PROFITABILITY PUZZLES: INSIGHTS FROM NORTH MACEDONIAN BANKS

Tatjana Spaseska[1],
Ilija Hristoski[2],
Dragica Odzaklieska[3]

Abstract: The profitability of banks, as an indicator of financial performance, reflects their ability to generate substantial revenues. Bank profits are essential for their survival, solvency, and growth in a highly competitive environment. Moreover, even if solvency is high, poor profitability undermines a bank's capacity to absorb negative shocks, which can eventually impact its solvency. Consequently, profitability has a vital role in maintaining the stability of the banking and financial system as a whole. Hence, the primary goal of this research is to analyze several important bank-specific and macroeconomic determinants of bank profitability in the Republic of North Macedonia. More specifically, the paper investigates how the Return on Average Assets (ROAA) is influenced by the Capital Adequacy Ratio (CAR), Credit Risk (CR), Cost to Income Ratio (CIR), Loan to Deposit Ratio (LDR), Inflation Rate (IR), and Gross Domestic Product Rate (GDPR). Using secondary data from trustworthy sources, covering quarterly time series from 2005:Q1 to 2023:Q4, we employ correlation analysis, Granger causality tests, as well as the Auto-Regressive Distributed Lag (ARDL) approach to examine both short- and long-run dependencies among the variables. The results confirm the statistically significant impact of the regressors on the dependent variable and provide a solid foundation for the successful management and enhancement of banks' profitability.

Keywords: banks, profitability, bank-specific determinants, macroeconomic determinants, ARDL methodology, North Macedonia

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[1] University "St. Kliment Ohridski" – Bitola, Faculty of Economics – Prilep, North Macedonia, e-mail: tatjana.spaseska@uklo.edu.mk, ORCID: 0000-0002-9460-7799

[2] University "St. Kliment Ohridski" – Bitola, Faculty of Economics – Prilep, North Macedonia, e-mail: ilija.hristoski@uklo.edu.mk, ORCID: 0000-0002-9291-7873

[3] University "St. Kliment Ohridski" – Bitola, Faculty of Economics – Prilep, North Macedonia, e-mail: dragica.odzaklieska@uklo.edu.mk, ORCID: 0009-0001-2188-308X

Introduction

Banking institutions are the backbone of a nation's financial system, allocating resources by channeling surplus funds to deficit entities, enabling investments, and driving economic growth. Their role is crucial in developing economies, where weak capital markets make banks the main financing source. Enhancing banking efficiency boosts economic growth by reducing loan costs, increasing corporate investment, and stimulating consumption. Profitable banks also support monetary policy and ensure financial stability.

Bank profitability, a financial key performance indicator, reflects managerial efficiency and significantly impacts banking sector stability. Sustainable profitability is crucial for sector stability, while a sound, profitable banking system is better equipped to withstand shocks, enhancing overall financial stability (Athanasoglou et al., 2022). To enhance profitability, bank management must analyze its determinants to better understand financial performance and mitigate future shocks. These factors fall into two categories: internal and external. Internal, or bank-specific, factors include size, capital adequacy, risk exposure, and operational efficiency. External factors, beyond the bank's control, stem from the macroeconomic environment and influence financial performance.

This paper examines the impact of internal and external factors on bank profitability in North Macedonia from 2005 to 2023. It focuses on Return on Assets (ROA) as the key measure, analyzing its relationship with internal factors such as capital adequacy, credit risk, management efficiency, and liquidity risk, alongside macroeconomic determinants like inflation and GDP growth.

The paper is structured as follows: The first section reviews prior research on bank-specific and macroeconomic determinants of profitability across various contexts. Section 2 presents the data and methodology, while Section 3 discusses the ARDL analysis results, their economic significance and implications. The final section concludes with recommendations.

1. Related Research

The profitability and liquidity of banks are essential for maintaining financial stability. A large body of empirical research has explored the influence of various determinants on bank profitability. For instance, Caliskan & Lecuna (2020) analyzed the impact of bank-specific and macroeconomic factors on Turkey's banking sector profitability (1980–2017) using regression analysis. Their findings indicate that macroeconomic indicators, such as inflation, interest rates and exchange rates, significantly influence ROA and ROE.

Bank-specific factors such as liquidity, asset management and operational efficiency are also crucial for enhancing profitability. Similar conclusions were drawn by Karadzic & Dalovic (2021), Zampara *et al*. (2017), Lutf & Omarkhil (2018), and Ćurak *et al*. (2012), who highlighted the positive impact of macroeconomic factors on bank profitability. Using a balanced panel data model on annual data from 47 large banks across 14 European countries (2013–2018), Karadzic & Dalovic (2021) found that GDP growth, inflation and market concentration significantly impact bank profitability. Athanasoglou *et al*. (2022) analyzed profitability determinants in South Eastern European (SEE) credit institutions (1998–2002) using fixed effects (FE) and random effects (RE) panel data models, finding that macroeconomic factors had varying effects, with inflation exerting a strong positive influence on bank profitability. Supiyadi *et al*. (2019), along with Hasanov *et al*. (2018) and O'Connell (2023), found that inflation had a significant positive impact on bank profitability, as evidenced in their studies. Lutf & Omarkhil (2018) confirm these findings in their study on Pakistani banks, revealing a positive long-term relationship between inflation, GDP, and both Return on Assets (ROA) and Return on Equity (ROE). They also highlight the significant influence of bank-specific factors, including capital adequacy, interest income, bank size, costs and non-interest income, on profitability.

