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Dragica Odzaklieska

“St. Kliment Ohridski” University - Bitola
 Faculty of Economics - Prilep
 Prilep, North Macedonia

dragica.odzaklieska@uklo.edu.mk

Ilija Hristoski

“St. Kliment Ohridski” University - Bitola
 Faculty of Economics - Prilep
 Prilep, North Macedonia

ilija.hristoski@uklo.edu.mk

Tatjana Spaseska

“St. Kliment Ohridski” University - Bitola
 Faculty of Economics - Prilep
 Prilep, North Macedonia

tatjana.spaseska@uklo.edu.mk

MACROECONOMIC DETERMINANTS OF CORPORATE DEBT: EVIDENCE FROM NORTH MACEDONIA

Abstract: Several important factors affect the financing of companies in North Macedonia today. The paper aims to explore how the Gross Loans to Non-Financial Sector / GDP ratio depends on the Inflation Rate, the Interest Rate of Non-financial Sector Loans, and the GDP. Based on the secondary data (quarterly time series) obtained from credible sources covering the period from 2015:Q1 to 2023:Q3, we employ the Auto-Regressive Distributed Lag (ARDL) approach to examine both the short- and long-run dependencies. The results confirm the statistically significant impact of the regressors on the dependent variable.

Keywords: Corporate debt, inflation, interest rate, GDP, ARDL methodology

1. INTRODUCTION

The corporate sector plays a pivotal role in generating gross domestic product and employment rates, thereby serving as a primary driver of economic growth. However, the success of the corporate sector is largely contingent upon access to financing. Financing is a critical and complex process essential for the survival, growth, and effective management of companies. However, securing reliable financing sources poses a significant challenge, directly impacting companies' strength and stability. In North Macedonia, companies typically exhibit a smaller structure, limiting their access to alternative financing options. Non-banking financial institutions play a modest role in funding the domestic corporate sector, and the use of debt financing through the domestic capital market is virtually non-existent. Consequently, credit funds emerge as the predominant source for supporting companies' operational and developmental activities. This scenario is further exacerbated by several significant macroeconomic and geopolitical events that adversely affect corporate financing. Notably, these include the military conflict between Russia and Ukraine, disruptions in global supply chains, escalating inflation, and increasing interest rates. According to the Financial Stability Report by the National Bank of the Republic of North Macedonia, the total debt within the domestic corporate sector has shown a consistent increase over recent years, culminating in a figure of 565,019 million Macedonian denars (MKD) at the close of 2022 (NBRNM, 2022a, pp. 69–71). Concurrently, the domestic debt attributed to the corporate sector has also seen an uptrend, reaching 232,408 million MKD by the end of 2022. This surge in borrowing needs is largely attributable to several factors, including the steep rise in energy prices, a considerably high inflation rate, and an overall escalation in operational expenses. For instance, within the Central and Southeast Europe region, the average inflation rate for 2022 stood at 13.3%. In comparison, the European Union recorded an inflation rate of 9.0%, while our country reported a higher figure of 14.2% (NBRNM, 2022b, p. 4). All these conditions have significantly elevated companies' financial needs, leading them to heavily rely on credit financing. Additionally, a considerable portion of the debt portfolio (47%) is subject to variable interest rates, underscoring the sector's vulnerability to interest rate risk. This factor becomes particularly critical amidst the current scenario of rising interest rates and the subsequent tightening of monetary policy. Given the lesser focus on corporate debt relative to public debt, despite both being major contributors to global indebtedness, the main goal of this study is to analyze the impact of macroeconomic determinants (i.e., interest rate,

inflation rate, and GDP) on the amount of corporate debt of the non-financial sector, specifically by analyzing the non-financial corporate debt-to-GDP ratio.

The remainder of the paper is organized as follows: Section 2 offers an overview of prior research pertinent to the topic. Section 3 details the data and methodology employed in this study and presents the results obtained. Section 4 interprets and discusses these findings. The final section concludes the paper and suggests directions for future research.

