International Journal of Banking, Risk and Insurance
12 (2) 2024, 29-45
http://publishingindia.com/ijbri/
doi: https://doi.org/10.21863/ijbri/2024.12.2.003

Submitted: 10 October, 2023
Accepted: 12 October, 2023

Informing Policy and Strategy: The Nexus of Macroeconomic Indicators and Financial Metrics in North Macedonia

Bojan Malchev*, Violeta Cvetkoska, Marina Trpeska*****

Abstract

This study employs machine learning and exponential smoothing techniques in Power BI to analyse the relationship between financial indicators and macroeconomic variables in North Macedonia. By rigorously examining correlations and forecasting tools for exponential smoothing, it uncovers a significant relationship between unemployment rates and the financial performance of banks. Positive correlations indicate that higher unemployment rates strengthen banks' financial resilience, while negative correlations highlight challenges during periods of elevated unemployment. Furthermore, it identifies key influencers affecting the unemployment rate, enhancing forecasting insights. The paper forecasts North Macedonia's average annual unemployment rate for 2022-2026, complete with a 95% confidence interval. These forecasts empower policymakers, researchers, and stakeholders with precise economic navigation tools. This research is vital for informed decision-making and strategic planning, benefiting policymakers, investors, and financial institutions. It also calls for deeper exploration of macroeconomic and financial metric relationships, promising improved forecasting and decision-making capabilities.

Keywords: Financial Indicators, Macroeconomic Indicators, Exponential Smoothing, Machine Learning, Regression Analysis, Forecasting

Introduction

The accurate forecasting of macroeconomic indicators is crucial for policymakers, investors, and financial institutions to make informed decisions and navigate the dynamic economic landscape. In embarking on this research endeavour, it was evident that a notable gap existed in the literature regarding the nexus of macroeconomic indicators and financial metrics specific to North Macedonia. Prior studies in this domain have predominantly focused on broader global contexts or have been limited in their scope, often neglecting the unique economic landscape of this region. Thus, this study aims to fill this critical void by conducting a comprehensive analysis that specifically targets North Macedonia.

This study focuses on the forecasting of macroeconomic indicators in North Macedonia using the financial statements of banks, aiming to uncover valuable insights and enhance forecasting accuracy. By combining the extensive financial statement data from 12 banks with carefully curated macroeconomic data, a symbiotic relationship is forged between the micro and macro aspects of the banking and economic landscape.

The financial statement data, collected from the Macedonian Stock Exchange website for the period 2017-2021, provides information on various financial indicators of the banks. These indicators include total

* PhD Students – Assistant, Ss Cyril and Methodius University in Skopje, Faculty of Economics - Skopje. Email: bojan.malcev@eccf.ukim.edu.mk

** Full-Time Professor, Ss Cyril and Methodius University in Skopje, Faculty of Economics - Skopje. Email: vcvetkoska@eccf.ukim.edu.mk

*** Full-Time Professor, Ss Cyril and Methodius University in Skopje, Faculty of Economics – Skopje. Email: marina.serafimoska@eccf.ukim.edu.mk

assets, deposits and short-term funding, equity, net income, loan loss reserves to gross loans ratio, equity to total assets ratio, capital funds to liabilities ratio, net interest margin, ROAA, return on average equity, cost to income ratio, net loans to total assets ratio, net loans to deposits and short-term funding ratio, and liquid assets to deposits and short-term funding ratio. These indicators are considered as potential predictors for forecasting the selected macroeconomic indicators.

The selected macroeconomic variables for this study are GDP growth rates, inflation rates, unemployment rate, average MKD/EUR exchange rate, and average MKD/USD exchange rate. These variables represent significant macroeconomic indicators that reflect the overall economic performance and stability of North Macedonia. To analyse and forecast these macroeconomic indicators, this study leverages the application of machine learning algorithm for regression analysis and forecasting tools for exponential smoothing within Power BI. These tools encompass a range of algorithms and techniques designed to analyse data, identify patterns, and make predictions. Power BI, developed by Microsoft, provides a powerful platform for visualizing and analysing data through interactive and dynamic dashboards and reports. It has gained popularity in academic research and has been extensively used in various studies involving data analysis and visualisation.

In this study, Power BI is employed to visually represent the variables from the financial statements of Macedonian banks and their relationships with the selected macroeconomic indicators. The “Key influencers” visualisation in Power BI holds particular significance in this study. It allows for the identification of key factors that significantly influence the macroeconomic indicators. By utilising the “Key influencers” visualisation, the study aims to uncover the financial statement variables that have the most impact on the macroeconomic indicators. This interactive visualisation enables researchers to explore and analyse the relationships in a dynamic and intuitive manner. In addition to the “Key influencers” visualisation, various other visualisations such as line charts, bar charts, scatter plots, and treemaps will be created in Power BI. These visualisations aid in exploring trends, patterns, and correlations between the macroeconomic indicators and the financial statement variables, enhancing the understanding of their relationships.

The ultimate goal of this study is to harness the predictive power of the financial indicators to forecast and anticipate the trajectory of the macroeconomic indicators. The primary finding of this study underscores a compelling relationship between unemployment rates and the financial performance of banks in North Macedonia. Furthermore, the identification of key influencers affecting unemployment rates provides a nuanced understanding of the underlying dynamics. The insights gained from this analysis have the potential to unlock a multitude of benefits, providing valuable information for policymakers, investors, and financial institutions to make informed decisions, formulate effective strategies, and navigate the ever-evolving economic environment with increased confidence and precision.

The paper is meticulously organised to facilitate a coherent exploration of the interplay between macroeconomic indicators and financial metrics in North Macedonia. Following this Introduction, we delve into the Literature Review, which offers a comprehensive survey of existing literature. This segues seamlessly into the Methodology and Data section, where we expound on the rigorous analytical framework. Subsequently, the Results and Analysis section unveils the empirical findings. Finally, the paper culminates in a Conclusion that synthesises these insights and delineates their implications for policymakers, investors, and financial institutions operating in North Macedonia.

Literature Review

Forecasting macroeconomic indicators from financial statements using machine learning techniques has gained significant attention in recent years. This approach combines the rich information embedded in financial statements with the predictive power of machine learning algorithms to generate accurate forecasts for macroeconomic indicators. By leveraging accounting data, such as balance sheets, income statements, and cash flow statements, researchers aim to provide timely and reliable predictions, enabling policymakers, investors, and financial institutions to make informed decisions. Thamprasert et al. (2022) compared seven prediction models, including traditional regression techniques and machine learning approaches, to enhance the feasibility of their approach through simulated trial and error experiments. The models assessed were Random Forest Regression, Gradient Boosting Regression, Artificial Neural Network (ANN), Decision Tree Regression, Ridge Regression, Second-degree Polynomial Regression, and Linear Regression. The study found that the Neural Network showed higher accuracy and was selected as the key component of the simulator. Additionally, the research demonstrated that nonlinear models, as presented in this paper, are better suited for optimising accuracy in labour productivity fitting.

Boyoukliev et al. (2022) utilised high-performance machine learning models employing CART Ensembles and the Bagging method. Their study demonstrates that by applying the Box-Jenkins approach to univariate ARIMA models, it becomes possible to incorporate lagged variables into the forecasting process for predicting the dependent variable with a one-month lead time. In their study, Ayushman et al. (2023) employed the ARIMA model to assess the influence of macroeconomic indicators on the performance of the Indian stock market, focusing on variables such as FDI, FIIs, exchange rate, and foreign exchange reserves over the period from 2017-18 to 2021-22, revealing significant effects of FIIs on stock market returns. In a related study, Nanda, et al. (2023) investigated the relationship between macroeconomic indicators and stock market performance in India during the pre-corona pandemic period, using OLS regression, ADF test, Granger causality, and VECM techniques (Nanda et al., 2023). Murari (2013) demonstrated the efficacy of the ARIMA (1,0,2) model in forecasting the short-term volatility of the Indian banking sector, utilising the CNX bank index of the National Stock Exchange of India, thus providing valuable insights for investors and speculators in formulating their short-run trading strategies.

According to Khan et al. (2022), their research investigates the performance of various machine learning (ML) algorithms, such as k-nearest neighbour (KNN), polynomial regression, ANN, and support vector machine (SVM). The dataset is divided into a training set covering data from January 1989 to December 2018 for algorithm training, and a test set comprising data from January 2019 to December 2020 for ML testing. Evaluation metrics include root mean square error (RMSE) and mean absolute error (MAE). The study reveals that parameter configurations significantly influence the performance of ML algorithms. For nonlinear data, the SVM RBF algorithm outperforms the SVM linear function, whereas the linear function performs better with less non-linearity. Additionally, lower polynomial degrees yield superior results in situations with less non-linearity when using polynomial regressors. Comparatively, the KNN algorithm demonstrates the poorest performance among the ML techniques. As for ANNs, a smaller number of hidden layers and neurons are effective for datasets with less non-linearity, while greater complexity is required for more nonlinear data.

