Asian Economic and Financial Review
ISSN(e): 2222-6737
ISSN(p): 2305-2147
DOI: 10.55493/5002.v14i9.5157
Vol. 14, No. 9, 683-694.

URL: www.aessweb.com

Predicting determinants of industrial firms' loan payment default: Logit model versus probit model

Lobna Abid[1+]
Saida Chibani[2]
Afif Masmoudi[3]

[1,2]*Higher Institute of Business Administration of Sfax, University of Sfax, Laboratory of Probability and Statistics - PB 1171, Sfax, Tunisia.*
[1]*Email: lobna.abid@isaas.usf.tn*
[2]*Email: chibani.saiida@gmail.com*
[3]*Faculty of Sciences of Sfax, Laboratory of Probability and Statistics - PB 1171, Sfax, Tunisia.*
[3]*Email: afif.masmoudi@fss.usf.tn*


(+ Corresponding author)

Article History
Received: 17 February 2024
Revised: 11 July 2024
Accepted: 31 July 2024
Published: 15 August 2024

Keywords
Default payment
Industrial firms
Logit model
Probit model
Risk.

JEL Classification:
C58; G33.

ABSTRACT

Appropriate control and management of credit risk has become the main concern of financial institutions, which are constantly developing models for analyzing, assessing and predicting this risk, particularly in view of the prudential standards required by central banks. The current research paper aims to specify the determinants of payment defaults in Tunisian companies in the industrial sector so as to develop a model with the optimal predictive precision of forecasting payment default when it relates to industrial firms functioning in the Tunisian environment. Within this framework, we compared two generalized linear models which correspond to the logit and probit models based on a sample of Tunisian industrial companies. The results revealed that debt ratio is the most important variable that increases the probability of default payment, while the solvency ratio reduces the probability of default payment. This study highlights the vital contribution of macroeconomic agents, such as GDP growth rate and inflation rate, in terms of the prediction of default payment.

Contribution/Originality: Currently, this study is the first in Tunisia to provide such an extensive analysis on industrial firms with regard to payment default. Incorporating macroeconomic variables in these models displays a great effect. The findings can be regarded as beneficial for policymakers in terms of enacting policies and regulations to make adequate decisions associated with default payment reduction.

1. INTRODUCTION

Firms in difficulty can be largely influenced by the risk of insolvency, regardless of their size (small, medium or large) and whether they operate in underdeveloped or developed economies. Furthermore, business failure affects both product and service companies and can belong to the primary, secondary or tertiary sectors. Nevertheless, the repercussions are much greater in relatively small economies that are socially, economically and politically fragile. In Tunisia, for example, relying on the Economic Enterprise Monitoring Committee, more than 2,540 failing businesses (with around 6,000 million Tunisian dinars in unpaid debts) have signed up to the law to reorganize companies in difficulty since 1995, the date on which the law was enacted. This number is almost negligible if we consider the 40,000 cases of failing companies filed each year in French or German courts and the 20,000 cases filed in UK courts.

Despite the relatively low number of cases handled annually in Tunisia, business failures represent a major problem, the consequences of which can have a significant impact on a nation of such a small size both geographically and economically. This refers to the fact that, according to development indicators, Tunisia is a developing economy that is composed mainly of family SMEs financed mainly by bank loans and where unemployment is endemic.

From this perspective, forecasting payment defaults has become a major concern for organizations in recent years and is regarded as one of the main research areas of interest. Political instability, rising public debt and high unemployment were already weighing on the Tunisian economy before the Covid-19 pandemic struck in early 2020.

Ten years after the events that triggered the Arab Spring, a growing number of businesses suffered financial difficulties and ceased trading. This has increased the scope for using a predictive model to investigate determinants of business failure in Tunisia. Notably, the most recent shock, Russia's invasion of Ukraine, and the rising level of inflation, have further intensified the need to opt for a predictive model for business failure.

Within this framework, the present research focuses on companies in the industrial area. The corresponding sample selection is based on unpaid or disputed trade receivables displaying an increase from 32.1% to 33.6% between 2018 and 2019, and from 44.2% to 45.4% between 2020 and 2021. Moreover, predicting the determinants of insolvency for Tunisian companies in the industrial sector is highly relevant at the present time.

In this respect, the main information source on solvability refers to the Tunisian Central Bank (TCB), which represents the basic provider of data dealing with industrial firms' prior payments and their financial features, such as solvency ratio, debt ratio, firm size, and financial macroeconomic indicators (real gross domestic product, growth rate, and inflation rate). These aspects indicate a firm's tendency to default on payments. Therefore, this data is required to set up an adequate model fit for predicting corporate credit default in order to evaluate credit risk determinants.