2. RELATED RESEARCH

The level of global debt experienced a significant surge following the 2008-09 global financial crisis. Global debt, encompassing the nonfinancial corporate sector, financial sector, government, and household debt, rose from 292% of the world's gross domestic product (GDP) in 2008 to 318% by 2018. Notably, nonfinancial corporate and government debt were primary drivers of the increase in global debt post-global financial crisis. Specifically, the ratio of nonfinancial corporate and government debt to GDP climbed from 78% to 92% and from 62% to 86%, respectively, during the period from 2008 to 2018, as reported by the Institute of International Finance (IIF) in 2019 (Abraham, Cortina, & Schmukler, 2020). In 2023, the global debt increased by over \$15 trillion, reaching a record peak of \$313 trillion. Despite this surge, the global debt-to-GDP ratio fell for the third consecutive year, primarily due to the performance of mature markets (IIF, 2024). Abraham, Cortina, & Schmukler (2020, p. 1) observed that in the aftermath of the global financial crisis, nonfinancial corporate debt experienced a significant rise, particularly in emerging economies. They pointed out that from 2008 to 2018, the ratio of corporate debt to gross domestic product (GDP) in these economies almost doubled, increasing from 56% to 96%. In contrast, this debt-to-GDP ratio remained relatively unchanged in developed economies during the same period. Therefore, during the decade following the global financial crisis, characterized by low interest rates, companies across various nations substantially increased their borrowing from banks and the financial markets. Indicators traditionally used to gauge excessive lending in corporate markets, such as the proportion of high-yield bond issuance, the prevalence of loans with minimal financial safeguards (covenant-lite lending), and the issuance of financial instruments backed by corporate loans (collateralized loan obligations or CLOs), have at times signaled concern. Additionally, while the availability of credit grew rapidly, the financial market's pricing of corporate credit risk dropped significantly. This decline in credit spreads, despite increased borrowing volumes and more lenient loan terms, suggested to many observers that a boom in corporate credit, driven by an oversupply, was underway. Such a boom, they feared, could exacerbate the impact of a future economic downturn (Wiltermuth & Haunss, 2019). According to the same source, some analysts argue that the rise in nonfinancial corporate debt could be viewed positively, suggesting that it indicates firms facing fewer financial constraints, enabling them to secure additional funds for profitable investment ventures and expansion. Moreover, accessing new funding beyond traditional banking channels could aid firms in diversifying their financing channels and bolstering their resilience against financial crises. Conversely, other studies suggest that the surge in nonfinancial corporate debt poses a threat to the global economy. In 2019, the United Nations recognized high nonfinancial corporate debt levels as one of the factors that could impair economic growth (UN, 2019). The escalation in nonfinancial corporate debt levels aligned with a period of diminishing investment and economic growth in emerging economies (WB, 2018). As a consequence, many researchers have strived to analyze the relationship between corporate debt and economic growth. The results of these studies have confirmed both positive and negative relationships. Hanousek and Shamshur (2011) discovered a negative, yet significant relationship between GDP and debt. On the contrary, Kayo and Kimura (2011) concluded that there is a positive and significant relationship between the GDP growth rate and debt.

Regarding the relationship between corporate debt and interest rates, as well as inflation rates, many researchers have confirmed that elevated levels of interest rates and inflation can indeed lead to higher debt-value ratios. Goodhart *et al.* (2022) demonstrated that elevated levels of corporate debt could hinder the transmission of monetary policy, rendering it less effective in controlling inflation both qualitatively and quantitatively. Their study revealed that the existence of legacy corporate debt undermines the ability of contractionary monetary policy to rein in inflation, and that increased debt results in a lesser reduction in inflation following monetary contractions. This outcome is contingent upon the income effect of corporate debt, impacting both aggregate demand and supply. Regarding the relationship between interest rates and corporate debt, modern macroeconomics suggests that the interest rate is a significant determinant of debt. A low interest rate in the economy encourages firms to utilize more debt, while a higher interest rate tends to discourage borrowing. In their research, Deesomsak, Paudyal, and Pescetto (2004) concluded that interest rates have a significant positive influence on debt levels.