Agu et al. (2022), have utilised four machine learning techniques, including Principal Component Regression (PCR), Ridge Regression (RR), Lasso Regression (LR), and Ordinary Least Squares (OLS). Among these methods, PCR demonstrated a notably high level of accuracy in predicting macroeconomic indicators, exhibiting minimal Mean Squared Error compared to RR, LR, and OLS. The analysis suggests that an increase in population, federal government expenditure, import rate, and export rate tends to correspond with an increase in GDP. On the other hand, foreign direct investment, exchange rate, and oil revenue appear to have a negative impact on GDP, resulting in a decrease in its value.

Liu and Liang (2023) employed various time series modeling techniques, encompassing univariate and multivariable modeling, as well as machine learning and regime-switching methods, to examine the dynamics of the unemployment rate (UR). The authors performed a decomposition of UR into temporary and permanent components and discovered that the rise in UR during the COVID-19 pandemic was largely driven by temporary layoffs. Furthermore, their research revealed that the credit card charge-off rate is primarily influenced by permanent UR, with temporary UR demonstrating limited predictive power. The study emphasized the importance of incorporating permanent UR, rather than the total UR, as a more robust indicator during economic downturns, particularly in credit risk modeling.

Wang (2022) conducted a study that integrated various technical indicators, such as Moving Average (MA), Relative Strength Index (RSI), Momentum Signal, and Bollinger Signal, alongside Machine Learning Signals like Support Vector Machine (SVM) and Long Short-Term Memory (LSTM) models. The research findings revealed that combining technical indicators with macroeconomic factors and employing machine learning techniques can result in superior returns, particularly when expected returns are high. Specifically, the combination of LSTM method and macroeconomics yielded higher returns within the expected returns range of 20% to 45%, outperforming other signals in terms of overall performance.

In their study, Takawira and Mwamba (2022) employed the random forest model, a machine-learning approach that utilizes categorization algorithms for data analysis and prediction. The findings indicate that key factors in evaluating and prioritizing credit ratings include the household debt-to-disposable income ratio, inflation, and exchange rates. The analysis suggests that positive changes in economic indicators such as Gross Domestic Product Growth, Real Effective Exchange Rates, Consumer Price Index Headline, and Household Debt to Disposable Income can lead to a favorable shift in credit ratings, benefiting the borrower.

Laygo-Matsumoto and Samonte (2021) investigated the integration of machine learning algorithms with macroeconomic indicators to predict GDP. They employed various predictive models and conducted Spearman's rank feature selection to identify the most relevant variables. The Gradient Boosting Machine yielded the lowest RSME of 2.09% and an RMSLE of 4%, making it the most effective model. Deep Learning and Distributed Random Forest models also produced favourable results. These findings suggest a significant correlation between macroeconomic indicators and GDP, highlighting the potential of machine learning algorithms for GDP prediction.

Taghiyeh et al. (2021) developed a loss forecasting framework for the credit card industry employing advanced machine learning models, including Lasso regression, Ridge regression, gradient boosting machine, and random forest. The proposed expert system comprises two variations that incorporate different methodologies for selecting lag indicators. This framework offers professionals in the credit card industry with a comprehensive perspective of the economy, enabling them to assess the impact of different macroeconomic conditions on future losses.

Zyatkov and Krivorotko (2021) developed a machine learning-based indicator to address the potential downturn of the US economy in the next 6, 12, and 24 months. By employing various methods such as k-nearest neighbors, SVM, fully connected neural network, and LSTM neural network, the researchers constructed this indicator. Through the application of roll-forward cross-validation, it was found that the most accurate prediction of future recession occurrences was achieved using a fully connected neural network. Additionally, the study demonstrated that all three indicators effectively anticipated the onset of the last six recessions experienced in the United States from 1976 to 2021, including the Early 1980s recession, Recession of 1981-82, Early 1990s recession, COM bubble recession, Great Recession, and COVID-19 recession.

Başoğlu, Kabran and Ünlü (2021) employed a two-step machine learning approach integrating a real-time bubble detection test with an SVM to forecast the occurrence of bubbles in the S&P 500 stock market. The study demonstrated that their methodology exhibited significant predictive capabilities, positioning it as a promising option for bubble prediction. Moreover, the experimental results highlighted the predictive potential of selected indicators such as GDP growth, inflation, short-term interest rates, long-term interest rates, unemployment rates, and balance of payments in forecasting bubbles in the S&P 500 market.

In their study, Qiu et al. (2020) utilized the random forest algorithm to evaluate and predict the monetary policy of the People's Bank of China. Their model incorporated 16 macroeconomic indicators as input variables and compared the performance of the random forest algorithm with three other machine learning algorithms (CART decision tree, SVM, and neural network algorithm), as well as a discrete selection model and a combined prediction model. The findings revealed that the random forest algorithm outperformed the other models in accurately predicting the direction of the central bank's monetary policy. These results emphasize the effectiveness of the random forest algorithm in forecasting the decisions of the central bank's monetary policy.

In their study, Pekar and Binner (2017) examined the effectiveness of integrating time series analysis models and machine-learning regression models, namely SARIMA(X), AdaBoost, and Gradient Boosting Regression. Their research revealed that incorporating exogenous variables related to intended purchases, in addition to lagged values of the consumer spending index, significantly enhanced the predictive performance compared to a baseline model that only considered lag variables. Notably, the inclusion of social media data as prediction variables in these models improved the accuracy of short-term forecasts of consumer spending. Specifically, for three- and seven-day forecast horizons, these variables contributed to an 11% to 18% improvement in forecast accuracy across all three models, surpassing the performance of models relying solely on autoregressive predictors (Pekar & Binner, 2017).

Ramli et al. (2015) employed a model stacking technique by combining SVM classifiers, logistic regression ensembles (LORENS), and nearest neighbor tree (NNT) methods. Their study demonstrated that the ensemble of classifiers used in the research exhibited comparable and relatively high levels of accuracy. The proposed method, known as the NNT, outperformed the other combined classifiers in terms of the area under the ROC curve. However, it is important to note that the computational time needed for the NNT was longer compared to the other methods (Ramli et al., 2015).

Datar et al. (2021) applied machine learning techniques, specifically the elastic net model, to develop and evaluate prediction models. Their study reveals that accounting information has incremental predictive value for longer-term GDP growth rates, such as quarters one year or more ahead. However, contrary to prior research, their analysis did not find substantial evidence that accounting information improves the accuracy of short-term GDP growth forecasts for the current and next quarters. These findings suggest that professional forecasters may possess superior insights regarding macroeconomic performance in the immediate future.

Wasserbacher and Spindler (2022) conducted a comparative analysis of the lasso machine learning technique and linear regression with the ordinary least squares (OLS) method. They highlighted the distinction between forecasting and planning tasks, emphasizing that forecasting involves prediction, while planning focuses on causal inference. The researchers warned against the common confusion of these concepts, considering it a critical pitfall that practitioners should actively avoid.

In their experiment, Coulombe et al. (2022) examined the essential features of machine learning and big data methodologies. The study involved a comprehensive pseudo-out-of-sample forecasting competition, comparing various models distinguished by four key attributes: nonlinearity, regularization, hyperparameter selection, and loss function. The investigation considered both data-rich and data-poor environments. The researchers concluded that machine learning demonstrates its usefulness in macroeconomic forecasting by effectively capturing significant nonlinearities that arise in uncertain conditions and financial frictions (Coulombe et al., 2022).

Medeiros et al. (2019) highlight the potential of machine learning (ML) techniques and accessible datasets to improve inflation forecasting. They utilize benchmark models, shrinkage techniques, factor models, ensemble methods such as random forests, and hybrid linear-random forest models. The authors emphasize that models like LASSO, RF, and others outperform traditional benchmark models, producing more accurate inflation forecasts.

Araujo and Gaglianone (2022) examined the performance of 50 forecasting methods, including various econometric models and machine learning techniques, such as Random Walk, ARMA, VAR, Elastic Net, LASSO, Ridge Regression, Random Forest, XGBoost, and Recurrent Neural Network (RNN). The study revealed that machine learning techniques have the potential to surpass traditional econometric models in certain scenarios. The empirical analysis indicated the presence of nonlinearities in inflation dynamics, which play a significant role in accurately predicting inflation.

Ranjani and Dharmadasa (2018) employed Johansen's co-integration and Vector Autoregressive Model (VAR) to explore the interplay between macroeconomic indicators and stock prices. They found a significant short-term relationship between share prices and the previous month's exchange rate, which exerted a negative influence. Variance decomposition highlighted the impact of shocks to price lag and exchange rate on short-term price variation. Granger Causality revealed a unidirectional relationship from exchange rate to share price, offering valuable market insights. The most accurate forecasts often relied on a combination of different methods, including tree-based approaches like random forest and xgboost, as well as incorporating breakeven inflation and survey-based expectations.