In this regard, firms' default predictions correspond to the pillar of financial engineering, which deploys different statistical models. Numerous researchers, such as Crook, Edelman, and Thomas (2007), assume that the standard approach applied to determine the probabilities of payment default is the logistic regression technique. Yet, this methodology has remained subject to multiple strict assumptions (Malley, Kruppa, Dasgupta, Malley, & Ziegler, 2012).

Relying on a wide range of studies, such as Hand and Henley (1997), the banking environment necessitates statistical models such as the probit analysis, discriminant analysis and logistic regression. In this study, we compare the performance of the logit and probit techniques and trace the industrial firms' payment defaults. A total of 4,000 firms makes up the study sample. This research is possibly the first to provide such an extensive analysis on industrial firms with respect to payment default.

The paper is structured as follows: In addition to the introduction, this study includes four sections as well as a conclusion. Section 2 provides a general overview of related works; Section 3 explains the methodology, data collection, and independent variables, as well as models' specifications; Section 4 discusses the findings for predicting default payment in the industrial domain; and Section 5 outlines certain pertinent and outstanding remarks.

2. RELATED WORKS

Multiple authors have tackled the topic of corporate default prediction in different countries using macroeconomic variables and financial ratios (Kim, Cho, & Ryu, 2022; Kristóf & Virág, 2020). The major target of these models is to categorize companies into two basic classes: distressed companies and failing companies. The 1990s witnessed the emergence of the first studies associated with predicting corporate default (Fitzpatrick, 1932; Merwin 1942). Beaver (1966) was the first to use statistical means and financial indicators to analyze and predict corporate failures; in fact, he conducted a univariate analysis using a unique discriminant ratio. Notably, the method in question has scarcely been applied due to its lack of robustness. Implementing the multiple discrimination model, Altman (1968) was accredited for being the first researcher to deploy several ratios simultaneously. This technique consisted of developing the z-score model, which discriminates between those that are faulty and those that are not and proved that five out of 22 ratios are significant. Due to the z-score model shortcomings, other procedures have been put forward to support companies in terms of forecasting their financial situation in the future (Zizi, Oudgou, & El Moudden, 2020).

Using a sample involving 74 Finnish companies, Back, Laitinen, Sere, and van Wezel (1996) found that liquidity proves to be the most significant factor in terms of business failure prediction.

Bunn and Redwood (2003) demonstrated that the current ratio decreases the probability of firm bankruptcy. This ratio is considered as one of the intrinsic variables to determine liquidity. Using 103 bankruptcy prediction models, Kovacova, Kliestik, Valaskova, Durana, and Juhaszova (2019) confirmed that the current ratio, which corresponds to a liquidity variable, is the most widely invested within the context of the Visegrád countries. In addition, solvency ratios can be considered as a preventive analysis of a company defaulting on payments (Abid, 2022; Pindado & Rodrigues, 2004). By adopting discriminant and logistic analysis regression, these authors inferred that a preventive diagnosis of companies' financial failure can be undertaken by solvency variables. In the Slovak context, Valaskova, Kliestik, and Kovacova (2018) perceived working capital and the ratio of working capital to total assets as an optimal predictors of a firm's financial state by employing multiple regression analyses. Using the logistic regression model, Sharifabadi, Mirhaj, and Izadinia (2017) revealed that profitability ratios reduce the probability of bankruptcy of Iranian firms that are listed on the stock exchange.

Macroeconomic variables have also been deployed along with financial and accounting variables (Vo, Pham, Ho, & McAleer, 2019). Fernández-Gámez, Soria, Santos, and Alaminos (2020) invested regulatory variables coupled with macroeconomic and accounting variables. In addition, accounting variables have been used in tandem with corporate governance variables (Ragab & Saleh, 2022), network-based variables (Liu, Wu, & Li, 2019) and auditing variables (see Muñoz-Izquierdo, Laitinen, Camacho-Miñano, and Pascual-Ezama (2020)).

Abid (2022) applied a logistic regression model to assess determinants of the payment default risk of companies in the services area. The findings demonstrated that solvency debt, profitability ratios, and loan amount are the main firm-specific factors specifying credit risk. Additionally, macroeconomic variables such as high inflation level as well as a decrease in the GDP growth rate are able to increase corporate credit risk. Raudzingana (2020) used the random effects (RE), pooled ordinary least squares (POLS), and fixed effects (FE) models to evaluate the influence of firm-specific and macroeconomic factors on corporate defaults. The results indicated that micro factors such as size, profitability, leverage, tangibility, and liquidity have an impact on corporate default payment. Macroeconomic factors such as inflation rate and 3-month T-bill rate are also considered as determinants for South African firms.