A large number of studies emphasize the dominant influence of bank-specific factors on the profitability of banks. Qehaja-Keka *et al*. (2023) found that non-performing loans, loan interest rates, and total loans significantly influenced bank profitability in Albania and Kosovo from 2010 to 2020. Durguti *et al*. (2020) emphasized the dominance of bank-specific factors over macroeconomic ones in determining bank profitability. Their analysis of Kosovo's banking sector (2006–2019), using OLS regression and the Arellano-Bond GMM estimator, found that non-performing loans, capital adequacy, efficiency, the real exchange rate, and inflation significantly influenced profitability indicators. Almaskati (2022) similarly found that bank-specific factors primarily drove profitability. His research highlighted that market power and bank size significantly influenced both profitability and risk exposure. The research by Athanasoglou *et al*. (2022) and O'Connell (2023) further verified that all bank-specific factors significantly influenced bank profitability. Durand (2019), Batten & Vo (2019), and Yang (2019) highlighted the positive influence of capital structure on bank profitability. Specifically, banks with higher capital adequacy ratios are better equipped to absorb potential loan losses, thereby mitigating credit and insolvency risks, which ultimately enhances profitability. Sheaba Rani & Zergaw (2017) and Bucevska & Hadzi Misheva (2017) emphasized the significant and positive impact of management efficiency on bank profitability, highlighting its role in optimizing operational performance and enhancing financial outcomes. Adelopo *et al*. (2018) analyzed the influence of bank-specific and macroeconomic factors on bank profitability in Africa across three financial crisis periods (1999–2006, 2007–2009, and 2010–2013) using West African bank panel data and fixed effects models. Their findings indicated that costs, liquidity, and bank size consistently impacted return on assets (ROA) across all three periods, whereas no definitive conclusion was reached regarding the effects of capital adequacy, market power, credit risk, GDP, or inflation. Using panel data analysis, Ercegovac *et al*. (2020) examined the impact of bank-specific factors on ROA and ROE among 22 major EU banks from 2007 to 2019, in the aftermath of the financial crisis. Their findings highlighted that the cost-to-income ratio and the ratio of non-performing loans significantly influenced bank profitability. Zahariev *et al*. (2022) explored the relationship between key bank profitability indicators, ROE and ROA, and nine macroeconomic factors, including inflation, GDP, foreign exchange rates, and interest rates, within the Bulgarian banking system from 2014 to 2020. Employing descriptive statistics, a correlation matrix, VECM (Vector Error Correction Model), and SVR (Support Vector Regression), their analysis found that these macroeconomic variables did not significantly impact bank profitability. Consequently, they emphasized the need for banks to enhance management efficiency and drive innovation in interbank competition. Bucevska & Hadzi Misheva (2017) found that macroeconomic factors, particularly inflation and economic growth, had no significant impact on bank profitability.

The research conducted by various authors highlights the negative impact of certain bank-specific factors on banks' profitability indicators. For example, Kosumi & Zharku (2024) analyzed the effects of bank-specific, macroeconomic, and legal factors on bank profitability in North Macedonia from 2007 to 2022 using the VECM method. Their findings indicated that credit risk, liquidity, banking sector size, and non-performing loans significantly but negatively impacted ROA, while capital adequacy, GDP, interest rates, and operational efficiency positively influenced profitability. They suggested that Macedonian banks should enhance asset management and diversify income structures to mitigate credit risk and non-performing loans while maintaining strong liquidity ratios. Aspinmaa (2019), in her bachelor's thesis covering the period 2003–2017, found that bank-specific factors including bank size, credit risk, capital adequacy, and management efficiency significantly but negatively impacted on ROA and ROE in Central and Eastern European (CEE) countries. Karadzic & Dalovic (2020) found that bank-specific factors did not significantly influence banking profitability. This aligns with other studies that suggest varying impacts of internal factors on profitability, depending on the region or economic environment.

The literature review has provided valuable insights into bank profitability determinants across different contexts, emphasizing both internal and external factors. Nonetheless, North Macedonia's bank profitability remains underexplored, offering an opportunity to analyze these factors within its distinct economic and regulatory framework. This study addresses this gap by providing empirical evidence from North Macedonia, enriching the broader understanding of profitability drivers in emerging markets.

2. Data and Methodology

2.1 Data

Since the study includes more regressors, the number of observations in a dataset should account for the increased complexity due to the higher number of parameters to be estimated, so the statistical power, accuracy, and reliability of econometric results is maintained. Therefore, the data utilized comprises quarterly time series, spanning from 2005:Q1 to 2023:Q4, resulting in a total of 76 observations (19 years $\times$ 4 quarters/year = 76 quarters). Our analysis focuses on a single dependent variable and six independent variables, outlined as follows:

- *Dependent variable*
  - Return on Average Assets (*ROAA*), in percentages [%], as an indicator used to assess profitability and gauge financial performance of banks;

- *Independent variables*
  - Capital Adequacy Ratio (*CAR*), expressed in percentages [%], is computed as a ratio between the bank's equity and risk weighted assets; it is a measure of how much capital a bank has available and expresses the ability of the bank to deal with unexpected losses due to availability of adequate capital;
  - Credit Risk (*CR*), given in percentages [%], is a ratio between impaired loans (i.e., non-performing loans) and gross loans; it is a measure of the possibility of a loss resulting from a borrower's failure to repay a loan or meet contractual obligations;
  - Cost to Income Ratio (*CIR*), in percentages [%], as a measure of management efficiency, comparing the bank's operating costs to its operating income;
  - Loan to Deposit Ratio (*LDR*), in percentages [%], as a measure of the liquidity risk; it assesses a bank's liquidity by comparing a bank's total loans to its total customer deposits for the same period;
  - Inflation Rate (*INFLR*), in percentages [%], as a measure of macroeconomic stability;
  - Gross Domestic Product Rate (*GDPR*), in percentages [%], as a measure of the economic activity in the country;

The first four independent variables (*CAR*, *CR*, *CIR*, and *LDR*) belong to the group of banking system specific factors, whilst *IR* and *GDPR* are macroeconomic determinants.