Our research embarks on uncharted territory within the academic landscape by conducting a comprehensive inquiry into the interplay between macroeconomic indicators and financial metrics in North Macedonia. Remarkably, our preliminary survey of existing literature has revealed a conspicuous absence of similar studies focusing on this specific regional context. This conspicuous gap in the literature underscores the pressing need for our research, as it seeks to fill this critical void by providing tailored insights and empirical evidence relevant to the North Macedonian economic milieu. Our study stands as a pioneering effort, poised to make a significant contribution to the body of knowledge in this domain.

Methodology and Data

Methodology

In order to predict the macroeconomic indicators in North Macedonia using data from the financial statements of the banks, this study leverages machine learning algorithm for regression analysis and forecasting tools for exponential smoothing, specifically using Power BI. ML algorithms for regression analysis and forecasting tools for exponential smoothing encompass a range of algorithms and techniques designed to analyse data, identify patterns, and make predictions. These tools can handle complex problems by capturing relationships between variables and predicting continuous values. By utilising these tools within Power BI, researchers can explore the connections between financial statements variables and macroeconomic indicators.

The choice of specific algorithms and techniques depends on the nature of the data and the problem at hand. While ML algorithms for regression analysis and forecasting tools for exponential smoothing provide promising results in macroeconomic forecasting, they also present challenges. The selection of appropriate hyperparameters remains critical for optimizing model performance. Additionally, overfitting and interpretability of models are ongoing concerns. It is essential to carefully assess the model's performance, particularly when dealing with small sample sizes or noisy data, and to ensure that the insights derived from the models can be effectively interpreted and explained.

The application of ML regression and forecasting tools for exponential smoothing has been widely recognized in various domains, including finance. Researchers have successfully employed these tools for credit scoring, fraud detection, and short-term prediction, demonstrating their effectiveness compared to traditional statistical models. As such, the utilization of ML regression and forecasting tools for exponential smoothing within Power BI offers a promising approach to uncovering valuable insights and enhancing the accuracy of macroeconomic forecasting in the context of North Macedonia.

Power BI will be utilized in this study to visually represent the variables from the financial statements of Macedonian banks and their relationships with the selected macroeconomic indicators. Power BI is a powerful business intelligence tool developed by Microsoft that enables users to visualise and analyse data through interactive and dynamic dashboards and reports. It has gained popularity in academic research and has been extensively used in various studies involving data analysis and visualisation (Palma-Ruizet al., 2022; Khatuwal & Puri, 2022; Carlisle, 2018). In the context of forecasting macroeconomic indicators using financial statements of banks, Power BI provides a comprehensive platform to explore the relationships between variables and uncover valuable insights. Power BI acts as a connector between analysis workflows, bringing an additional level of interactivity that enhances the dynamism and interactivity of presentations (Carlisle, 2018).

Various types of visualisations will be employed to provide a comprehensive understanding of the data. One of the key visualisations that will be emphasized is the "Key influencers" visualisation in Power BI. This visualisation is particularly useful in highlighting the relationship between the macroeconomic indicators and the financial statement variables. It allows for the identification of key factors that significantly influence macroeconomic indicators, providing valuable insights for forecasting purposes. By utilizing the "Key influencers" visualisation, the study aims to uncover the key drivers or predictors among the financial statement variables that have the most impact on the macroeconomic indicators. This interactive visualisation will enable researchers to explore and analyse the relationships in a dynamic and intuitive manner. It will provide insights into which financial indicators have the strongest influence on the macroeconomic indicators and how changes in these variables affect the overall economic performance. In addition to the "Key influencers" visualisation, Power BI will be leveraged to create various other visualisations such as line charts, bar charts, scatter plots, and treemaps. These visualisations will allow for exploring trends, patterns, and correlations between the macroeconomic indicators and the financial statement variables.

Data

The financial statement data for the 12 banks in North Macedonia were collected from the Macedonian Stock Exchange website for the period 2017-2021. These financial statements provided information on various financial indicators of the banks, including total assets, deposits and short-term funding, equity, net income, loan loss reserves to gross loans ratio, equity to total assets ratio, capital funds to liabilities ratio, net interest margin, ROAA, return on average equity, cost to income ratio, net loans to total assets ratio, net loans to deposits and short-term funding ratio, and liquid assets to deposits and short-term funding ratio. These indicators were considered as potential predictors for forecasting macroeconomic indicators.

In addition to the financial statement data, macroeconomic data for the same period were collected from the National Bank of North Macedonia. The selected macroeconomic variables included in this study are: GDP growth rates, inflation rates, unemployment rate, average MKD/EUR exchange rate, and average MKD/USD exchange rate. These variables were chosen as the target variables for the forecasting models, as they represent significant macroeconomic indicators that reflect the overall economic performance and stability of the country.

By amalgamating the extensive financial statement data with carefully curated macroeconomic data, this study aimed to forge a symbiotic relationship between the micro and macro aspects of the banking and economic landscape in North Macedonia. The ultimate goal is to harness the predictive power of the financial indicators to forecast and anticipate the trajectory of the macroeconomic indicators. Such insights have the potential to unlock a multitude of benefits, aiding policymakers, investors, and financial institutions in making informed decisions, formulating effective strategies, and navigating the dynamic and ever-evolving economic environment with increased confidence and precision.

Table 1: Descriptive Statistics of the Variables

	N	*Minimum*	*Maximum*	*Mean*	*Std. Deviation*
Total assets	60	44337.1	2732112.5	789532.936	787250.2827
Deposits & short term funding	60	35800.8	2408628.3	644687.767	661388.5113
Equity	60	5296.8	384041.8	102625.732	110318.4066
Net Income	60	-3428.8	48304.5	12062.090	16267.0223
Loan Loss Res. / Gross Loans (%)	60	.6	20.2	4.530	3.5055
Equity / Total assets (%)	60	6.8	18.1	12.284	2.5292
Cap. Funds / Liabilities (%)	60	10.8	25.8	16.217	3.1843
Net Interest Margin (%)	60	2.2	5.5	3.896	.7576
Return on Avg Assets (ROAA) (%)	60	-6.1	3.0	.998	1.2331
Return on Avg Equity (ROAE) (%)	60	-50.2	24.9	8.160	9.6749
Cost to Income Ratio (%)	60	35.5	96.5	65.991	18.2017
Net Loans / Total assets (%)	60	36.0	77.2	62.677	9.0047
Net Loans / Dep. & ST Funding (%)	60	40.9	99.3	77.373	13.2266
Liquid Assets / Dep. & ST Funding (%)	60	12.6	48.9	26.683	8.2856
GDP (real growth rates, in %)	5	-4.7	3.9	1.420	3.6072
Inflation (average, on a cum. basis, in %)	5	.8	3.2	1.620	.9230
Unemployment rate (in %)	5	15.70	22.40	18.4800	2.92267
Average MKD/EUR exchange rate	5	61.51	61.67	61.5780	.07155
Average MKD/USD exchange rate	5	52.11	54.95	53.5920	1.37986

Source: Own elaboration.

The provided descriptive statistics offer valuable insights into various financial and economic indicators. Notably, the average total assets of the observed entities amount to approximately \$789,532.936, with a considerable standard deviation of \$787,250.2827, signifying significant variation in asset sizes. This indicates the presence of entities with vastly different financial capacities within the sample. In terms of funding sources, the mean value for deposits and short-term funding is \$644,687.767, reflecting the average amount obtained from these sources and again showcasing substantial variability with a standard deviation of \$661,388.5113.

The equity, representing the value of shareholders' ownership, has an average of \$102,625.732, with a significant standard deviation of \$110,318.4066, highlighting the diversity in ownership structures and financial strengths among the entities. Additionally, the mean net income is \$12,062.090, indicating the average profitability, with a standard deviation of \$16,267.0223, implying varying levels of financial performance. The loan loss reserves as a percentage of gross loans have a mean of 4.530%, denoting the average level of reserves set aside for potential loan losses, while the equity to total assets ratio has a mean of 12.284%, indicating the proportion of assets financed by shareholders.

The average net interest margin stands at 3.896%, representing the difference between interest income and interest expenses as a percentage of interest-earning assets and reflecting the profitability of core banking activities. The return on average assets (ROAA) has a mean of 0.998%, indicating the average return generated by assets, while the return on average equity (ROAE) has a mean of 8.160%, representing the average return on shareholders' equity investment. The cost-to-income ratio has a mean of 65.991%, reflecting the average proportion of costs incurred relative to total income, which serves as a measure of efficiency. The net loans to total assets ratio stands at 62.677%, indicating the proportion of assets allocated to loans, and the net loans to deposits and short-term funding ratio is 77.373%, denoting the extent of reliance on these funding sources for lending activities. Lastly, the average GDP growth rate is 1.420%, providing an overview of the economic growth experienced, while inflation has an average cumulative rate of 1.620%, reflecting the average increase in prices. The unemployment rate stands at 18.480%, representing the proportion of the labour force without employment. These descriptive statistics offer valuable insights into the financial and economic landscape, showcasing the diversity and variation within the entities and providing a foundation for further analysis and research.