In order to predict bankruptcy in US banks, Affes and Hentati-Kaffel (2019) adopted logistic regression models and canonical discriminant analysis. The authors corroborated that financial ratios which represent earnings ability, assets quality, capital adequacy, and liquidity correspond to key determinants in terms of forecasting bankruptcy. The empirical findings suggest that the logit model outperforms discriminant analysis at the level of good classification rate.

Recently, Zhang, Zhao, and Yao (2022) handled the default risk of firms in China. They proved that the continuous increase of a company's liquidity is one of the most crucial signs of corporate default in China.

In addition to traditional data such as financial ratios (Ciampi, Demi, Magrini, Marzi, & Papa, 2021) it is intrinsic to set up predictive models of corporate default using data such as information relating to the banking relationship (Bartoli, Ferri, Murro, & Rotondi, 2013). This information is considered private data that is linked to specific services supplied by the company. It can be invested to forecast loan repayment, such as use of credit lines, checking accounts, credit and debit cards, and investment portfolios. According to Aghabarari, Guettler, Naeem, and Van Doornik (2021) the goodness of fit of this private information ranges depending on the context, such as in Italy, where small banks mainly win the informational profits of lending relationships.

3. RESEARCH METHODOLOGY

In order to assess the prediction accuracy in terms of industrial firms' situations, logistic regression (LR) and the probit model were adopted to forecast whether a firm will be in payment default or not. Our ultimate objective was to search for the most relevant and appropriate model.

3.1. Data and Variables

The choice of variables remains an issue when developing models to study the determinants of corporate default. However, no consensus has been reached on the techniques and construction of consistent financial and accounting ratios.

In this regard, we selected financial and macroeconomic indicators that demonstrated a significant predictive power and an ability to examine the determinants of corporate default.

This research covers the period from 2016 to 2020, and the sample comprises 4,000 observations derived from the industrial sector. The data was collected from the World Bank (WB), the Tunisian Central Bank (TCB), and the National Institute of Statistics (NIS).

Table 1 depicts the names, measures and sources of the variables.

Table 1. Variables used in the empirical study.

Variables	Formula	Source
Dependent variable		
Payment default	$= \begin{cases} 1 \; if\ company\ payment\ defaults \\ 0 \;\; if\ the\ company\ is\ sound \end{cases}$	(TCB)
Explanatory variables		
X1: Return on assets (ROA)	Net income/Total assets	(TCB)
X2: Return on equity (ROE)		
X3: Solvency ratio	Net income/Equity	
X4: Debt ratio	Total assets/Total debt	(NIS)
X5: Firm size	Total debt/Total assets	
X6: Inflation rate		(NIS)
X7: Real GDP growth rate	Ln(Total assets)	

The statistics summary of the variables is illustrated in Table 2.

Table 2. Statistical description of variables.

	y	X_1	X_2	X_3	X_4	X_5	X_6	X_7
Count	4149.000	4149.000	4.149^e-3	4.149^e+03	4.149^e+03	4.149^e+03	4149.000	4149.000
Mean	0.025789	0.046164	-3.892152^e+06	2.991770^e+10	9.9647945^e+06	2.293716^e+10	0.052557	0.017045
Std.	0.158525	0.116025	7.244161^e+08	2.066824^e+09	1.154144^e+08	5.654184^e+10	0.013755	0.010002
Min.	0.000000	-0.842805	-8.054645^e+09	4.209939^e-01	0.000000^e+00	3.809519^e+06	0.036300	0.010002
25%	0.000000	0.004585	2.741007^e-02	1.619544^e+09	1.900463^e-01	9.070505^e+08	0.048000	0.011174
50%	0.000000	0.035125	1.270135^e-01	2.577310^e+09	3.122490^e-01	3.347725^e+09	0.053100	0.014020
75%	0.000000	0.085366	2.725544^e-01	3.946525^e-01	4.635561^e-01	1.804600^e+10	0.073100	0.022442
Max.	1.000000	0.753947	9.854544^e+09	9.976273^e+09	2.375331^e+09	8.930000^e+11	0.074700	0.025109

Note: "e" indicates an exponent.
For example: *4.149000e+03 means 4.149000 ** $\mathbf{10^{-3}}$.

3.2. Econometric Estimates and Results

3.2.1. Estimating Strategy

For the predictive modeling techniques, we compared the logistic regression and probit techniques to predict the default probability firms in the industrial area. We note:

$$Y = \begin{cases} 1 \text{ if the company has a payment default,} \\ \quad 0 \text{ otherwise} \end{cases}$$

The logit and probit regressions correspond to predictive models that are widely adopted in binary classification. These techniques display the same approach but differ in terms of the form of the link function.