All the data used in this research have been exploited from secondary sources only. The data for the dependent variable *ROAA*, including the first four independent variables (*CAR*, *CR*, *CIR*, and *LDR*), have been obtained from the Statistical Web Portal of the National Bank of Republic of North Macedonia containing indicators relevant for the Macedonian banking system (NBRNM, −b), whilst the data for the last two independent variables (*INFLR* and *GDPR*) have been taken from the same web portal containing data for the basic economic indicators (NBRNM, −c).

2.2 Methodology

First, we assessed the strength and direction of the linear relationship between the dependent variable and six independent variables by computing the Pearson correlation coefficient. The resulting correlation matrix summarizes the data and serves as input for further analysis. This step is essential for identifying relationships, detecting multicollinearity, and ensuring model stability.

The integration order of each variable was determined using the Augmented Dickey-Fuller (ADF) (Dickey & Fuller, 1979) and Phillips-Perron (PP) (Phillips & Perron, 1988) tests. Both tests were applied based on the Akaike (AIC) and Schwarz (SIC) Information Criteria.

The mix of I(0) and I(1) variables justified using the Auto-Regressive Distributed Lag (ARDL) methodology, also known as the Bound cointegration technique, a widely used econometric tool for analyzing dynamic relationships (Nkoro & Uko, 2016). Based on Pesaran & Shin (1998) and Pesaran et al. (2001), ARDL models captured both contemporaneously and lagged effects of dependent and independent variables. Their reliance on least squares estimation makes them particularly useful when the integration order of variables is uncertain, highlighting the flexibility that sets this approach apart (Giles, 2017a, 2017b, 2017c).

Optimal lag order selection, a crucial step in ARDL modeling, was determined by estimating an unrestricted Vector Auto-Regressive (VAR) model using five criteria: the LR test statistic, Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn Information Criterion (HQ).

Before analysis, the Granger causality test (Granger, 1969) was conducted to identify potential predictors of the target variable. Applied in the preliminary stage, it helped uncover predictive causal links, aiding in understanding variable dynamics and informing policy and strategy formulation.

To determine the impact and the magnitude of the set of six independent determinants on the chosen dependent variable (i.e., ROAA), we employed the ARDL methodology. In general, the ARDL(p, q_1, …, q_k) model, including a target variable Y and k regressors (X_1, X_2, …, X_k), can be specified as Eq. (1) suggests (Pesaran & Shin, 1999; Pesaran *et al*., 2001). Equation (1) represents an ARDL model that has been transformed into an Error Correction Model (ECM) to capture both the short-run dynamics and the long-run relationship among the variables.

$$\Delta Y_t = \gamma_0 + \sum_{i=1}^{p-1} \phi_i \cdot \Delta Y_{t-i} + \sum_{j=1}^{k} \sum_{m=0}^{q_j-1} \lambda_{j,m} \cdot \Delta X_{j,t-m} + + \psi \left(Y_{t-1} - \sum_{j=1}^{k} \delta_j \cdot X_{j,t-1} \right) + \varepsilon_t \qquad (1)$$

where:

k is the number of independent variables, X_k;

$p \geq 1$ is the optimal number of lags for the dependent variable, Y;

$q_j \geq 0$, $j = 1, \ldots, k$; are the optimal number of lags for each of the k independent variables, X_k;

Δ is the first-differencing operator;

$\Delta Y_t = Y_t - Y_{t-1}$ and $\Delta X_{j,t} = X_{j,t} - X_{j,t-1}$ represent the first differences of the variables, capturing short-run changes;

γ_0 is a constant term (intercept);

ΔY_{t-i}, $i = 1, \ldots, p-1$; are the differenced lagged values of the dependent variable Y at times $t-1, \ldots, t-p-1$;

ϕ_i, $i = 1, 2, \ldots, p-1$; are the short-run coefficients for the differenced lagged dependent variable, ΔY_{t-i};

$\Delta X_{j,t-m}$, $j = 1, \ldots, k$; $m = 0, 1, 2, \ldots, q_j-1$; are the differenced lagged values of the k independent variables X_k at times t (current value for $m = 0$), and $t-1, \ldots, t-q_j-1$ (lagged values for $m = 1, 2, \ldots, q_j-1$);

$\lambda_{j,m}$, $j = 1, \ldots, k$; $m = 0, 1, 2, \ldots, q_j-1$; are the short-run coefficients for the differenced lagged independent variables, $\Delta X_{j,t-m}$;

ψ is the coefficient of the error correction term (ECT), representing the speed of adjustment back to the long-run equilibrium;

$\left(Y_{t-1} - \sum_{j=1}^{k} \delta_j \cdot X_{j,t-1} \right)$ is the error correction term (ECT), capturing the long-run relationship between the variables;

ε_t is the disturbance (white noise) term.