Results and Analysis

Prior to delving into the utilization of Power BI, a comprehensive analysis was conducted to examine the relationship between the two groups of indicators. To achieve this, a correlation matrix was constructed, given in Table 2 (Appendix 1), providing valuable insights into the interplay between these variables. This initial step serves as a foundation for the subsequent analysis, shedding light on the potential connections and dependencies that exist between the financial metrics and macroeconomic indicators under investigation.

The correlation matrix provides insights into the relationship between financial variables derived from banks' financial reports and macroeconomic indicators. Specifically, it examines the connections between total assets, deposits and short-term funding, equity, net income, loan loss reserves to gross loans ratio, equity to total assets ratio, capital funds to liabilities ratio, net interest margin, ROAA, return on average equity, cost-to-income ratio, net loans to total assets ratio, net loans to deposits and short-term funding ratio, and liquid assets to deposits and short-term funding ratio of banks with macroeconomic indicators such as GDP growth rates, inflation rates, unemployment rate, average MKD/EUR exchange rate, and average MKD/USD exchange rate.

The results of the correlation analysis reveal several statistically significant relationships. Firstly, there is a positive correlation between the unemployment rate and total assets, as well as deposits and short-term funding at a significant level of 0.01. This suggests that as the unemployment rate increases, banks tend to experience higher total assets and increased deposits and short-term funding. Secondly, a positive correlation is observed between the unemployment rate and equity, as well as net income, significant at a level of 0.05. This implies that higher unemployment rates may coincide with increased equity and net income for banks.

On the other hand, there are negative correlations between the unemployment rate and several financial variables. At a significant level of 0.01, negative correlations are observed between the unemployment rate and equity to total assets ratio, capital funds to liabilities ratio, net interest margin, net loans to total assets ratio, and net loans to deposits and short-term funding ratio. These findings suggest that as the unemployment rate rises, the aforementioned financial indicators tend to decrease, indicating potential challenges faced by banks in these areas.

Furthermore, at a significant level of 0.05, a negative correlation is identified between the unemployment rate and the ratio of liquid assets to deposits and short-term funding. This implies that higher unemployment rates may be associated with a lower proportion of liquid assets relative to deposits and short-term funding. In addition to the correlation relationships involving the unemployment rate and the financial variables, it is important to note that the other four macroeconomic indicators, namely GDP growth rates, inflation rates, average MKD/EUR exchange rate, and average MKD/USD exchange rate, do not exhibit statistically significant correlations with the variables derived from the financial reports of banks.

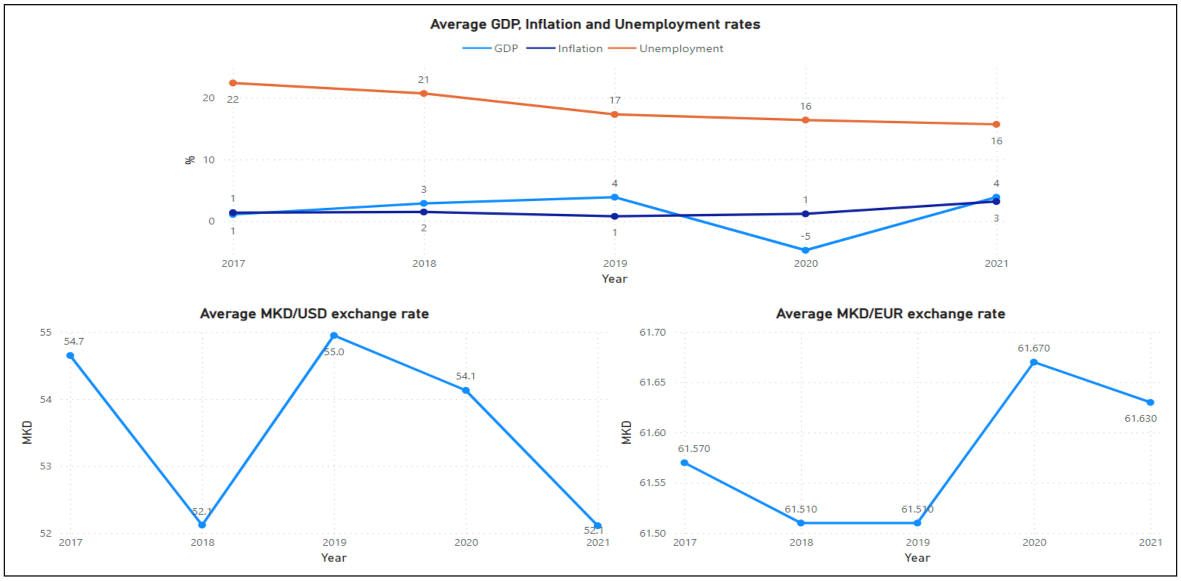
The lack of statistically significant correlations implies that changes in these macroeconomic indicators do not have a strong and consistent relationship with the financial variables under consideration. This suggests that variations in GDP growth rates, inflation rates, and exchange rates do not directly impact or influence the specific financial metrics analysed in this study.

It is worth noting that the absence of statistically significant correlations does not necessarily indicate a lack of relationship between the macroeconomic indicators and the financial variables. Other factors and complexities may come into play, which might limit the observable correlations in the data analysed. It is possible that these macroeconomic indicators have indirect or more nuanced effects on the financial performance of banks, which may not be captured by the correlations alone.

Therefore, the focus of this analysis suggests that the unemployment rate is a particularly influential macroeconomic indicator with respect to the financial variables derived from the banks' financial reports. This implies that changes in the unemployment rate are more likely to have a discernible impact on the financial activities, positions, and ratios of banks compared to the other macroeconomic indicators considered in this study. Overall, while the unemployment rate demonstrates statistically significant correlations with various financial variables, the lack of significant correlations between the other four macroeconomic indicators and the financial metrics suggests that further research and analysis are needed to explore the complex relationships between these macroeconomic factors and the financial performance of banks.

Using Power BI, the variables used in the study are visually represented including total assets, deposits and short-term funding, equity, net income, loan loss reserves to gross loans ratio, equity to total assets ratio, capital funds to liabilities ratio, net interest margin, ROAA, return on average equity, cost-to-income ratio, net loans to total assets ratio, net loans to deposits and short-term funding ratio, and liquid assets to deposits and short-term funding ratio, as well as GDP growth rates, inflation rates, unemployment rate, average MKD/EUR exchange rate, and average MKD/USD exchange rate).

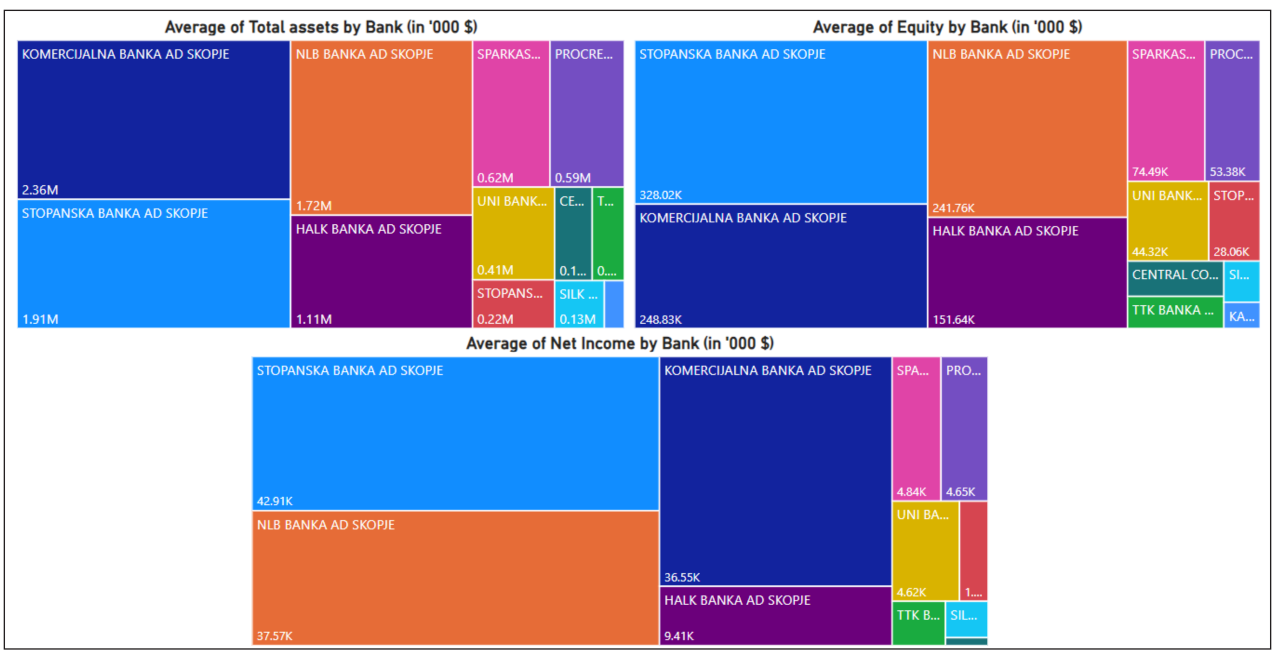
These visualisations enhance the interpretability of the data, enabling policymakers, investors, and financial institutions to make informed decisions and formulate strategies based on the insights derived from the analysis. Fig. 1 provides a comprehensive overview of the selected macroeconomic variables, as discussed earlier in the study. These visual representations offer a clear and intuitive display of the trends and patterns in GDP growth rates, inflation rates, unemployment rate, average MKD/EUR exchange rate, and average MKD/USD exchange rate. Fig. 1 effectively captures the historical trajectories and fluctuations of these macroeconomic indicators, setting the foundation for further analysis.