3. DATA, METHODOLOGY, AND RESULTS

3.1. Data

The data utilized comprises quarterly time series, spanning from 2015:Q1 to 2023:Q3, resulting in a total of 35 observations. Our analysis focuses on a single dependent variable and four independent variables, outlined as follows:

- *Dependent variable*
 - Gross Loans to Non-Financial Sector/GDP ratio (*GLOANS2GDP*), in percentages [%], as a measure of corporate debt;
- *Independent variables*
 - Inflation Rate (*INFLRATE*), in percentages [%], as a measure of macroeconomic stability;
 - Interest Rate of Non-Financial Sector Loans (*INTRATE*), in percentages [%], as a measure of macroeconomic stability;
 - Real Gross Domestic Product (*GDP*), given at current prices in millions of Macedonian denars [MKD], as a measure of the economic activity in the country;
 - A dummy variable (*DUMMY*), which takes a value of 0 (zero) for the period from 2015:Q1 to 2020:Q1 and again from 2023:Q1 to 2023:Q3, and a value of 1 (one) for the period from 2020:Q2 to 2022:Q4; It is being introduced as a fixed regressor to capture the cumulative economic impacts of the COVID-19 crisis and consequently, the Russian-Ukrainian conflict on the Macedonian economy; its values have been estimated based on the analysis of graphical representations of variables *GLOANS2GDP* and *INFLRATE*, where the structural disturbances were the most obvious.

All the data used in this research have been exploited from secondary sources only, i.e. the data for the dependent variable *GLOANS2GDP* were obtained from the Statistical Web Portal of the National Bank of Republic of North Macedonia (NBRNM, –) and from the State Statistical Office official website (MAKStat Database, –), the data for *INTRATE* were obtained from the Statistical Web Portal of the National Bank of Republic of North Macedonia (NBRNM, –), the data for *INFLRATE* were taken over from the Macedonian Ministry of Finance’s website (MoF, –), whilst the data about GDP were taken over from the State Statistical Office web pages (MAKStat Database, –).

3.2. Methodology

To determine the impact and the magnitude of the chosen independent macroeconomic determinants on the corporate debt, the initial regression equation we are estimating, in its most rudimentary form, can be specified as follows (Eq. 1):

$$GLOANS2GDP = f(INFLRATE, INTRATE, GDP, DUMMY) \quad (1)$$

The order of integration of each of the individual variables has been determined using two tests, the Augmented Dickey-Fuller Test (ADF Test) (Dickey & Fuller, 1979) and the Phillips-Perron Test (PP Test) (Phillips & Perron, 1988).

The optimal lag order selection has been conducted after estimating the unrestricted/standard Vector Auto-Regressive (VAR) model using five criteria: the sequential modified LR test statistic (LR criterion), the Final Prediction Error (FPE criterion), the Akaike Information Criterion (AIC), the Schwarz Information Criterion (SIC), and the Hannan-Quinn Information Criterion (HQ). In the specification of the unrestricted/standard VAR model and all other analyses, we have used the original time series data (i.e. raw data) of endogenous variables *GLOANS2GDP*, *INFLRATE*, *INTRATE*, and *GDP*, as well as the variable *DUMMY* and *C* as exogenous variables, because this approach preserves the original characteristics of the data, allowing the analysis of how changes in the actual variables are related over time, including any real long-term trends and seasonal patterns. Our intention was not exploration of the short-term dynamics or the relationship among variables after removing the effects of trends and seasonal cycles.

The analysis of the impact of independent variables on the dependent variable is being carried out by building and evaluating a corresponding ARDL (Auto-Regressive Distributed Lag) model (Pesaran & Shin, 1998; Pesaran *et al.*, 2001).