3.2.1.1. The Logit Model

The current study's explanatory variable corresponds to the default payment of Tunisian industrial firms; it acquires the value of 1 in the case of default, and 0 otherwise. Considering this specificity, we used the logistic regression model to forecast the probability of defaulting payments. In this binary model, we attempt to assess the probability payment of the event occurrence y_i = 1 (default) of industrial firm *i* as a function of a variable's factor *xi*. We present the underlying model as indicated by the latent variable y 1. Therefore, this model corresponds to the linear function of vector y:

$$y_i^* = \beta_0 + \beta_i x_i$$

The following logistic transformation is used so that it takes only 0 or 1:

$$\log\left(\frac{P(Y=1|X)}{1-P\ (Y=1|X)}\right) = b_0 + b_1 X_1 + \cdots + b_7 X_7$$

In the current research, the logistic regression model employs the dependent variable Y_i taking a value of 1 (Y = 1) if a default payment occurs. Otherwise, Y_i takes a value of 0 (Y = 0) if no default payment occurs.
The relationship between the predictor variables and the dependent ones is indicated by:

$$((P\ (Y_i = 1|X_i)) = \frac{1}{1+e^{-Z_i}}$$

$$(P\ (Y_i = 0|X_i) = 1 - P\ (Y_i = 1|X_i)$$

The estimation of the logit model coefficients yields the score of each firm Z_a

$$Z_i = \beta_0 + \sum_{j=1}^{p} \beta_j X_{ij}$$

Next, the probability of default is computed for each company.

3.2.1.2. The Probit Model

In statistics, the probit model corresponds to a binomial regression model, which was introduced by Bliss (1934), and it represents a special case of the generalized linear model.
Let the latent sample linear model be:

$P(Y=1) = \Phi\ (b_0 + b_1X_1 + \cdots + b_7X_7)$, where Φ expresses the cumulative function of the normal distribution N(0,1), X_i= vector of explanatory variables, and b refers to a parameter vector.

The dependent variable $Y\tilde{i}$ refers to a binary latent variable (i.e., taking the value 0 or 1) which measures default probability. The error term follows a normal distribution.

3.2.2. Validation and Evaluation of the Model

3.2.2.1. Validation

Model validation is an integral part of any estimation process. It represents a key step in the evolution of any predictive model. From this perspective, various procedures and metrics have been used in literature to validate a model. We selected the most relevant ones for this stage, and they are indicated as follows:

3.2.2.2. Estimation of B Parameters Using the Maximum Likelihood Method

In this step, we estimate regression vector β by the maximum likelihood method to predict a future value of y, which is denoted by ŷ. Both models are estimated by maximum likelihood, i.e., by maximizing the likelihood function.

The maximum likelihood method involves maximizing the application:

$$\ell(\beta|X,Y) = L(\beta|X,Y) = \prod_{i=1}^{n} P\,(Y_i = 1|X_i)^{yi}\,(1 - P(Y_i = 1|X_i)^{1-yi}$$

Therefore,

$$L(\beta) = \log L\ (\beta|X,Y) = \sum_{i=1}^{n}\{y_i \log(P(Y_i = 1|X_i)) + (1 - yi)\log\ (1 - P(Y_i = 1|X_i)\ \}$$

Where: $\{P(Y_i = 1|X_i\}\ \frac{1}{1+e^{-Z_i}}$ *in the Logit Model, and* $P\ (Y_i = 1|X_i) =$ $\Phi\ (Z_i\ )$ *in the probit model*

$$\hat{\beta}^{nv} = Argmax\ L(\beta) \qquad \beta \in \mathbb{R}^8$$

Note that $\hat{\beta}^{nv}$ verifies $\frac{\partial}{\partial\beta}L(\hat{\beta}^{nv}) = 0$.

3.2.2.3. Comparison of the Logit and Probit Models using the AIC and BIC Criteria

The AIC and BIC criteria are used to compare different models. The lower the AIC (BIC) is, the more appropriate the model fits the data. However, the model with the lowest AIC (BIC) for a set of predictors, is not necessarily well fitted to the data.

By definition, the Akaike Information Criterion (AIC) was developed by Akaike (1974) for a p-variable model, and is defined by:

$$AIC = -2L(\hat{\beta}^{nv}) + 2p,$$

Where L corresponds to the log-likelihood of the logistic regression model and 2p stands for the parameter number function.

Another model selection criterion is the Bayesian Information Criterion (BIC). For a p-parameter model, it is defined as follows:

$$BIC = -2L(\hat{\beta}^{nv}) + p\ln(n)$$

For each competing model, the choice criterion is calculated, and the model with the smallest AIC or BIC is selected.

The results of the comparison between both models, presented in Table 3, reveal that the probit model outperforms the logit model.