Source: Own elaboration.

Fig. 1: Macroeconomic Indicators

Moving on to Fig. 2, it offers a visual depiction of the banks' size based on total assets, equity, and net income. These key financial indicators reflect the financial strength and performance of the banks. By presenting this information visually, Fig. 2 enables a quick and comparative assessment of the banks' relative positions and their contributions to the overall financial landscape. The visual representation allows for easy identification of banks with substantial assets, significant equity holdings, and notable net income figures.

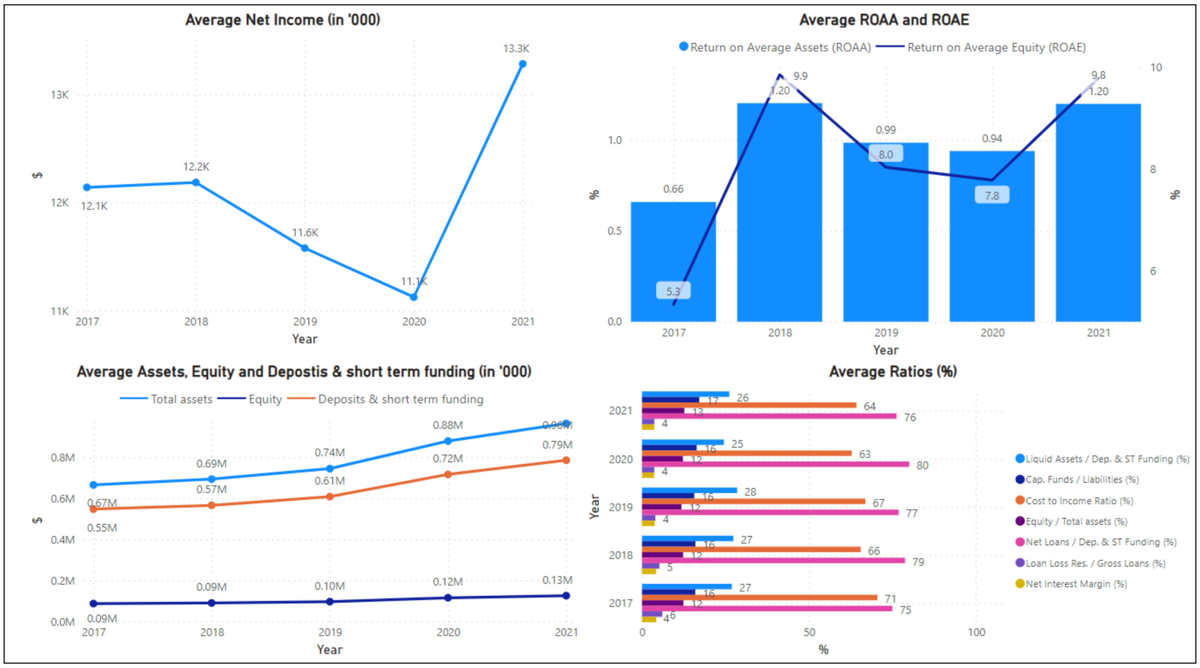


Source: Own elaboration.

Fig. 2: Banks' Size

Finally, Fig. 3 illustrates the distribution of variables derived from the financial statements of the banks, as discussed earlier in the study. This visualisation provides a graphical representation of the data, allowing for a better understanding of the dispersion and patterns within the financial statement variables.

Fig. 3 aids in identifying any outliers, clusters, or noteworthy trends among the variables, providing valuable insights into the financial landscape of the banks. This visual representation facilitates a more comprehensive analysis of the relationships and interplay between the financial statement variables and the macroeconomic indicators.



Source: Own elaboration.

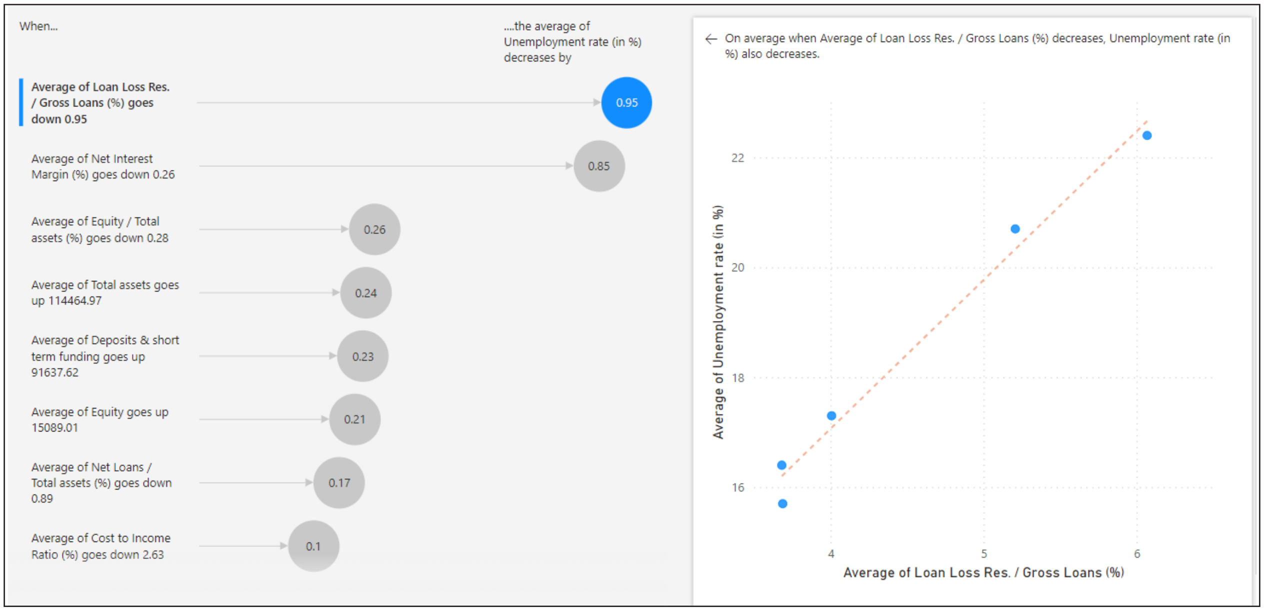
Fig. 3: Banks' Financial Statements Indicators

The "Key influencers" tool in Power BI provides valuable insights into the relationship between the unemployment rate and the financial statement variables. In this analysis, the unemployment rate is considered as the dependent variable, as it is the only macroeconomic indicator that shows correlation with some of the financial statement variables. The results from the "Key influencers" analysis, presented in Fig. 4, highlight several important findings.

Firstly, when the average loan loss reserves to gross loans ratio decreases by 0.95%, the average unemployment rate also decreases by 0.95%. This suggests that a decrease in loan loss reserves, which indicates a more favourable credit quality, is associated with a decrease in the unemployment rate. Secondly, a decrease of 0.26% in the net interest margin is associated with an average decrease of 0.85% in the unemployment rate. This implies that a narrower net interest margin, which reflects lower profitability from interest-earning assets, may contribute to a decrease in the unemployment rate.

Furthermore, when the equity to total assets ratio decreases, the average unemployment rate decreases by 0.26%. This indicates that a decrease in the proportion of equity relative to total assets is associated with a decline in the unemployment rate. Additionally, an increase in total assets by $114,464.97 is correlated with an average decrease of 0.24% in the unemployment rate. Similarly, an increase in deposits and short-term funding by $91,637.62 is associated with an average decrease of 0.23% in the unemployment rate. These findings suggest that expansion in the size and funding of the banks is linked to a reduction in the unemployment rate.

Moreover, an increase in equity by $15,089.01 is correlated with an average decrease of 0.21% in the unemployment rate. This implies that an increase in the capital base of the banks may contribute to a decrease in unemployment. Furthermore, a decrease of 0.89% in the net loans to total assets ratio is associated with an average decrease of 0.17% in the unemployment rate. This indicates that a lower ratio of net loans to total assets, which suggests a lower lending activity, is linked to a decrease in the unemployment rate. Lastly, a decrease of 2.63% in the cost-to-income ratio is associated with an average decrease of 0.1% in the unemployment rate. This suggests that a reduction in the cost-to-income ratio, indicating improved efficiency, may contribute to a decrease in the unemployment rate.

