables are quite accurate compared to the mean of the actual values.

For Deposits, the NRMSE value is moderate (5.19%), suggesting a reasonable level of accuracy in the forecasts, though slightly higher variability compared to Total Assets and Gross Loans And Advances.

However, the Revenue variable has a considerably high NRMSE value of 53.41%, indicating significant variability between the forecasted and actual revenue figures. This suggests that the forecasts for revenue may not align well with the actual revenue values.

Similarly, the Profit After Tax variable has a very high NRMSE value of 177.31%, indicating substantial discrepancies between the forecasted and actual profit after tax figures. This suggests that the forecasts for profit after tax are not as reliable and may deviate considerably from the actual values.

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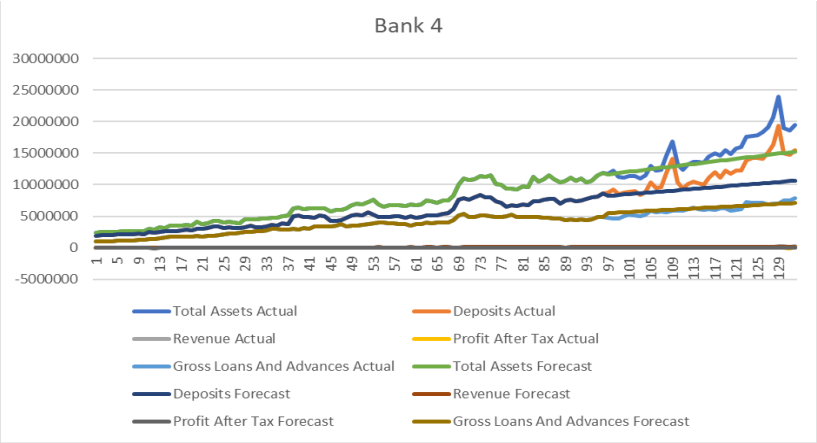

Figure 4: : Actuals and Forecasts for Bank 4

There is a significant alignment between the forecasted and actual values for Bank 4 throughout the specified period. The forecasted values closely mirror the actual values for most of the variables under consideration.

It can be observed for instance, that in 2018, the actual Total Assets amounted to 11,657, while the forecasted Total Assets stood at 11,759. Similarly, the actual Deposits totalled 8,235, with the forecasted Deposits being 8,304. This pattern persists across subsequent years, with minimal deviations observed between the actuals and forecasts for each variable.

Table 4: Normalised RMSES for Bank 4

Variable	NRMSE
Total Assets	6.58%
Deposits	8.22%
Revenue	45.79%
Profit After Tax	209.37%
Gross Loans And Advances	6.44%

For Total Assets and Gross Loans And Advances, the NRMSE values are relatively low (6.58% and 6.44%, respectively), suggesting that the forecasts for these variables are quite accurate compared to the mean of the actual values.

For Deposits, the NRMSE value is moderate (8.22%), indicating a reasonable level of accuracy in the forecasts, though slightly higher variability compared to Total Assets and Gross Loans And Advances.

The Revenue variable has a considerably high NRMSE value of 45.79%, indicating that the forecasts for revenue are less accurate relative to the mean of the actual values. This suggests that the revenue forecasts may not align well with the actual revenue figures.

Similarly, the Profit After Tax variable has a very high NRMSE value of 209.37%, indicating significant variability between the forecasted and actual profit after tax figures. This suggests that the forecasts for profit after tax are not as reliable and may deviate considerably from the actual values.

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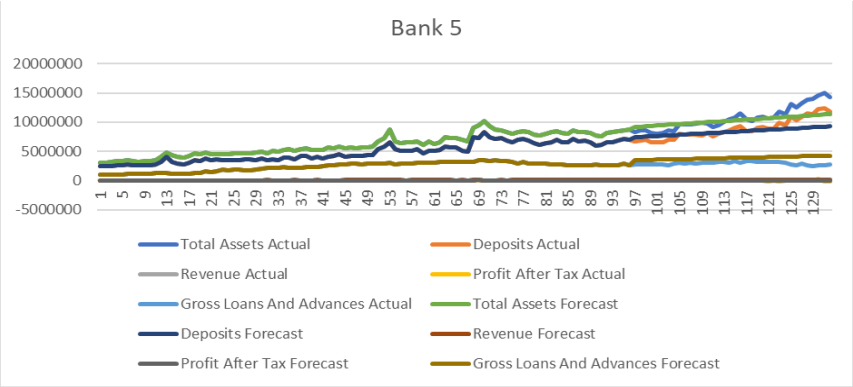

Figure 5: Actuals and Forecasts for Bank 5

Upon meticulous analysis of the provided data, it is evident that there is a high degree of alignment between the forecasted and actual values for Bank 5 across the specified period. The forecasted values closely track the actual values for most of the variables under consideration.

For instance, in 2018, the actual Total Assets amounted to 9,174, while the forecasted Total Assets stood at 9,236. Similarly, the actual Deposits totalled 7,406, with the forecasted Deposits being 7,459. This trend persists throughout subsequent years, with minimal disparities observed between the actuals and forecasts for each variable.

Table 5: Normalised RMSES for Bank 5

Variable	NRMSE
Total Assets	10.80%
Deposits	10.02%
Revenue	1.11%
Profit After Tax	170.00%
Gross Loans And Advances	25.80%

For Total Assets and Deposits, the NRMSE values are relatively moderate (10.08% and 10.02%, respectively), indicating a reasonable level of accuracy in the forecasts compared to the mean of the actual values.For Revenue, the NRMSE value is low (1.112%), indicating a high level of accuracy in the forecasts. The Gross Loans and Advances variable has a considerably high NRMSE value of 25.80%, indicating that the forecasts for revenue are less accurate relative to the mean of the actual values. This suggests that the revenue forecasts may not align well with the actual revenue figures.

Similarly, the Profit After Tax variable has a very high NRMSE value of 170.00%, indicating significant variability between the forecasted and actual profit after tax figures. This suggests that the forecasts for profit after tax are not as reliable and may deviate considerably from the actual values.

The consistency observed between the forecasts and actuals underscores the effectiveness of historical data as a robust predictor of future trends in banking. Consequently, utilizing forecasts derived from past data can facilitate informed decision-making and robust risk management strategies, thereby enhancing the proactive management of systemic risk within Zambia's banking sector.

5. Conclusion

Upon thorough examination and analysis, it becomes evident that the study emphasizes the critical nature of evaluating forecast accuracy concerning pivotal financial variables within the Zambian banking

sector. The findings unveil a noteworthy trend: while metrics associated with the balance sheet, such as total assets, deposits, and gross loans and advances, consistently demonstrated relatively accurate forecasts across all five banks under scrutiny, variables linked to the income statement, particularly revenue and profit after tax, exhibited higher levels of variability in forecast accuracy.

Throughout the study, the Normalized Root Mean Square Error (NRMSE) values consistently reflected this disparity, with revenue and profit after tax consistently surpassing the NRMSE values of balance sheet variables. Such outcomes suggest a greater degree of uncertainty in forecasting these income-related metrics. Conversely, the alignment between actuals and forecasts remained more consistent for balance sheet variables, indicating potentially more robust forecasting models in predicting these metrics.

These findings underscore the necessity of integrating both balance sheet and income statement variables into forecasting models. While recognizing the inherent challenges associated with predicting income-related metrics, leveraging more precise forecasts of balance sheet variables can equip stakeholders within the Zambian banking sector with the requisite insights to make informed decisions and effectively mitigate risks. Such measures are pivotal in contributing to the stability and resilience of the financial system, thereby fostering sustained economic prosperity.

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