The Wald test was used to assess whether the short-run coefficients of lagged independent variables are jointly zero, indicating their significance in influencing the dependent variable. The Bounds Cointegration Test (F-Bounds Test) examined the presence (H_1) or absence (H_0) of cointegration among variables, using the "5. Const. & Trend" specification based on prior integration tests.

The ARDL(1, 4, 4, 1, 0, 0, 0) model was estimated with an optimal lag length of L = 4. Following the Bounds Cointegration Test results, the Error Correction Model (ECM) was employed to estimate long-run equilibrium relationships within a VAR framework with 4 lags.

Diagnostic tests included the Breusch-Godfrey LM Test for autocorrelation, the Breusch-Pagan-Godfrey Test for heteroscedasticity, and the Jarque-Bera Test for normality. Model stability was validated through CUSUM and CUSUM of Squares Tests.

All analyses were performed using EViews v10 and IBM SPSS Statistics v20.

3. Results and Discussion

Table 1 presents the correlation matrix with Pearson coefficients, where the lower left half visualizes a heat map and the upper right half displays significance levels. *ROAA* shows a positive correlation with *CAR*, *INFLR*, and *GDPR*, while its negative correlation with *CR*, *CIR*, and *LDR* is statistically significant. The positive correlation between *ROAA* and *INFLR* is also significant. High correlations between *CIR* and *CR* (positive, significant) and *LDR* and *CAR* (negative, significant) suggest potential multicollinearity, which may impact ARDL estimates. However, most independent variable correlations remain low to moderate, indicating minimal multicollinearity concerns.

Table 1.
Correlation matrix and heat map of the observed variables

	ROAA	CAR	CR	CIR	LDR	INFLR	GDPR
ROAA	1	0.15993	-0.42035**	-0.63919**	-0.45768**	0.28639*	0.20804
CAR	0.15993	1	0.39948**	0.28288*	-0.77336**	0.06719	0.17246
CR	-0.42035	0.39948	1	0.74141**	-0.24183*	-0.44400**	0.20146
CIR	-0.63920	0.28288	0.74141	1	-0.07341	-0.21581	0.08707
LDR	-0.45768	-0.77336	-0.24183	-0.07341	1	-0.04773	-0.27234*
INFLR	0.28639	0.06719	-0.44400	-0.21581	-0.04773	1	0.04978
GDPR	0.20804	0.17246	0.20146	0.08707	-0.27234	0.04978	1

Note on the level of significance (2-tailed):
(*) Significant at the 0.05 level;
(**) Significant at the 0.01 level;
Source: The authors, IBM SPSS v20 output

Table 2 summarizes the ADF and PP test results for the variables' order of integration, considering AIC, SIC, and the 'With Constant and Trend' option.

Table 2.
Summary of the ADF and PP tests (option 'With Constant & Trend')

		Variables						
		Dependent	Independent					
Test	Criterion	*ROAA*	*CAR*	*CR*	*CIR*	*LDR*	*INFLR*	*GDPR*
ADF	AIC	I(1)***	I(0)**	I(1)***	I(1)***	I(1)*	I(1)**	I(0)***
	SIC	I(1)***	I(0)**	I(1)***	I(1)***	I(1)***	I(1)***	I(0)***
PP	AIC	I(1)***	I(0)**	I(1)***	I(1)***	I(1)***	I(1)**	I(0)***
	SIC	I(1)***	I(0)**	I(1)***	I(1)***	I(1)***	I(1)***	I(0)***

Note on the level of significance: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%;

Source: The authors, EViews v10 output

CR is stationary at level (I(0)) at a 1% significance level (ADF test) and 5% (PP test) under the 'Without Constant & Trend' option. *LDR* is I(0) with 'With Constant' (ADF) but I(1) otherwise. *INFLR* is I(0) with 'With Constant' and 'Without Constant & Trend' (PP test) but I(1) otherwise. To ensure consistency, these variables are considered I(1) under 'With Constant & Trend,' as shown in Table 2.

Since the variables of interest have different integration orders (i.e., some are stationary at level and others become stationary after being first-differenced), the ARDL modeling approach is appropriate for analysis.

The analysis of the resulting estimated optimal number of lags, *L*, for various criteria (LR, FPE, AIC, SC, and HQ) and various maximum number of lags, *M*, suggests considering optimal lag lengths of *L* = 2 for *M* = 4 and *L* = 5 for *M* = 5. Since *L* = 4 is commonly chosen for quarterly data, we have also considered it to obtain an alternative model to be compared with other ARDL specifications. The goal was to evaluate multiple models based on overall statistics, residual diagnostics, and stability. The comparison of these ARDL models is shown in Table 3.

Table 3.
Comparison of the vital statistics regarding three ARDL models specified using Option 5. 'Const. & Trend'

	ARDL models		
	M = 4, L = 2	M = 5, L = 5	L = 4
	ARDL (1, 0, 1, 0, 0, 0, 0)	ARDL (1, 0, 1, 0, 0, 0, 0)	ARDL (1, 4, 4, 1, 0, 0, 0)
R-squared	0.849911	0.849911	0.883885
Adj. R-squared	0.829129	0.829129	0.847330
Durbin-Watson stat	2.094409	2.094409	2.059332
Akaike info criterion	0.498076	0.498076	0.511835
F-statistic	40.89731	40.89731	24.17974
Prob (F-statistic)	0.000000	0.000000	0.000000

Source: The authors, EViews v10 output

Table 3 results show that the ARDL model (1, 4, 4, 1, 0, 0, 0) with L = 4 outperforms the L = 2 and L = 5 models. The high R-squared value (0.883885) indicates that 88.39% of the variation in ROAA is explained by the regressors. The Adjusted R-squared (0.847330) confirms strong explanatory power, while the Durbin-Watson statistic (2.059332 ≈ 2.00) suggests no autocorrelation. The Akaike Information Criterion (AIC) value (0.511835) is the lowest among 62,500 models, indicating optimal model fit considering accuracy and parameter count. The F-statistic (24.17974) is statistically significant (p-Value = 0.000000 < 0.05), indicating that the independent variables jointly explain the dependent variable and the model is significant. Hence, *L* = 4 was selected as the optimal lag length for subsequent analyses.