Table 3. Logistic regression and probit regression results for the industry sector.

Model	AIC	BIC
Logit	416.2966	461.1038
Probit	414.3562	459.1634

3.2.3. Econometric Findings

3.2.3.1. Correlation Matrix Examination

Once the predictive model has been established, its validity needs to be assured.

The second method for assessing the performance of predictive models refers to the use of machine learning. The confusion matrices of both models are portrayed in Figures 1 and 2:

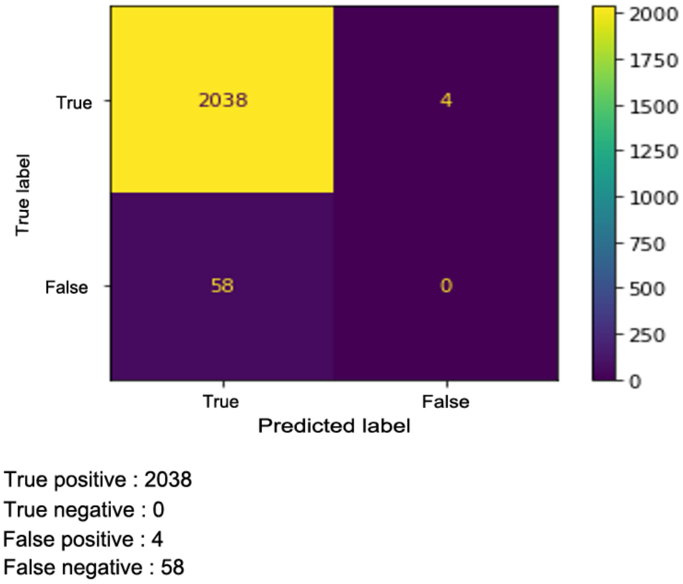

Figure 1. Confusion matrix of the probit model.

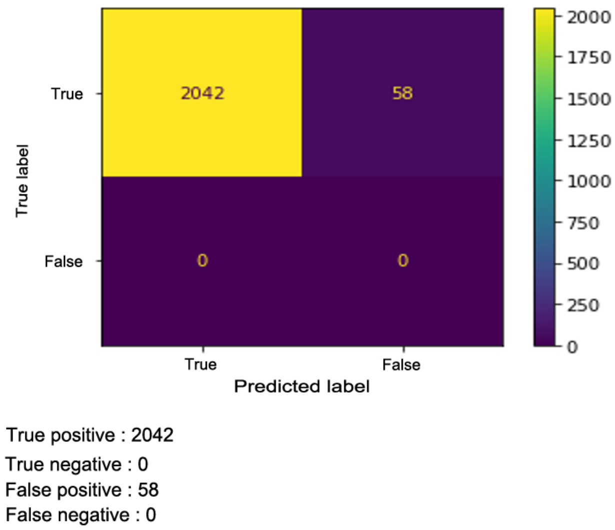

Figure 2. Confusion matrix of the logit model.

Figure 1 demonstrates that 2,038 observations are well predicted, and 62 observations are poorly predicted. We can therefore assert the significance of this regression model thanks to its convenient prediction.

The confusion matrix presented in Figure 2 indicates that 2,042 observations are well predicted, and 58 observations are poorly predicted. We can equally state that this regression model is significant with good prediction.

To more easily interpret the confusion matrix and assess the model's performance, there are numerous measures that can also be used, such as accuracy, sensitivity, prevalence, precision, and the F-score.

Based on the results derived from the comparison between both models (see Table 4), the probit model proves to be more convenient than the logit model.

Table 4. Comparison of results between the logit and probit models.

Metric name	Logit	Probit
Accuracy	97%	98%
Sensitivity	97%	97%
Prevalence	97%	99%
Precision	97%	99%
F score	97%	98%

3.2.3.2. Results and Discussion

The probit model regression findings for the industry sector are outlined in Table 5.

Table 5. Probit regression findings for the industry sector.

	Coefficient	Std. err	Z	P > |z|	[0.025	0.975]
Constant	-2.4997	1.0782	-2.3184	0.0204	-4.6129	-0.3865
ROA (X_1)	-3.5244	0.6271	-5.6213	0.0000	-4.7532	-2.2955
ROE (X_2)	-0.0000	0.0000	-2.7286	0.0064	-0.0000	-0.0000
Solvency ratio (X_3)	-0.0118	0.0352	-0.3344	0.7381	-0.0807	0.0572
Debt ratio (X_4)	-0.0000	0.0000	-0.0127	0.9899	-0.0000	-0.0000
Size of firm (X_5)	-0.0000	0.0000	-1.8726	0.0611	-0.0000	-0.0000
Inflation rate (X_6)	0.1234	0.0479	2.5769	0.0100	0.0296	0.2173
Real GDP growth rate (X_7)	-0.2886	0.1863	-1.5496	0.1212	-0.6537	0.0764