The general ARDL(p, q_1, q_2, q_3) regression model, regarding its four-variable representation (the variable *DUMMY* is a fixed regressor without time lags), which is comprised of a dependent variable, Y_t , and three regressors, $X_{k,t}$, $k = 1, \dots, 3$, is given by Eq. 2:

$$\begin{aligned} \Delta Y_t = & \beta_0 + \sum_{i=1}^p \lambda_i \cdot \Delta Y_{t-i} + \\ & + \sum_{j=0}^{q_1} \delta_{1j} \cdot \Delta X_{1,t-j} + \sum_{j=0}^{q_2} \delta_{2j} \cdot \Delta X_{2,t-j} + \sum_{j=0}^{q_3} \delta_{3j} \cdot \Delta X_{3,t-j} + \\ & + \varphi_1 \cdot Y_{t-1} + \varphi_2 \cdot X_{1,t-1} + \varphi_3 \cdot X_{2,t-1} + \varphi_4 \cdot X_{3,t-1} + \varepsilon_t \end{aligned} \quad (2)$$

where:

- Y_t is the dependent variable;
- $X_{k,t}$, $k = 1, \dots, 3$; are the three independent variables;
- Δ is the first-differencing operator;

$p \geq 1$ is the optimal number of lags for the dependent variable;
 $q_k \geq 0, k = 1, \dots, 3$; are the optimal number of lags for the three independent variables;
 $Y_{t-i}, i = 1, 2, \dots, p$; are the lagged values of the dependent variable;
 $X_{k,t-j}, j = 0, 1, 2, \dots, q_k; k = 1, \dots, 3$; are the lagged values of the three independent variables;
 β_0 is a constant (intercept);
 $\lambda_i, i = 1, 2, \dots, p$; are the short-run coefficients of dependent variables;
 $\delta_{kj}, j = 0, 1, 2, \dots, q_k; k = 1, \dots, 3$; are the short-run coefficients of the three independent variables;
 φ_1 is the long-run coefficient of the dependent variable;
 $\varphi_p, p \in \{2, 3, 4\}$; are the long-run coefficients of the three independent variables;
 ε_t is the disturbance (white noise) term.

Since it turned out that the time series are integrated of different orders (either I(0) or I(1)), the Bounds Cointegration Test (i.e. F-Bounds Test) was conducted to estimate the absence (hypothesis H0) or presence (hypothesis H1) of cointegration among the variables. It was performed choosing “ARDL – Auto-regressive Distributed Lag Model” as a method, with variables *GLOANS2GDP*, *INFLRATE*, *INTRATE*, and *GDP* used as dynamic regressors, the variable *DUMMY* used as a fixed regressor, and choosing the option “1. None” in the Trend specification field, since the level of integration of the variables was previously determined for the option “Without Constant & Trend”.

The rest of the analysis was conducted using the Auto-Regressive Distributed Lag (ARDL) methodology with $p_{opt} = 4$ lags by estimating the ARDL(1, 3, 4, 4) model and also with $p_{opt} = 3$ lags by estimating the ARDL(3, 1, 3, 3) model. Each of these two regression models has been estimated taking into account the following five options: (1) Option #1. No intercept or trend in cointegrating equation (CE) or test VAR; (2) Option #2. Intercept (no trend) in CE – no intercept in VAR; (3) Option #3. Intercept (no trend) in CE and test VAR; (4) Option #4. Intercept and trend in CE – no intercept in VAR; and (5) Option #5. Intercept and trend in CE – intercept in VAR. In both cases, it turned out that the best model fit is obtained using “Option #1. No intercept or trend in cointegrating equation (CE) or test VAR”.

Based on the findings of the Bounds Test of Cointegration, the Error Correction Model (ECM) of the regression equation (2) has been used for estimating the coefficients of the long-run equilibrium among the variables of interest, based on a VAR model with 4 lags ($p_{opt} = 4$ lags) and Option #1. No intercept or trend in cointegrating equation (CE) or test VAR.

As a constituent part of the analysis of the ECM, we have checked two types of causality relationships: the long-run and the short-run causality:

- *The long-run causality*; In economics, the term “long-run” denotes a theoretical concept centered around equilibrium, referring to a period during which all economic variables of interest are flexible and have adequate time to adjust. The concept of long-run causality emphasizes the importance of the Error Correction term within the ECM (Error Correction Model) equation.
- *The short-run causality*; The short-run encapsulates the notion that an economy’s response to various stimuli varies based on the time it has to adjust. The concept of the short-run is not tied to a specific timeframe; instead, it depends on the economic variable in question. In the short-run, the economic variables being studied are unable to fully adjust to reach a new equilibrium, i.e. a state where opposing forces are in balance. The short-run causality relationship is determined by evaluating the joint significance of the lags of a specific first-differenced variable within the ECM (Error Correction Model) equation, typically assessed using the Wald test.