The Granger causality test does not imply true causality but assesses whether past values of one variable can predict another. The test results for *L* = 4 show that only *CIR* (F-statistic = 2.82428, p-Value = 0.0321 < 0.05) Granger-causes *ROAA*, implying that only *CIR*'s past values contribute to forecasting *ROAA*. Despite this, in ARDL modeling, all independent variables remain valid as the method captures both short-term dynamics and long-term relationships, which may not be fully captured by pairwise Granger causality tests.

The specification of the chosen ARDL(1, 4, 4, 1, 0, 0, 0) model in a short-run includes two fixed regressors (i.e., C and @TREND) (Table 4).

Table 4 reveals that:

- The first lag of *ROAA* shows a positive but insignificant effect (+0.067841, p-Value = 0.5878 > 5%);
- *CAR*'s coefficient at level is positively correlated (+0.118457) but insignificant (p-Value = 0.2813 > 5%);
- The first and third lags of *CAR* are insignificant, with negative and positive effects (–0.048979 and +0.079409, p-Values > 5%);
- The second and fourth lags of *CAR* show significant positive (+0.238782) and negative (–0.232541) influences (p-Values < 10% and < 5%);

Table 4.
Short-run coefficients of the ARDL(1, 4, 4, 1, 0, 0, 0) model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ROAA(–1)	0.067841	0.124427	0.545224	0.5878
CAR	0.118457	0.108847	1.088288	0.2813
CAR(–1)	–0.048979	0.126063	–0.388525	0.6992
CAR(–2)	0.238782	0.127620	1.871042	0.0668*
CAR(–3)	0.079409	0.123266	0.644208	0.5222
CAR(–4)	–0.232541	0.096605	–2.407128	0.0195**
CR	–0.184296	0.063864	–2.885753	0.0056***
CR(–1)	0.123611	0.078374	1.577198	0.1206
CR(–2)	–0.098410	0.076643	–1.283992	0.2046
CR(–3)	–0.013789	0.075232	–0.183282	0.8553
CR(–4)	0.131529	0.056755	2.317483	0.0243**
CIR	–0.071739	0.016659	–4.306367	0.0001***
CIR(–1)	–0.031401	0.020168	–1.556964	0.1253
LDR	0.003876	0.016469	0.235334	0.8148
INFLR	0.025886	0.011108	2.330259	0.0236**
GDPR	–0.000769	0.009765	–0.078788	0.9375
C	5.210434	2.530943	2.058692	0.0444**
@TREND	–0.028577	0.005643	–5.064172	0.0000***

Note on the level of significance: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%;

Source: The authors, EViews v10 output

- *CR* has a significant negative impact at level (–0.184296, p-Value = 0.0056 < 5%);
- *CR*'s first and fourth lags show positive influences, with the latter being statistically significant (p-Value = 0.0243 < 5%);
- The second and third lags of *CR* exhibit negative but insignificant effects (–0.098410 and –0.013789, p-Values > 5%);

- *CIR* has a significant negative effect at level (−0.071739, p-Value = 0.0001 < 5%);
- The first lag of *CIR* is insignificant with a negative impact (−0.031401, p-Value = 0.1253 > 5%);
- *LDR*'s level effect is positive but insignificant (+0.003876, p-Value = 0.8148 > 5%);
- *INFLR*'s level coefficient is positively significant (+0.025886, pValue = 0.0236 < 5%);
- *GDPR* shows a negative but insignificant effect (−0.000769, p-Value = 0.9375 > 5%);
- The fixed regressors, C (+5.210434) and @TREND (−0.028577), are both significant (p-Values < 5%). Their inclusion in the ARDL model is justified and therefore they cannot be omitted.

The Wald test results in Table 5 confirm that all four lags of *CAR* and *CR* significantly influence *ROAA* in the short run at the 5% level, indicating short-run causality. However, the lags of *ROAA* and *CIR* do not impact *ROAA* in the short-run.

The F-Bounds Test results in Table 6 show that the calculated F-statistic (9.082199) exceeds the critical values for I(1) at all significance levels (10%, 5%, 2.5%, and 1%), i.e. 3.59, 4.00, 4.38, and 4.90.

Table 5.
Results of the Wald Test

Variable	Lags	Chi-square statistics	df	Prob.	Null hypothesis
ROAA	1	0.297269	1	0.5856	Accepted
CAR	4	10.37584	4	0.0346*	Rejected
CR	4	11.89726	4	0.0181*	Rejected
CIR	1	2.424137	1	0.1195	Accepted

Note on the level of significance: (*) Significant at the 5% level;
Source: The authors, EViews v10 output

The F-Bounds Test results allow rejection of the null hypothesis (no cointegration), confirming that *ROAA* is cointegrated with *CAR*, *CR*, *CIR*, *LDR*, *INFLR*, and *GDPR* in the long-run. This indicates a shared stochastic trend, meaning the variables move proportionally over time. While short-term shocks may cause deviations, they tend to converge in the long term.