Basically, companies in difficulty display a low economic profitability (ROA) and solvency (solvency ratio) and are notably more indebted. They are also marked with long payment arrears. Thus, departing from the findings obtained in this study on a sample of 4,000 companies in Tunisia's industrial sector, we infer that the profitability and solvency variables have a proven goodness of fit in terms of discriminating between healthy and unhealthy companies. These results align with those reported in previous studies by Altman (1968); Mselmi, Lahiani, and Hamza (2017); Gregova, Valaskova, Adamko, Tumpach, and Jaros (2020) and Zizi et al. (2020). Furthermore, the results indicate that the degree of indebtedness significantly affects the probability of default payment. This suggests that as more indebted firms are more likely to fail, choices regarding firms' financial structure need to be considered. These results are consistent with those obtained by Vivet (2011) and Gallucci, Santullli, Modina, and Formisano (2023).

In terms of firm size, our results do not agree with those found in literature emphasizing that larger firms have lower payment default values. In the Tunisian environment, all companies (commercial, industrial and agricultural), regardless of their size, can use a risky strategy that increases the default probability. In contrast, the outcome of this study suggests that company size has no impact on credit quality. This finding conforms with an earlier study performed by Belaid, Boussaada, and Belguith (2017) and is inconsistent with recent research by Kanapickienė, Kanapickas, and Nečiūnas (2023) and Modina, Pietrovito, Gallucci, and Formisano (2023), who argued that the risk of bankruptcy decreases as a firm's lifetime increases.

Changes in economic conditions, such as high inflation rates, can cause financial difficulties for companies. In this study, the inflation rate exerts a positive and significant influence on the probability of corporate default since inflation erodes the real value of debt repayment. These results are in accordance with those reported by Dimitrios, Helen, and Mike (2016); Makri, Tsagkanos, and Bellas (2014); Kanapickienė et al. (2023) and Manrai and Gupta (2023).

The real GDP growth rate refers to a country's economic situation from one period to the next. It is ubiquitous in the majority of studies that take non-productive credit into account. The results revealed that strong economic growth would decrease the likelihood of default across the board. Thus, the coefficient associated with the real GDP growth rate is negative and significant. This result aligns with the findings of various studies, such as Louzis, Vouldis, and Metaxas (2012) and Kanapickienė et al. (2023).

4. CONCLUSION

The problem of corporate financial failure has been extensively addressed. Yet, in times of economic turmoil, the issue of corporate solvency and its forecasting becomes paramount. In this regard, in order to ensure firms' long-term survival, it is necessary to assess the determinants of business failure.

In this research, we undertook an econometric study aiming at assessing the factors that account for the failure of companies in the industrial sector in the Tunisian context through comparing two regression models. This problem was handled using five financial ratios, namely the debt ratio, the economic and financial profitability ratios, the solvency ratio, and company size. Two macroeconomic variables were invested, namely the inflation rate and the GDP growth rate.

The optimal predictive accuracy was obtained by the probit model. We can therefore infer the significance of the probit model for predicting bankruptcy, as well as its relevance for assessing the credit risk of industrial companies. To accomplish our objective, we selected a sample of 4,000 Tunisian companies in the industrial sector. The data was gathered from the Central Bank of Tunisia from 2016 to 2020. The results demonstrate that default can be determined by four financial ratios, namely the solvency ratio, the debt ratio, and economic and financial profitability. Macroeconomic variables equally have an impact on the default rate of Tunisian companies in the industrial sector.

However, this work has certain deficiencies that need to be highlighted. First, the size of the sample is quite limited owing to the difficulties with respect to financial information for Tunisian companies in the industrial sector. Second, we compared two techniques for predicting corporate credit risk. In addition to traditional methods, we found intelligent techniques (such as decision trees, neural networks, and expert systems) were used in different others studies. It would therefore be interesting to carry out this study again using a larger sample of companies, and in addition to these two traditional techniques, employ other techniques involving artificial intelligence and compare the results.

To further this study, numerous research directions can be explored, and fruitful lines of investigation can be addressed to assess the variables that best account for industrial companies' performance through examining the determinants of company payment defaults for each industrial sector, breaking them down by activity branch such as manufacturing, wholesale and retail trade, and other industries. Forecasting the probability and timing of defaults for business loans would also be a useful topic for future research.