Finally, the resulting ECM underwent diagnostic checks on the residuals. Specifically, we tested the residuals for the presence of serial correlation (autocorrelation) using the Breusch-Godfrey Serial Correlation LM Test, heteroscedasticity (using the Breusch-Pagan-Godfrey Heteroskedasticity Test), and normality of distribution (using the Jarque-Bera Test). The stability of the overall model has been proved using the CUSUM Test and CUSUM of Squares Test).

All the analyses have been carried out using the econometric package EViews v10.

3.3. Results

Since the results of the Augmented Dickey-Fuller (ADF) test for both Schwarz Information Criterion (SIC) and Akaike Information Criterion (AIC) were not conclusive for variables *INFLRATE* and *INTRATE* because both of them exhibited obvious trends in their raw format, we have used their de-trended time series (*INFLRATE_DT* and *INTRATE_DT*) to determine their order of integration. The de-trending operation was carried out using the Hodrick-Prescott (HP) Filter where the smoothing parameter $\lambda = 1,600$ (for quarterly time series). In addition, the variable *GDP* exhibited both seasoning and trending features in its raw format, so the de-seasoned and de-trended time series (*GDP_DSDT*) was used for conducting the ADF and PP tests. The de-seasoning operation was conducted using the STL Decomposition (Seasonal-Trend decomposition using LOESS). Table 1 contains a summary of the ADF and PP tests vis-à-vis the variables’ order of integration.

Table 1: Summary of the ADF and PP tests

Option	Information criterion	Test	Variables			
			GLOANS2GDP	INFLRATE_DT	INTRATE_DT	GDP_DSDT
Without Constant & Trend	Akaike Information Criterion (AIC)	PP	I(1)***	I(0)**	I(1)***	I(0)***
		ADF	I(1)***	I(0)**	I(0)**	I(0)***
	Schwarz Information Criterion (SIC)	PP	I(1)***	I(0)**	I(1)***	I(0)***
		ADF	I(1)***	I(0)***	I(0)***	I(0)***

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

Source: The authors, EViews v10 output

Assuming the option “Without Constant & Trend”, both the ADF and PP tests, using the AIC and SIC criteria confirm that two of the variables (*INFLRATE_DT* and *GDP_DSDT*) are stationary at level, i.e. their order of integration is I(0), the variable *GLOANS2GDP* becomes stationary after being first differenced, i.e. I(1), and the variable *INTRATE_DT*, according to the ADF test, is stationary at level, i.e. I(0), while according to the PP test it becomes stationary after being first differenced, i.e. I(1). Because the variables of interest are integrated of different orders, i.e. some of them are stationary at level and others become stationary after being first-differenced, the Auto-Regressive Distributed Lag (ARDL) model can be constructed.

The results of the VAR lag order selection criteria show that the estimations of three out of five lag order selection criteria (i.e. LR, FPE, and SC) indicated the value Lag = 3 as an optimal lag length, whilst the rest two lag order selection criteria (i.e. AIC and HQ) suggest the value Lag = 4 as an optimal lag length. Since two different values for an optimal lag length were suggested, we have continued our study by constructing two different ARDL models, one with $p_{opt} = 4$ lags, and another one with $p_{opt} = 3$ lags. In the first case, we have estimated the ARDL(1, 3, 4, 4) model, whilst in the second one we have estimated the ARDL(3, 1, 3, 3) model. In both cases we have taken into account Option #1, “No intercept or trend in cointegrating equation (CE) or test VAR”. The direct comparison of the basic statistics between the two models showed that the ARDL(1, 3, 4, 4) model fits better the time series data (R-squared = 96,84%, Adjusted R-squared = 93.68%, AIC = 2.505796) than the ARDL(3, 1, 3, 3) model, as portrayed by numbers given in Table 2. As a result, the rest of this subsection will refer solely to the ARDL(1, 3, 4, 4) model.