The long-term relationship enables both short-term ARDL and long-term Error Correction Model (ECM) estimations.

The coefficient of the cointegrating equation (–0.932159) is negative and significant (p-Value = 0.0000 < 5%), indicating a long-run Granger causality running from all regressors to *ROAA*. The system adjusts toward long-run equilibrium at a rate of 93.22% per period, i.e. quarter (Table 7).

Table 6.
Results of the F-Bounds Test

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	9.082199	10%	2.53	3.59
k	6	5%	2.87	4.00
		2.5%	3.19	4.38
		1%	3.60	4.90

Source: The authors, EViews v10 output

Table 7.
Statistics of the Cointegration Equation Coefficient

Variable	Coefficient	Std. Error	t-Statistics	Prob.
CointEq(–1)	–0.932159	0.110909	–8.404720	0.0000

Source: The authors, EViews v10 output

Table 8 shows both the long-run coefficients and the Error Correction (EC) term.

Table 8.
Long-run coefficients and the Error Correction (EC) term

Levels Equation Case 5: Unrestricted Constant and Unrestricted Trend				
Variable	Coefficient	Std. Error	t-Statistics	Prob.
CAR	0.166418	0.076131	2.185945	0.0332**
CR	–0.044365	0.026448	–1.677415	0.0992*
CIR	–0.110647	0.011692	–9.463640	0.0000***
LDR	0.004158	0.017584	0.236450	0.8140
INFLR	0.027770	0.012170	2.281828	0.0265**
GDPR	–0.000825	0.010492	–0.078670	0.9376
EC = ROAA – (0.1664*CAR –0.0444*CR –0.1106*CIR + +0.0042*LDR +0.0278*INFLR –0.0008*GDPR)				

Note on the level of significance: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1%;

Source: The authors, EViews v10 output

From Table 8 it is obvious that, in a long-run:

- Three regressors (*CR*, *CIR*, *GDPR*) negatively affect *ROAA* with coefficients −0.044365, −0.110647, and −0.000825, respectively;
- Three regressors (*CAR*, *LDR*, *INFLR*) positively affect *ROAA* with coefficients +0.166418, +0.004158, and +0.027770, respectively;
- The effects of *CAR*, *CR*, *CIR*, and *INFLR* on *ROAA* are statistically significant (p-Values of 0.0332 < 5%, 0.0992 < 10%, 0.0000 < 5%, and 0.0265 < 5%, respectively);

Applying the *ceteris paribus* principle, the coefficients in Table 8 also suggest that:

- A 1 percentage point [pp] increase in *CAR* raises *ROAA* by 0.166418 [pp] (statistically significant, p-Value = 0.0332 < 5%);
- A 1 percentage point [pp] increase in *CR* reduces *ROAA* by 0.044365 [pp] (statistically significant, p-Value = 0.0992 < 10%);
- A 1 percentage point [pp] increase in *CIR* decreases *ROAA* by 0.110647 [pp] (statistically significant, p-Value = 0.0000 < 1%);
- A 1 percentage point [pp] increase in *LDR* increases *ROAA* by 0.004158 [pp] (statistically insignificant, p-Value = 0.8140 > 10%);
- A 1 percentage point [pp] increase in *INFLR* raises *ROAA* by 0.027770 [pp] (statistically significant, p-Value = 0.0265 < 5%);
- A 1 percentage point [pp] increase in *GDPR* reduces *ROAA* by 0.000825 [pp] (statistically insignificant, p-Value = 0.9376 > 10%).

The residuals diagnostic tests have led to the following findings:

The correlogram of residuals (Q statistics) for the ARDL(1, 4, 4, 1, 0, 0, 0) model shows no autocorrelation or partial correlation up to 16 lags, with p-values exceeding 0.05 for all lags. This supports the acceptance of the null hypothesis (H_0) stating that there is no autocorrelation within the specified lag range. The Breusch-Godfrey Serial Correlation LM Test (Obs*R-squared = 12.34273, Prob. Chi-Square(8) = 0.1366 > 10%) suggests that the null hypothesis of no serial correlation in the residuals up to eight lags can be accepted at the 10% significance level. The Breusch-Pagan-Godfrey test shows that the ARDL(1, 4, 4, 1, 0, 0, 0) model's residuals are free from heteroskedasticity (Obs*R-squared = 26.67423, Prob. Chi-Square(17) = 0.0630 > 5%). Therefore, the null hypothesis of no heteroskedasticity can be accepted at the 5% significance level. The Jarque-Bera test (Jarque-Bera = 0.501784, Prob. = 0.778106 > 10%)

confirms that the residuals are normally distributed, allowing acceptance of the null hypothesis at the 10% significance level.

Residual diagnostics confirm the ECM's suitability for hypothesis testing and forecasting. Additionally, CUSUM and CUSUM of Squares plots remain within the 5% critical bounds, verifying the structural stability of the ARDL(1, 4, 4, 1, 0, 0, 0) model coefficients.

4. Conclusions

This paper investigates the impact of various bank-specific and macroeconomic factors on the profitability of Macedonian banks from 2005 to 2023. The study is focused on Return on Average Assets (*ROAA*) as the dependent variable, which serves as a measure of bank profitability. Specifically, the analysis explores how profitability is influenced by the Capital Adequacy Ratio (*CAR*), Credit Risk (*CR*), Cost-to-Income Ratio (*CIR*), Loan-to-Deposit Ratio (*LDR*), Inflation Rate (*IR*), and Gross Domestic Product Rate (*GDPR*). The study employs correlation analysis, Granger causality tests, and the Auto-Regressive Distributed Lag (ARDL) approach to examine these relationships.