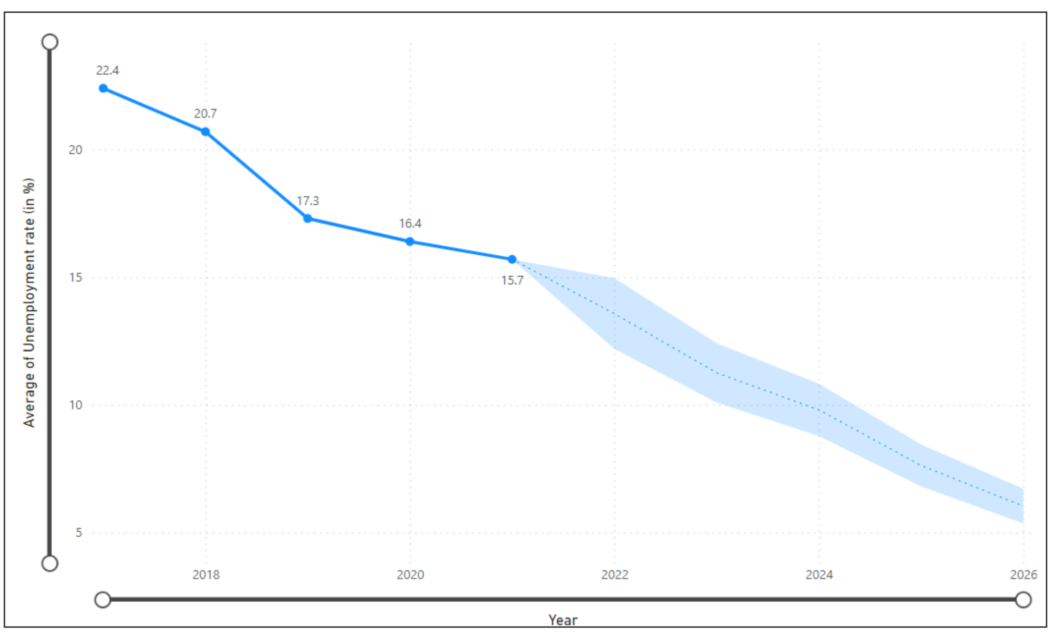


Source: Own elaboration.

Fig. 4: Key Influencers Analysis

Overall, the "Key influencers" tool provides valuable insights into the relationships between the financial statement variables and the unemployment rate. These findings can be instrumental in understanding the dynamics and potential drivers of the unemployment rate, enabling policymakers and stakeholders to make informed decisions and implement strategies to address unemployment challenges.

Finally, as the last application of Power BI in the research, we made a prediction of the average annual unemployment rate for North Macedonia for the period



Source: Own elaboration.

Fig. 5: Unemployment Rate Forecasting

from 2022-2026 using the "Forecasting" option in Power BI, which employs exponential smoothing. In the forecasting analysis conducted in Power BI, the annual average unemployment rate for the period of 2022-2026 was predicted, incorporating a 95% confidence interval. The results of this analysis are presented in Fig. 5, offering valuable insights into the projected range of unemployment rates for each year.

According to the findings, the average unemployment rate is forecasted to fall within the following intervals: 14.96% to 12.19% in 2022, 12.42% to 10.10% in 2023, 10.83% to 8.78% in 2024, 8.45% to 6.81% in 2025, and 6.72% to 5.36% in 2026. These intervals provide a range of potential values for each year, taking into account the inherent uncertainty in forecasting. The inclusion of a 95% confidence interval in the forecast results signifies the level of confidence associated with the predicted ranges. It indicates that there is a 95% probability that the actual unemployment rate will fall within the presented intervals. This interval provides a measure of uncertainty and aids in understanding the potential variability in the unemployment rate projections.

The forecasted intervals in Fig. 5 offer valuable information for policymakers, researchers, and stakeholders involved in economic planning and decision-making. The ranges provide a sense of the potential future trajectory of the unemployment rate and enable a better assessment of the economic landscape. Understanding the potential range of unemployment rates can assist in formulating appropriate policies, evaluating the effectiveness of existing measures, and anticipating the impacts on various sectors of the economy. It is important to note that forecasting is inherently subject to various assumptions and limitations, and external factors can significantly influence the actual unemployment rate. Therefore, continuous monitoring and updating of the forecasted ranges are necessary to ensure accurate and timely decision-making. Overall, the forecasting analysis presented in Fig. 5, along with the associated 95% confidence intervals, contributes to a more comprehensive understanding of the projected average unemployment rate for the years 2022-2026. This information serves as a valuable tool for policymakers and stakeholders to navigate the economic landscape and make informed decisions based on the projected range of unemployment rates.

Conclusion

In this paper, we conducted an analysis of the relationship between financial indicators derived from the financial statements of banks in North Macedonia and macroeconomic indicators. This analysis served as a foundation for subsequent forecasting and analysis using machine learning algorithms for regression analysis and forecasting tools for exponential smoothing within Power BI. The correlation matrix revealed significant relationships between the unemployment rate and various financial indicators, suggesting that changes in the unemployment rate have a discernible impact on the financial activities and positions of banks. Additionally, the lack of significant correlations between other macroeconomic indicators and financial metrics indicates the need for further research to explore the complex relationships between these factors.

To visualize and analyse the data, Power BI was employed as a powerful business intelligence tool. It served as a connector between analysis workflows, enhancing the dynamism and interactivity of presentations. Power BI facilitated the visual representation of variables from the financial statements of Macedonian banks, allowing policymakers, investors, and financial institutions to make informed decisions based on the insights derived from the analysis. Various visualisations were employed to provide a comprehensive understanding of the data. The first visual representation, we gained an insightful overview of the chosen macroeconomic variables. This encompassed a historical perspective, offering a nuanced understanding of the trajectories and fluctuations of GDP growth rates, inflation rates, unemployment rate, average MKD/EUR exchange rate, and average MKD/USD exchange rate. Moving on, the second graphical presentation provided a comparative assessment of banks' size, determined by their total assets, equity, and net income. This visual depiction afforded a clear perspective on their respective positions and contributions within the financial landscape. Additionally, the third visual aid focused on the distribution of variables derived from the financial statements of the banks, instrumental in identifying outliers, clusters, and underlying trends within the dataset.

Among the visualisations, the "Key influencers" tool in Power BI played a crucial role in understanding the relationship between the unemployment rate and financial statement variables. It identified key factors significantly influencing the unemployment rate, offering valuable insights for forecasting purposes. The "Key influencers" analysis revealed several notable findings, such as the impact of changes in loan loss reserves to gross loans ratio, net interest margin, equity to total assets ratio, total assets, deposits and short-term funding, equity, net loans to total assets ratio, and cost to income ratio on the unemployment rate. Moreover, Power BI facilitated the forecasting of the average annual unemployment rate for North Macedonia from 2022 to 2026. The forecasting analysis incorporated a 95% confidence interval to account for inherent uncertainty, offering valuable insights into the projected range of unemployment rates for each year. These ranges provided policymakers, researchers, and stakeholders with a sense of the potential future trajectory of the unemployment rate and enabled a better assessment of the economic landscape. While the forecasting analysis presented valuable insights, it is important to acknowledge that forecasting is subject to various assumptions and limitations. External factors and unforeseen events can significantly influence the actual unemployment rate. Therefore, continuous monitoring and updating of forecasted ranges are necessary to ensure accurate and timely decision-making.

Overall, this study contributes to a better understanding of the interplay between micro and macro aspects of the banking and economic landscape in North Macedonia, paving the way for improved forecasting and decision-making in the future. Moving forward, there are several promising avenues for future research in this domain. Firstly, an extended longitudinal study could offer deeper insights into the evolving relationship between macroeconomic indicators and financial metrics in North Macedonia. A comparative analysis across different regions or countries could provide valuable comparative perspectives, shedding light on potential regional-specific factors influencing the relationships observed.

Furthermore, incorporating additional variables, such as regulatory changes or geopolitical events, could enhance the comprehensiveness of the analysis, providing a more robust framework for forecasting and decision-making. Lastly, exploring advanced machine learning algorithms and data analytics techniques could offer refined predictive models, potentially improving forecast accuracy and practical applicability of the research findings. These avenues collectively represent fertile ground for future investigations, promising to advance our understanding of the intricate interplay between financial and macroeconomic dynamics in North Macedonia and beyond.

References

Agu, S. C., Onu, F. U., Ezemagu, U. K., & Oden, D. (2022). Predicting gross domestic product to macroeconomic indicators. *Intelligent Systems with Applications*, *14*, 200082.

Altan, A., & Karasu, S. (2019). The effect of kernel values in support vector machine to forecasting performance of financial time series. *The Journal of Cognitive Systems, 4*(1), 17-21.

Araujo, G. S., & Gaglianone, W. P. (2023). Machine learning methods for inflation forecasting in Brazil: New contenders versus classical models. *Latin American Journal of Central Banking*, *4*(2), 100087.