Funding: This study received no specific financial support.
Institutional Review Board Statement: Not applicable.
Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Data Availability Statement: The corresponding author can provide the supporting data of this study upon a reasonable request.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

REFERENCES

Abid, L. (2022). A logistic regression model for credit risk of companies in the service sector. *International Research in Economics and Finance*, *6*(2), 1-10. https://doi.org/10.20849/iref.v6i2.1179

Affes, Z., & Hentati-Kaffel, R. (2019). Predicting US banks bankruptcy: Logit versus canonical discriminant analysis. *Computational Economics, 54*, 199-244. https://doi.org/10.2139/ssrn.2826599

Aghabarari, L., Guettler, A., Naeem, M., & Van Doornik, B. (2021). Is there help indeed, if there is help in need? The case of credit unions during the global financial crisis. *Economic Inquiry, 59*(3), 1215-1233. https://doi.org/10.1111/ecin.12982

Akaike, H. (1974). A new look at the statistical model identification. *IEEE Transactions on Automatic Control*, *19*(6), 716–723. https://doi.org/10.1109/tac.1974.1100705

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, *23*(4), 589-609. https://doi.org/10.2307/2978933

Back, B., Laitinen, T., Sere, K., & van Wezel, M. (1996). Choosing bankruptcy predictors using discriminant analysis, logit analysis, and genetic algorithms. *Turku Centre for Computer Science Technical Report*, *40*(2), 1-18. https://doi.org/10.2139/ssrn.2826599

Bartoli, F., Ferri, G., Murro, P., & Rotondi, Z. (2013). Bank–firm relations and the role of Mutual Guarantee Institutions at the peak of the crisis. *Journal of Financial Stability*, *9*(1), 90-104. https://doi.org/10.2139/ssrn.1729655

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research*, 71-111. https://doi.org/10.2307/2490171

Belaid, F., Boussaada, R., & Belguith, H. (2017). Bank-firm relationship and credit risk: An analysis on Tunisian firms. *Research in International Business and Finance*, *42*, 532-543. https://doi.org/10.1016/j.ribaf.2017.04.011

Bliss, C. I. (1934). The method of probits. *Science*, *79*(2037), 38-39.

Bunn, P., & Redwood, V. (2003). *Company accounts-based modelling of business failures and the implications for financial stability*. Retrieved from Bank of England Working Papers 210, Bank of England:

Ciampi, F., Demi, S., Magrini, A., Marzi, G., & Papa, A. (2021). Exploring the impact of big data analytics capabilities on business model innovation: The mediating role of entrepreneurial orientation. *Journal of Business Research*, *123*, 1-13. https://doi.org/10.1016/j.jbusres.2020.09.023

Crook, J. N., Edelman, D. B., & Thomas, L. C. (2007). Recent developments in consumer credit risk assessment. *European Journal of Operational Research*, *183*(3), 1447-1465.

Dimitrios, A., Helen, L., & Mike, T. (2016). Determinants of non-performing loans: Evidence from Euro-area countries. *Finance Research Letters*, *18*, 116-119. https://doi.org/10.1016/j.frl.2016.04.008

Fernández-Gámez, M. Á., Soria, J. A. C., Santos, J. A. C., & Alaminos, D. (2020). European country heterogeneity in financial distress prediction: An empirical analysis with macroeconomic and regulatory factors. *Economic Modelling*, *88*, 398-407. https://doi.org/10.1016/j.econmod.2019.09.050

Fitzpatrick, P. J. (1932). A comparison of ratios of successful industrial enterprises with those of failed firms. *Certified Public Accountant*, 727-731.

Gallucci, C., Santullli, R., Modina, M., & Formisano, V. (2023). Financial ratios, corporate governance and bank-firm information: A Bayesian approach to predict SMEs' default. *Journal of Management and Governance*, *27*(3), 873-892. https://doi.org/10.1007/s10997-021-09614-5

Gregova, E., Valaskova, K., Adamko, P., Tumpach, M., & Jaros, J. (2020). Predicting financial distress of Slovak enterprises: Comparison of selected traditional and learning algorithms methods. *Sustainability*, *12*(10), 3954. https://doi.org/10.3390/su12103954

Hand, D. J., & Henley, W. E. (1997). Statistical classification methods in consumer credit scoring: A review. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *160*(3), 523-541. https://doi.org/10.1111/j.1467-985x.1997.00078.x

Kanapickienė, R., Kanapickas, T., & Nečiūnas, A. (2023). Bankruptcy prediction for micro and small enterprises using financial, non-financial, business sector and macroeconomic variables: The case of the Lithuanian construction sector. *Risks*, *11*(5), 97. https://doi.org/10.3390/risks11050097

Kim, H., Cho, H., & Ryu, D. (2022). Corporate bankruptcy prediction using machine learning methodologies with a focus on sequential data. *Computational Economics*, *59*(3), 1231-1249. https://doi.org/10.1007/s10614-021-10126-5