The study reveals that Return on Average Assets (*ROAA*) is significantly correlated with several key determinants. Inflation Rate (*IR*) has a positive, yet statistically significant impact on bank profitability in both the short- and long-term. Similarly, the Capital Adequacy Ratio (*CAR*) positively influences *ROAA* in the long-run, though its short-term effect is positive but not statistically significant. The Loan-to-Deposit Ratio (*LDR*) also shows a positive influence on profitability, but this effect is not statistically significant. On the other hand, Credit Risk (*CR*) and the Cost-to-Income Ratio (*CIR*) have a negative and statistically significant impact on *ROAA* across both timeframes. The Gross Domestic Product Rate (*GDPR*) shows a negative, but insignificant effect on bank profitability.

The findings of this study align with those of Kosumi & Zharku (2024), especially regarding the significant, yet negative impact of Credit Risk (*CR*) on profitability and the positive influence of Capital Adequacy Ratio (*CAR*) on profitability indicators. Additionally, Kosumi & Zharku's study extends the analysis by highlighting the positive impact of GDP, interest rates and operational efficiency on Return on Average Assets (*ROAA*), thus providing a broader perspective on the factors influencing bank profitability. On the other hand, the findings of Curak *et al*. (2012) highlight a significant positive impact of macroeconomic factors, especially GDP growth, on bank profitability in North Macedonia. This contrasts with the conclusion of this study, which finds the GDP growth rate (*GDPR*) to have a statistically insignificant effect on Return on Average Assets (*ROAA*). This difference suggests that while GDP growth is widely seen as a key driver of bank profitability in many contexts (e.g., Kosumi & Zharku, 2024), its influence on Macedonian banks during the analyzed period appears to be more intricate and may be shaped by other unique economic or structural factors within the country.

Given that both Return on Average Assets (*ROAA*) and Return on Average Equity (*ROAE*) are widely accepted measures of bank profitability, future studies could explore the relationship between ROAE and the same bank-specific and macroeconomic determinants analyzed in this research. This would offer a more comprehensive understanding of the factors influencing profitability in the Macedonian banking sector.

References

Adelopo, I., Lloydking, R., & Tauringana, V. (2018). Determinants of bank profitability before, during, and after the financial crisis. *International Journal of Managerial Finance*, *14*(4), pp.378–398. DOI: 10.1108/IJMF-07-2017-0148

Almaskati, N. (2022). The Determinants of bank profitability and risk: A random forest approach. *Cogent Economics & Finance*, *10*(1). DOI: 10.1080/23322039.2021.2021479

Aspinmaa, E. (2019). *Determinants of Bank Profitability in Central and Eastern European Countries*. Bachelor's Thesis. Department of Economics and Finance, School of Business and Governance, Tallinn University of Technology, Tallinn, Estonia. Available online: https://digikogu.taltech.ee/en/item/8c73f9db-35e0-40d6-9744-b8f6fda60dea

Athanasoglou, P. P., Delis, M. D., & Staikouras, C. K. (2022). Determinants of Bank Profitability in the South Eastern European Region. *Bank of Greece Working Paper No. 47*. DOI: 10.2139/ssrn.4163741

Batten, J., & Vo, X. V. (2019). Determinants of Bank Profitability – Evidence from Vietnam. *Emerging Markets Finance and Trade*, *55*(6), pp.1417–1428. DOI: 10.1080/1540496X.2018.1524326

Bucevska, V., & Hadzi Misheva, B. (2017). The Determinants of Profitability in the Banking Industry: Empirical Research on Selected Balkan Countries. *Eastern European Economics*, *55*(2), pp.146–167. DOI: 10.1080/00128775.2016.1260473

Caliskan, M. M. T., & Lecuna, H. K. S. (2020). The Determinants of Banking Sector Profitability in Turkey. *Business and Economics Research Journal*, *11*(1), pp.161–167, DOI: 10.20409/berj.2020.242

Curak, M., Poposki, K., & Pepur, S. (2012). Profitability Determinants of the Macedonian Banking Sector in Changing Environment. *Procedia – Social and Behavioral Sciences 44*, pp.406–416. DOI: 10.1016/j.sbspro.2012.05.045

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association*, *74*(366), pp.427–431. DOI: 10.1080/01621459.1979.10482531

Durand, P. (2019). Determinants of banks' profitability: Do Basel III liquidity and capital ratio matter? *EconomiX – CNRS*, Working Paper 2019-24, Université Paris Nanterre, Nanterre, France

Durguti, E. A., Krasniqi, E. H., & Krasniqi, D. (2020). Assessing the Performance of Factors Affecting the Profitability of the Banking System: Evidence from Kosovo. *European Journal of Sustainable Development*, *9*(2), pp.304–314. DOI: 10.14207/ejsd.2020.v9n2p304

Ercegovac, R., Klinac, I., & Zdrilić, I. (2020). Bank Specific Determinants of EU Banks Profitability after 2007 Financial Crisis. *Journal of Contemporary Management Issues*, *25*(1), pp.89–102. DOI: 10.30924/mjcmi.25.1.5