Ayushman, V., & Kumar. (2023). An analytical study of the impact of macroeconomic variables on the performance of the Indian stock market with special reference to NSE and BSE. *International Journal of Banking, Risk and Insurance, 11*(1), 29-35. Retrieved from http://www.publishingindia.com/ijbri/56/an-analytical-study-of-the-impact-of-macroeconomic-variables-on-the-performance-of-the-indian-stock-market-with-special-reference-to-nse-and-bse/32021/76853/

Başoğlu Kabran, F., & Ünlü, K. D. (2021). A two-step machine learning approach to predict S&P 500 bubbles. *Journal of Applied Statistics*, *48*(13-15), 2776-2794.

Boyoukliev, I. V., Kulina, H. N., & Gocheva-Ilieva, S. G. (2022). Modelling and forecasting of EUR/USD exchange rate using ensemble learning approach. *Cybernetics and Information Technologies*, *22*(4), 142-151.

Cao, L. J., & Tay, F. E. H. (2003). Support vector machine with adaptive parameters in financial time series forecasting. *IEEE Transactions on Neural Networks*, *14*(6), 1506-1518.

Carlisle, S. (2018). Software: Tableau and microsoft power Bi. *Technology| Architecture + Design*, *2*(2), 256-259. doi:https://doi.org/10.1080/24751448.2018.1497381

Chen, W. H., Shih, J. Y., & Wu, S. (2006). Comparison of support-vector machines and back propagation neural networks in forecasting the six major Asian stock markets. *International Journal of Electronic Finance*, *1*(1), 49-67.

Cheng, K., Huang, N., & Shi, Z. (2021). Survey-based forecasting: To average or not to average. *Behavioral Predictive Modeling in Economics*, 87-104.

Datar, S., Jain, A., Wang, C. C., & Zhang, S. (2020). Is accounting useful for forecasting GDP growth? A machine learning perspective. *A Machine Learning Perspective.*

Evans, P. (2022). Review of power BI in technical services. *TCB: Technical Services in Religion & Theology, 30*(1), 10-10.

Gao, Z., Yang, J., & Tan, S. (2013). Forecasting chinese GDP with mixed frequency data set: A generalized lasso granger method. In *Advances in Swarm Intelligence: 4th International Conference, ICSI 2013, Harbin, China, June 12-15, 2013, Proceedings, Part II 4* (pp. 163-172). Springer Berlin Heidelberg.

Goulet Coulombe, P., Leroux, M., Stevanovic, D., & Surprenant, S. (2022). How is machine learning useful for macroeconomic forecasting? *Journal of Applied Econometrics*, *37*(5), 920-964.

Huang, W., Nakamori, Y., & Wang, S. Y. (2005). Forecasting stock market movement direction with support vector machine. *Computers & Operations Research*, *32*(10), 2513-2522.

Ince, H., & Trafalis, T. B. (2008). Short-term forecasting with support vector machines and application to stock price prediction. *International Journal of General Systems*, *37*(6), 677-687.

Khan, M. A., Abbas, K., Su'ud, M. M., Salameh, A. A., Alam, M. M., Aman, N.,...Aziz, R. C. (2022). Application of machine learning algorithms for sustainable business management based on macro-economic data: Supervised learning techniques approach. *Sustainability*, *14*(16), 9964.

Khatuwal, V. S., & Puri, D. (2022, April). *Business intelligence tools for dashboard development.* In 2022 3rd International Conference on Intelligent Engineering and Management (ICIEM) (pp. 128-131). IEEE.

Kurani, A., Doshi, P., Vakharia, A., & Shah, M. (2023). A comprehensive comparative study of artificial neural network (ANN) and support vector machines (SVM) on stock forecasting. *Annals of Data Science*, *10*(1), 183-208.

Laygo-Matsumoto, S., & Samonte, M. J. (2021, November). Philippine Economic Growth: GDP Prediction using Machine Learning Algorithms. In *2021 4th International Conference on Computing and Big Data* (pp. 15-20).

Li, M., & Fu, Y. (n.d.). Prediction of supply chain financial credit risk based on PCA-GA-SVM Model. *Sustainability, 14,* 16376. doi:https://doi.org/10.3390/su142416376

Liagkouras, K., & Metaxiotis, K. (2020). Stock market forecasting by using support vector machines. *Machine Learning Paradigms: Advances in Deep Learning-based Technological Applications*, *18,* 259-271.

Liu, Z., & Liang, H. (2023). Permanent layoff and consumer credit card loss forecasting. *Managerial Finance*, *49*(5), 789-807.

Medeiros, M. C., Vasconcelos, G. F., Veiga, Á., & Zilberman, E. (2021). Forecasting inflation in a data-rich environment: The benefits of machine learning methods. *Journal of Business & Economic Statistics*, *39*(1), 98-119.

Murari, K. (2013). Volatility modeling and forecasting for banking stock returns. *International Journal of Banking, Risk and Insurance, 1*(2). Retrieved from http://www.publishingindia.com/ijbri/56/volatility-modeling-and-forecasting-for-banking-stock-returns/250/1876/

Nanda, S., Sahoo, B., & Biswal, B. K. (2023). Performance of the Indian stock market in relation to macroeconomic indicators during the pre-corona pandemic period. *Journal of Commerce and Accounting Research, 12*(2), 51-60. Retrieved from http://www.publishingindia.com/jcar/47/performance-of-the-indian-stock-market-in-relation-to-macroeconomic-indicators-during-the-pre-corona-pandemic-period/32036/76935/

Palma-Ruiz, J. M., Torres-Toukoumidis, A., González-Moreno, S. E., & Valles-Baca, H. G. (2022). An overview of the gaming industry across nations: using analytics with power BI to forecast and identify key influencers. *Heliyon, 8*(2). doi:https://doi.org/10.1016/j.heliyon.2022.e08959

Pekar, V., & Binner, J. (2017, September). Forecasting consumer spending from purchase intentions expressed on social media. *Association for Computational Linguistics.*

Qiu, C., Li, T., & Qiu, X. (2020, June). Research on forecasting of China's monetary policy based on random forest algorithm. *Journal of Physics: Conference Series*, *1549*(3), p. 032078. IOP Publishing.

Ramli, N. A., Ismail, M. T., & Wooi, H. C. (2015). Measuring the accuracy of currency crisis prediction with combined classifiers in designing early warning system. *Machine Learning*, *101*, 85-103.

Ranjani, R. P. C., & Dharmadasa, W. N. D. (2018). The impact of macro economic variables on stock prices: Evidence from Colombo stock exchange. *Journal of Commerce and Accounting Research, 7*(2). Retrieved from http://www.publishingindia.com/jcar/47/the-impact-of-macro-economic-variables-on-stock-prices-evidence-from-colombo-stock-exchange/676/4735/

Taghiyeh, S., Lengacher, D. C., & Handfield, R. B. (2021). Loss rate forecasting framework based on macroeconomic changes: Application to US credit card industry. *Expert Systems with Applications*, *165*, 113954.

Takawira, O., & Mwamba, J. W. M. (2022). An analysis of sovereign credit ratings using random forest. *International Journal of Economics and Finance Studies*, *14*(1), 29-87.

Thamprasert, K., Dawod, A. Y., & Chakpitak, N. (2022). Simulated trial and error experiments on productivity. *IAES International Journal of Artificial Intelligence*, *11*(4), 1570.

Vapnik, V. N. (1999). An overview of statistical learning theory. *IEEE Transactions on Neural Networks*, *10*(5), 988-999.

Wang, Q. (2022). Risk-adapting stock trading system associated technical with macroeconomic indicators. *Mobile Information Systems*.

Wasserbacher, H., & Spindler, M. (2022). Machine learning for financial forecasting, planning and analysis: Recent developments and pitfalls. *Digital Finance*, *4*(1), 63-88.

Zyatkov, N., & Krivorotko, O. (2021, September). Forecasting Recessions in the US Economy Using Machine Learning Methods. In *2021 17th International Asian School-Seminar" Optimization Problems of Complex Systems (OPCS),* pp. 139-146. IEEE.