Table 2: Comparative analysis of the two ARDL models

Max. number of lags	$p_{opt} = 4$	$p_{opt} = 3$
Model	ARDL(1, 3, 4, 4)	ARDL(3, 1, 3, 3)
Number of models evaluated	500	192
R-squared	0.968422	0.911968
Adjusted R-squared	0.936844	0.848390
Durbin-Watson statistics	2.517215	2.033564
Akaike info criterion	2.505796	3.342144

Source: The authors, EViews v10 output

The results of the F-Bounds Test show that the calculated F-statistic is equal to 10.66373, which is higher than the critical values of the upper bound I(1) at all levels of significance (10%, 5%, 2.5%, and 1% level of significance), i.e. higher than the critical values of 3.10, 3.63, 4.16, and 4.84, respectively. This means that the null hypothesis H0, claiming that there is no cointegrating relationship, can be rejected in favor of H1 at all levels of significance, which implies that the variable *GLOANS2GDP* is cointegrated with *INFLRATE*, *INTRATE*, and *GDP* in the long-run, i.e. all variables share a common stochastic trend, moving together in proportion over the long term. Consequently, even if short-term shocks affect the movements of individual series, they will converge over time. The presence of a long-term relationship among the variables suggests that their time series are interconnected and can be linearly combined in the long-run. This enables not only the estimation of a short-term ARDL model but also the estimation of a long-term Error Correction Model (ECM).

The coefficient of the cointegrating equation (−0.720088) is both negative and statistically significant (p-Value = 0.0000 ≤ 5%), as shown in Table 3. It means that there is a long-run Granger causality running from all the regressors to *GLOANS2GDP*. The speed of the adjustment from a short-run towards long-run equilibrium is 72.01%, i.e. the system corrects its previous period of disequilibrium at a speed of 72.01% within one period of time (a quarter).

Table 3: Statistics of the coefficient of the cointegration equation

Variable	Coefficient	Std. Error	t-Statistics	Prob.
CointEq(-1)	−0.720088	0.100649	−7.154434	0.0000

Source: The authors, EViews v10 output

The specification of the ARDL(1, 3, 4, 4) model is presented by Table 4.

Table 4: Details of the ARDL(1, 3, 4, 4) specification

Variable	Coefficient	Std. Error	t-Statistics	Prob.
GLOANS2GDP(-1)	0.279912	0.123657	2.263613	0.0389
INFLRATE	0.392164	0.237359	1.652199	0.1193
INFLRATE(-1)	-1.146715	0.444622	-2.579079	0.0210
INFLRATE(-2)	-0.070331	0.423413	-0.166104	0.8703
INFLRATE(-3)	0.723865	0.342698	2.112257	0.0518
INTRATE	9.618357	2.626150	3.662532	0.0023
INTRATE(-1)	-5.391390	2.642863	-2.039981	0.0594
INTRATE(-2)	-11.43068	3.576639	-3.195928	0.0060
INTRATE(-3)	-2.376933	8.484757	-0.280142	0.7832
INTRATE(-4)	11.11965	6.249519	1.779281	0.0955
GDP	6.26E-06	2.01E-05	0.312125	0.7592
GDP(-1)	4.34E-05	1.81E-05	2.402521	0.0297
GDP(-2)	3.95E-05	1.45E-05	2.721562	0.0158
GDP(-3)	-1.70E-05	1.67E-05	-1.021866	0.3230
GDP(-4)	8.74E-05	2.07E-05	4.227189	0.0007
DUMMY	4.138704	0.961516	4.304355	0.0006

Source: The authors, EViews v10 output

The long-run coefficients and the Error Correction (EC) term are presented in Table 5.