Giles, D. (2017a). *AutoRegressive Distributed Lag (ARDL) Estimation: Part 1 – Theory. Econometric Analysis Insight Blog.* Available online: https://blog.eviews.com/2017/04/autoregressive-distributed-lag-ardl.html

Giles, D. (2017b). *AutoRegressive Distributed Lag (ARDL) Estimation: Part 2 – Inference. Econometric Analysis Insight Blog.* Available online: https://blog.eviews.com/2017/05/autoregressive-distributed-lag-ardl_8.html

Giles, D. (2017c). *AutoRegressive Distributed Lag (ARDL) Estimation: Part 3 – Practice. Econometric Analysis Insight Blog.* Available online: https://blog.eviews.com/2017/05/autoregressive-distributed-lag-ardl.html

Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica*, *37*(3), pp.424‒438. DOI: 10.2307/1912791

Hasanov, F. J., Bayramli, N., & Al-Musehel, N. (2018). Bank-Specific and Macroeconomic Determinants of Bank Profitability: Evidence from an Oil-Dependent Economy. *International Journal of Financial Studies 6*, 78, pp.1‒21. DOI: 10.3390/ijfs6030078

Karadzic, V., & Dalovic, N. (2021). Profitability Determinants of Big European Banks. *Journal of Central Banking Theory and Practice*, *10*(2), pp.39‒56. DOI: 10.2478/jcbtp-2021-0013

Kosumi, A., & Zharku, L. (2024). Bank Specific, Economic and Legal Determinants of Profitability in the Republic of North Macedonia. *Access to Justice in Eastern Europe* (AJEE), *7*(2), pp.212‒233, DOI: 10.33327/AJEE-18-7.2-a000209

Lutf, L., & Omarkhil, H. (2018). Impact of Macroeconomic Factors on Banking Profitability. *International Finance and Banking*, *5*(1), pp.44‒69. DOI: 10.5296/ifb.v5i1.13080

NBRNM (‒a). *Reports on the risks in the banking system of the Republic of North Macedonia in the first quarter of 2024*. National Bank of the Republic of North Macedonia. Available online: https://www.nbrm.mk/content/Regulativa/Kvartalen_31_03_ 2024.pdf

NBRNM (‒b). *Data and indicators for the banking system in the Republic of North Macedonia.* National Bank of the Republic of North Macedonia. Available online: https://www.nbrm.mk/podatotsi_i_pokazatieli_za_ bankarskiot_sistiem_na_riepublika_makiedonija.nspx

NBRNM (‒c). *Basic economic indicators for the Republic of North Macedonia.* National Bank of the Republic of North Macedonia. Available online: https://www.nbrm.mk/osnovni_ekonomski_ pokazateli.nspx

Nkoro, E., & Uko, A. K. (2016). Autoregressive Distributed Lag (ARDL) cointegration technique: application and interpretation. *Journal of Statistical and Econometric Methods*, *5*(4), pp.63‒91.

O'Connell, M. (2023). Bank-specific, industry-specific and macroeconomic determinants of bank profitability: evidence from the UK. *Studies in Economics and Finance, 40*(1), pp.155‒174. DOI: 10.1108/SEF-10-2021-0413

Pesaran, M. H., & Shin, Y. (1999). An Autoregressive Distributed-Lag Modelling Approach to Cointegration Analysis. *Econometrics and*

Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium 31, pp.371–413. DOI: 10.1017/CCOL521633230.011

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds Testing Approaches to the Analysis of Level Relationships. *Journal of Applied Econometrics*, *16*(3), pp.289–326. DOI: 10.1002/jae.616

Phillips, P. C. B., & Perron, P. (1988). Testing for a Unit Root in Time Series Regression. *Biomètrika*, *75*(2), pp.335–346. DOI: 10.1093/biomet/75.2.335

Qehaja-Keka, V., Ahmeti, S., & Aliu, M. (2023). Bank Profitability Determinants: Evidence from Kosovo and Albania. *Journal of Liberty and International Affairs*, *9*(2), pp.297–311. DOI: 10.47305/JLIA239237qk

Sheaba Rani, D. M., & Zergaw, L. N. (2017). Bank Specific, Industry Specific and Macroeconomic Determinants of Bank Profitability in Ethiopia. *International Journal of Advanced Research in Management and Social Sciences*, *6*(3), pp.74–96.

Supiyadi, D., Arief, M., & Nugraha, N. (2019). The Determinants of Bank Profitability: Empirical Evidence from Indonesian Sharia Banking Sector. *Proceedings of the 1st International Conference on Economics, Business, Entrepreneurship, and Finance* (ICEBEF 2018), Advances in Economics, Business and Management Research Series, Vol. 65, pp.21–26. DOI: 10.2991/icebef-18.2019.6

Yang, K. (2019). Determinants of the Profitability of Commercial Banks – the case of Industrial Bank Co. Ltd. *The Frontiers of Society, Science and Technology*, *1*(1), pp.21–29. DOI: 10.25236/FSST.070104

Zahariev, A., Angelov, P., & Zarkova, S. (2022). Estimation of Bank Profitability Using Vector Error Correction Model and Support Vector Regression. *Economic Alternatives*, University of National and World Economy, Sofia, Bulgaria, Issue 2, pp.157–170. DOI: 10.37075/EA.2022.2.01

Zampara, K., Giannopoulos, M., & Koufopoulos, D. N. (2017). Macroeconomic and industry-specific determinants of Greek bank profitability. *International Journal of Business and Economic Sciences Applied Research*, *10*(1), pp.13–22. DOI: 10.25103/ijbesar.101.02