Kovacova, M., Kliestik, T., Valaskova, K., Durana, P., & Juhaszova, Z. (2019). Systematic review of variables applied in bankruptcy prediction models of Visegrad group countries. *Oeconomia Copernicana*, *10*(4), 743-772. https://doi.org/10.24136/oc.2019.034

Kristóf, T., & Virág, M. (2020). A comprehensive review of corporate bankruptcy prediction in Hungary. *Journal of Risk and Financial Management*, *13*(2), 35. https://doi.org/10.3390/jrfm13020035

Liu, J., Wu, C., & Li, Y. (2019). Improving financial distress prediction using financial network-based information and GA-based gradient boosting method. *Computational Economics*, *53*, 851-872. https://doi.org/10.1007/s10614-017-9768-3

Louzis, D. P., Vouldis, A. T., & Metaxas, V. L. (2012). Macroeconomic and bank-specific determinants of non-performing loans in Greece: A comparative study of mortgage, business and consumer loan portfolios. *Journal of Banking & Finance*, *36*(4), 1012-1027. https://doi.org/10.2139/ssrn.1703026

Makri, V., Tsagkanos, A., & Bellas, A. (2014). Determinants of non-performing loans: The case of Eurozone. *Panoeconomicus*, *61*(2), 193-206. https://doi.org/10.2298/pan1402193m

Malley, J. D., Kruppa, J., Dasgupta, A., Malley, K. G., & Ziegler, A. (2012). Probability machines. *Methods of Information in Medicine, 51*(01), 74-81.

Manrai, R., & Gupta, K. P. (2023). Investor's perceptions on artificial intelligence (AI) technology adoption in investment services in India. *Journal of Financial Services Marketing, 28*(1), 1-14. https://doi.org/10.1057/s41264-021-00134-9

Merwin, C. L. (1942). Financing small corporations in five manufacturing industries, 1926–1936. In: NBER Books. https://doi.org/10.2307/2280341.

Modina, M., Pietrovito, F., Gallucci, C., & Formisano, V. (2023). Predicting SMEs' default risk: Evidence from bank-firm relationship data. *The Quarterly Review of Economics and Finance, 89*, 254-268. https://doi.org/10.1016/j.qref.2023.04.008

Mselmi, N., Lahiani, A., & Hamza, T. (2017). Financial distress prediction: The case of French small and medium-sized firms. *International Review of Financial Analysis, 50*, 67-80. https://doi.org/10.1016/j.irfa.2017.02.004

Muñoz-Izquierdo, N., Laitinen, E. K., Camacho-Miñano, M. D. M., & Pascual-Ezama, D. (2020). Does audit report information improve financial distress prediction over Altman's traditional Z-Score model? *Journal of International Financial Management & Accounting, 31*(1), 65-97. https://doi.org/10.1111/jifm.12110

Pindado, J., & Rodrigues, L. F. (2004). Parsimonious models of financial insolvency in small companies. *Small Business Economics, 22*, 51-66. https://doi.org/10.2139/ssrn.283782

Ragab, Y. M., & Saleh, M. A. (2022). Non-financial variables related to governance and financial distress prediction in SMEs–evidence from Egypt. *Journal of Applied Accounting Research, 23*(3), 604-627. https://doi.org/10.1108/jaar-02-2021-0025

Raudzingana, D. (2020). *Determinants of corporate default: The case of South Africa*. Doctoral Dissertation.

Sharifabadi, M. R., Mirhaj, M., & Izadinia, N. (2017). The impact of financial ratios on the prediction of bankruptcy of small and medium companies. *QUID: Investigación, Ciencia y Tecnología, 1*, 164-173.

Valaskova, K., Kliestik, T., & Kovacova, M. (2018). Management of financial risks in Slovak enterprises using regression analysis. *Oeconomia Copernicana, 9*(1), 105-121. https://doi.org/10.24136/oc.2018.006

Vivet, D. (2011). *Development of a financial health indicator based on companies' annual accounts.* National Bank of Belgium Working Paper, No. 213.

Vo, D. H., Pham, B. N. V., Ho, C. M., & McAleer, M. (2019). Corporate financial distress of industry level listings in Vietnam. *Journal of Risk and Financial Management, 12*(4), 155. https://doi.org/10.3390/jrfm12040155

Zhang, X., Zhao, Y., & Yao, X. (2022). Forecasting corporate default risk in China. *International Journal of Forecasting, 38*(3), 1054-1070. https://doi.org/10.1016/j.ijforecast.2021.04.009

Zizi, Y., Oudgou, M., & El Moudden, A. (2020). Determinants and predictors of SMEs' financial failure: A logistic regression approach. *Risks, 8*(4), 107. https://doi.org/10.3390/risks8040107