Appendix 1

Table 2: Correlation matrix

		Total assets	Deposits & short term funding	Equity	Net Income	Loan Loss Res. / Gross Loans (%)	Equity / Total assets (%)	Cap. Funds / Liabilities (%)	Net Interest Margin (%)	Return on Avg Assets (ROAA) (%)	Return on Avg Equity (ROAE) (%)	Cost to Income Ratio (%)	Net Loans / Total assets (%)	Net Loans / Dep. & ST Funding (%)	Liquid Assets / Dep. & ST Funding (%)	GDP (real growth rates, in %)	Inflation (average, on a cumulative basis, in %)	Unemploy ment rate (in %)	Average MKD/EUR exchange rate	Average MKD/USD exchange rate
Total assets	Pearson Correlation	1	.997**	.959**	.917**	.259*	.338**	.061	-.227	.505**	.436**	-.823**	-.330*	-.257*	.222	.138	-.365	.994**	-.578	.094
	Sig. (2-tailed)		.000	.000	.000	.046	.008	.642	.081	.000	.001	.000	.010	.047	.088	.825	.545	.000	.307	.880
	N	60	60	60	60	60	60	60	60	60	60	60	60	60	60	5	5	5	5	5
Deposits & short term funding	Pearson Correlation	.997**	1	.943**	.915**	.275*	.301*	.024	-.236	.497**	.435**	-.827**	-.380**	-.318*	.263*	.146	-.355	.995**	-.578	.088
	Sig. (2-tailed)	.000		.000	.000	.034	.020	.858	.070	.000	.001	.000	.003	.013	.042	.815	.557	.000	.307	.888
	N	60	60	60	60	60	60	60	60	60	60	60	60	60	60	5	5	5	5	5
Equity	Pearson Correlation	.959**	.943**	1	.930**	.245	.520**	.255*	-.101	.524**	.411**	-.803**	-.174	-.113	.069	.100	-.489	.953*	-.646	.099
	Sig. (2-tailed)	.000	.000		.000	.059	.000	.049	.442	.000	.001	.000	.184	.388	.600	.873	.403	.012	.239	.874
	N	60	60	60	60	60	60	60	60	60	60	60	60	60	60	5	5	5	5	5
Net Income	Pearson Correlation	.917**	.915**	.930**	1	.332**	.428**	.212	-.020	.613**	.512**	-.857**	-.251	-.226	.144	.091	-.069	.943*	-.292	.031
	Sig. (2-tailed)	.000	.000	.000		.009	.001	.105	.877	.000	.000	.000	.053	.083	.272	.885	.913	.016	.634	.961
	N	60	60	60	60	60	60	60	60	60	60	60	60	60	60	5	5	5	5	5
Loan Loss Res. / Gross Loans (%)	Pearson Correlation	.259*	.275*	.245	.332**	1	.021	.224	.142	-.261*	-.309*	-.261*	-.500**	-.460**	.259*	-.561	.268	-.828	.761	-.265
	Sig. (2-tailed)	.046	.034	.059	.009		.871	.086	.278	.044	.016	.044	.000	.000	.046	.325	.663	.083	.135	.667
	N	60	60	60	60	60	60	60	60	60	60	60	60	60	60	5	5	5	5	5
Equity / Total assets (%)	Pearson Correlation	.338**	.301*	.520**	.428**	.021	1	.725**	.312*	.320*	.120	-.266*	.135	.218	-.298*	-.008	.369	-.964**	.388	-.329
	Sig. (2-tailed)	.008	.020	.000	.001	.871		.000	.015	.013	.363	.040	.304	.094	.021	.989	.541	.008	.518	.589
	N	60	60	60	60	60	60	60	60	60	60	60	60	60	60	5	5	5	5	5
Cap. Funds / Liabilities (%)	Pearson Correlation	.061	.024	.255*	.212	.224	.725**	1	.378**	.123	-.033	-.067	.229	.275*	-.478**	-.026	.336	-.964**	.381	-.309
	Sig. (2-tailed)	.642	.858	.049	.105	.086	.000		.003	.349	.802	.609	.078	.034	.000	.967	.581	.008	.527	.613
	N	60	60	60	60	60	60	60	60	60	60	60	60	60	60	5	5	5	5	5
Net Interest Margin (%)	Pearson Correlation	-.227	-.236	-.101	-.020	.142	.312*	.378**	1	.037	-.007	-.046	.235	.200	-.231	-.090	.358	-.969**	.451	-.321
	Sig. (2-tailed)	.081	.070	.442	.877	.278	.015	.003		.778	.959	.727	.070	.126	.076	.886	.554	.006	.446	.598
	N	60	60	60	60	60	60	60	60	60	60	60	60	60	60	5	5	5	5	5
Return on Avg Assets (ROAA) (%)	Pearson Correlation	.505**	.497**	.524**	.613**	-.261*	.320*	.123	.037	1	.973**	-.611**	.079	.091	.105	-.013	.845	-.421	.723	-.301
	Sig. (2-tailed)	.000	.000	.000	.000	.044	.013	.349	.778		.000	.000	.549	.489	.425	.983	.072	.481	.168	.622
	N	60	60	60	60	60	60	60	60	60	60	60	60	60	60	5	5	5	5	5
Return on Avg Equity (ROAE) (%)	Pearson Correlation	.436**	.435**	.411**	.512**	-.309*	.120	-.033	-.007	.973**	1	-.561**	.053	.055	.187	-.296	.225	.359	.466	.251
	Sig. (2-tailed)	.001	.001	.001	.000	.016	.363	.802	.959	.000		.000	.689	.677	.152	.629	.716	.553	.429	.684
	N	60	60	60	60	60	60	60	60	60	60	60	60	60	60	5	5	5	5	5
Cost to Income Ratio (%)	Pearson Correlation	-.823**	-.827**	-.803**	-.857**	-.261*	-.266*	-.067	-.046	-.611**	-.561**	1	.242	.177	-.201	.633	-.106	-.283	-.448	.372
	Sig. (2-tailed)	.000	.000	.000	.000	.044	.040	.609	.727	.000	.000		.063	.177	.124	.252	.865	.645	.449	.538
	N	60	60	60	60	60	60	60	60	60	60	60	60	60	60	5	5	5	5	5
Net Loans / Total assets (%)	Pearson Correlation	-.330*	-.380**	-.174	-.251	-.500**	.135	.229	.235	.079	.053	.242	1	.932**	-.700**	.104	.328	-.963**	.299	-.209
	Sig. (2-tailed)	.010	.003	.184	.053	.000	.304	.078	.070	.549	.689	.063		.000	.000	.868	.590	.008	.625	.735
	N	60	60	60	60	60	60	60	60	60	60	60	60	60	60	5	5	5	5	5
Net Loans / Dep. & ST Funding (%)	Pearson Correlation	-.257*	-.318*	-.113	-.226	-.460**	.218	.275*	.200	.091	.055	.177	.932**	1	-.663**	.060	.293	-.970**	.318	-.176
	Sig. (2-tailed)	.047	.013	.388	.083	.000	.094	.034	.126	.489	.677	.177	.000		.000	.924	.632	.006	.602	.777
	N	60	60	60	60	60	60	60	60	60	60	60	60	60	60	5	5	5	5	5
Liquid Assets / Dep. & ST Funding	Pearson Correlation	.222	.263*	.069	.144	.259*	-.298*	-.478**	-.231	.105	.187	-.201	-.700**	-.663**	1	-.216	.390	-.881*	.712	.105
	Sig. (2-tailed)	.088	.042	.600	.272	.046	.021	.000	.076	.425	.152	.124	.000	.000		.727	.517	.048	.177	.867
	N	60	60	60	60	60	60	60	60	60	60	60	60	60	60	5	5	5	5	5
GDP (real growth rates, in %)	Pearson Correlation	.138	.146	.100	.091	-.561	-.008	-.026	-.090	-.013	-.296	.633	.104	.060	-.216	1	.326	.132	-.679	-.307
	Sig. (2-tailed)	.825	.815	.873	.885	.325	.989	.967	.886	.983	.629	.252	.868	.924	.727		.592	.833	.208	.615
	N	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
Inflation (average, on a cumulative basis, in	Pearson Correlation	-.365	-.355	-.489	-.069	.268	.369	.336	.358	.845	.225	-.106	.328	.293	.390	.326	1	-.337	.413	-.734
	Sig. (2-tailed)	.545	.557	.403	.913	.663	.541	.581	.554	.072	.716	.865	.590	.632	.517	.592		.579	.489	.158
	N	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
Unemploy ment rate (in %)	Pearson Correlation	.994**	.995**	.953*	.943*	-.828	-.964**	-.964**	-.969**	-.421	.359	-.283	-.963**	-.970**	-.881*	.132	-.337	1	-.535	.138
	Sig. (2-tailed)	.000	.000	.012	.016	.083	.008	.008	.006	.481	.553	.645	.008	.006	.048	.833	.579		.353	.825
	N	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
Average MKD/EUR exchange rate	Pearson Correlation	-.578	-.578	-.646	-.292	.761	.388	.381	.451	.723	.466	-.448	.299	.318	.712	-.679	.413	-.535	1	-.072
	Sig. (2-tailed)	.307	.307	.239	.634	.135	.518	.527	.446	.168	.429	.449	.625	.602	.177	.208	.489	.353		.909
	N	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
Average MKD/USD exchange rate	Pearson Correlation	.094	.088	.099	.031	-.265	-.329	-.309	-.321	-.301	.251	.372	-.209	-.176	.105	-.307	-.734	.138	-.072	1
	Sig. (2-tailed)	.880	.888	.874	.961	.667	.589	.613	.598	.622	.684	.538	.735	.777	.867	.615	.158	.825	.909	
	N	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5

Source: Own elaboration.