Table 5: Long-run coefficients and the Error Correction (EC) term

Levels Equation				
Case 1: No Constant and No Trend				
Variable	Coefficient	Std. Error	t-Statistics	Prob.
INFLRATE	-0.140283	0.321236	-0.436696	0.6686
INTRATE	2.137237	0.272829	7.833602	0.0000
GDP	0.000222	1.37E-05	16.20767	0.0000
EC = GLOANS2GDP - (-0.1403*INFLRATE + 2.1372*INTRATE + 0.0002*GDP)				

Source: The authors, EViews v10 output

The residuals diagnostic tests have led to the following findings:

- Based on the Breusch-Godfrey Serial Correlation LM Test (Prob. Chi-Square(2) = 0.1405 > 10%), the null hypothesis of no serial correlation in the residuals up to two lags is accepted at a 10% significance level;
- Similarly, according to the Breusch-Pagan-Godfrey Heteroskedasticity Test (Prob. Chi-Square(16) = 0.8201 > 10%), the null hypothesis of no heteroskedasticity in the residuals up to 16 lags is accepted at a 10% significance level;
- Additionally, the Jarque-Bera Test (Prob. = 0.507404 > 10%) indicates that the null hypothesis of normally distributed residuals is accepted at a 10% significance level.

The residual diagnostics indicate that the ECM is appropriately specified for hypothesis testing and forecasting. Furthermore, CUSUM and CUSUM of Squares test plots fall within the 5% critical bounds, confirming the stability of the ARDL model coefficients, ensuring structural stability.

4. DISCUSSION

Based on the specification of the ARDL(1, 3, 4, 4) model presented in Table 5, in the short-run:

- The first lag of the dependent variable *GLOANS2GDP* has a positive (+0.279912) and statistically significant influence (p-Value = 0.0389 ≤ 5%) on the current value of *GLOANS2GDP* at 5% level of significance;
- At level, the value of the variable *INFLRATE* (+0.392164), as well as its third lag (+0.723865) positively affect the current value of *GLOANS2GDP*; In addition, the impact of the third lag is statistically significant at 10% level of significance (p-Value = 0.0518 ≤ 10%); However, the first (-1.146715) and the second lag (-0.070331) of the variable *INFLRATE* negatively affect the current value of *GLOANS2GDP*; The impact of the first lag of *INFLRATE* is statistically significant at 5% level of significance (p-Value = 0.0210 ≤ 5%);
- At level, the value of the variable *INTRATE* positively (+9.618357) and statistically significantly affects the current value of *GLOANS2GDP* at 1% level of significance (p-Value = 0.0023 ≤ 1%); Also the fourth lag of *INTRATE* positively (+11.11965) and statistically significantly affects the current value of *GLOANS2GDP* at

10% level of significance ($p\text{-Value} = 0.0955 \leq 10\%$); The impacts of the first, second, and the third lag of *INTRATE* are all negative (-5.391390 , -11.43068 , and -2.376933 , respectively); Moreover, the first and the second lag of *INTRATE* are statistically significant at 10% ($p\text{-Value} = 0.0594 \leq 10\%$) and 1% ($p\text{-Value} = 0.0060 \leq 1\%$), respectively;

- At level, the value of the variable *GDP* positively ($+0.00000626$), but statistically insignificantly affects the current value of *GLOANS2GDP*; The first, the second, and the fourth lag of *GDP* both positively ($+0.0000434$, $+0.0000395$, and $+0.0000874$) and statistically significantly affect the current value of *GLOANS2GDP* at 5%, 5%, and 1% level of significance, respectively ($p\text{-Value} = 0.0297 \leq 5\%$; $p\text{-Value} = 0.0158 \leq 5\%$; and $p\text{-Value} = 0.0007 \leq 1\%$); The third lag of *GDP* negatively, yet statistically insignificantly affects the current value of *GLOANS2GDP*;
- At level, the value of the dummy variable *DUMMY* positively ($+4.138704$) and statistically significantly ($p\text{-Value} = 0.0006 \leq 1\%$) affects the current value of *GLOANS2GDP* at 1% level of significance;
- Based on the Chi-square Test statistics obtained by the application of the Wald Test on variables' time lags, it can be concluded that there are short-run Granger causalities running from each variable's time lags toward the target variable *GLOANS2GDP*, i.e. each group of time lags of inherent to independent variables can jointly influence the current value of *GLOANS2GDP* in a short-run.

The diverse statistical significance of lag coefficients suggests complex dynamics among observed variables, including non-relational relationships. The relationship between the dependent and independent variables evolves over time, with varying lags exerting different degrees of influence and magnitudes.

On the other hand, based on the results given in Table 7, in the long-run:

- One of the regressors (*INFLRATE*) has a negative (-0.140283), yet statistically insignificant impact on the target variable *GLOANS2GDP*;
- Two regressors (*INTRATE* and *GDP*) have a positive impact on *GLOANS2GDP* ($+2.137237$ and $+0.000222$, respectively);
- The impacts of independent regressors *INTRATE* and *GDP* on the dependent variable *GLOANS2GDP* are both statistically significant ($p\text{-Value}=0.0000 \leq 1\%$) at all levels of significance;
- Having minded the *ceteris paribus* principle:
 - The increase of *INFLRATE* by 1 percentage points [pp] will decrease *GLOANS2GDP* by 0.140283 [pp] (statistically not significant impact, $p\text{-Value} = 0.6686 > 10\%$);
 - The increase of *INTRATE* by 1 [pp] yields an increase of *GLOANS2GDP* by 2.137237 [pp] (statistically significant impact, $p\text{-Value} = 0.0000 < 5\%$);
 - The increase of *GDP* by 1 million [MKD] is expected to increase *GLOANS2GDP* by 0.000222 [pp] (statistically significant impact, $p\text{-Value} = 0.0000 < 5\%$).

5. CONCLUSION

This paper investigates the impact of several key determinants on corporate debt in North Macedonia from 2015:Q1 to 2023:Q3. Specifically, it focuses on the Gross Loans to Non-Financial Sector/GDP ratio as a proxy for corporate debt and examines its relationship with the Inflation Rate, Interest Rate of Non-Financial Sector Loans, and GDP. The empirical analysis employs the Auto-Regressive Distributed Lag (ARDL) method for time series analysis using the EViews v10 econometric package. The study findings, which are entirely in line with actual economic situation in North Macedonia, reveal that the Inflation Rate (*INFLRATE*) has a negative long-term effect on the Gross Loans to Non-Financial Sector/GDP ratio (*GLOANS2GDP*), and both the first and second lags exhibit negative impacts in the short-run. However, the third lag positively influences the current value of the target variable, albeit with statistically significant impact at a 10% level of significance. These outcomes are attributed to the high variability observed in the independent variable *INFLRATE*. Conversely, the Interest Rate of Non-Financial Sector Loans (*INTRATE*) and the Gross Domestic Product (*GDP*) demonstrate positive and statistically significant relationships with *GLOANS2GDP* in the long-run. Global challenges such as the energy crisis and high inflation rates have adversely affected economic growth. Specifically, in 2022, real GDP experienced a growth rate of 2.10%, marking a decline from the 3.90% growth observed in 2021. However, due to government interventions in 2022 and the implementation of restrictive monetary and credit policies in the Republic of North Macedonia, growth in gross domestic product has been observed in the second and third quarters of 2023. The high inflation rate escalates business operation costs and amplifies uncertainty and risk premiums, thereby exerting a negative impact on gross investments. From the second quarter of 2022 onwards, Macedonian companies encountered a significant surge in the inflation rate, reaching its pinnacle in the fourth quarter of 2022 at 19.40%. In an effort to mitigate inflationary pressure and expectations, the National Bank of Republic of North Macedonia initiated a gradual rise in the base interest rate, climbing from 3.67% in the second quarter of 2021 to 5.36% in the third quarter of 2023. Despite this interest rate hike, corporate sector indebtedness persists at a high level, affirming the dominance of bank loans as the primary financing source for Macedonian businesses. Future research will focus on exploring the influence of additional macroeconomic indicators, such as gross investments to GDP ratio, on the indebtedness levels within the corporate sector. This investigation will aim to broaden our understanding of the factors affecting corporate financial behavior and risk management strategies.

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