The Study of Behavioral Significance in the Process of Lending Decision

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Abstract. *A wide range of statistical techniques are used in building scoring models. Most of these statistical models are applicable to build an efficient credit scoring system that can be effectively used for predictive purposes. Techniques such as weight-of-evidence measurement, regression analysis, discriminant analysis, probit analysis, logistic regression, linear programming, Cox's proportional hazard model, support vector machines, decision trees, neural networks, k-nearest-neighbor , genetic algorithms, and genetic programming are all techniques widely used in building credit scoring models by credit analysts, researchers, lenders, and computer software developers and vendors. Advanced statistical methods vs. traditional statistical methods: advanced statistical techniques such as neural networks and genetic programming offer an alternative to conventional statistical techniques such as discriminant analysis, probit analysis and logistic regression. The point of using sophisticated techniques such as neural networks is their ability to model highly complex functions, and of course this is in contrast to traditional linear techniques such* as linear regression and linear discriminant analysis.

Keywords: finance, analysis, behavior, credit, economic.

JEL Classification: G4 - Behavioral Economics

1. Introduction

In a study it was indicated that to define credit scoring, the term should be divided into two components, credit and scoring. First, the word "credit" simply means "buy now, pay later." It is derived from the Latin word "credo", meaning "I believe" or "I trust". Second, the word "scoring" refers to "the use of a numerical tool to rank order cases according to real or perceived quality in order to discriminate between them and ensure objective and consistent decisions." Therefore, scores can be presented as "numbers" to represent a single quality, or "grades" that can be presented as "letters" or "labels" to represent one or more qualities (Anderson, 2007). Accordingly, credit scoring can be simply defined as “the use of statistical models to transform relevant data into numerical measures that guide credit decisions. It is the industrialization of trust, a logical future development of subjective credit ratings (Beynon, M.J. - 2005) first offered by credit bureaus in the 19th century, which was driven by the need for objective, fast, consistent decisions and made made possible by technological advances (Anderson, 2007). Additionally, “credit scoring is the use of statistical models to determine the likelihood that a potential borrower will not accept a loan. Credit scoring models are widely used to evaluate business, real estate and consumer loans” (Gup & Kolari, 2005).

The objective of credit scoring models is to assign loan customers either good credit or bad credit (Lee et al, 2002) or predict bad lenders (Lim & Sohn, 2007). Probably the earliest use of statistical scoring to distinguish between "good" and "bad" candidates was by Durand (1941), who analyzed data from financial services such as commercial and industrial banks and companies financial. With the widespread use of credit scoring in the United States and the United Kingdom, credit scoring models became well known and the credit scoring literature expanded.

The credit score was primarily dedicated to evaluating people who were granted loans, both existing and new customers. Credit analysts, based on predetermined scores, reviewed customers' credit history and creditworthiness to minimize the likelihood of delinquency and default (Al Amari, 2002). The classification of good and bad credit is of fundamental importance and is indeed the objective of a credit scoring model (Lim & Sohn, 2007; Lee et al, 2002). From the literature review, characteristics such as gender, age, marital status, dependents, telephone, education level, occupation, time at current address, and credit card ownership are widely used in building models of scoring (Sustersic et al, 2009; Sarlija et al, 2004). Current working time, loan amount, loan duration, home owner, monthly income, bank accounts, car ownership, mortgage, loan purpose, collateral, and others were also used in building the scoring models (Ong et al. 2005; Chen, 2005; Greene, 1998). In some cases, the list of variables was expanded to include personal information about the spouse, such as age, salary, bank account. Of course, several variables are less frequently used in building scoring models, such as worst account status, time in work, time with bank and others (Bellotti and Crook, 2009; Banasik and Crook, 2007).

2. Research methodology

The choice of the multiple linear regression method was based on its strength as a statistical data manipulation tool and its simplicity in development, implementation and operation. Linear regression is a statistical analysis that depends on modeling a relationship between two types of variables, dependent (response) and independent (predictor). The main purpose of regression is to examine whether the independent variables are successful in predicting the outcome variable and which independent variables are significant predictors of the outcome.

The equation of the multiple regression model is as follows:

$$y = b_1 + b_2 * x_2 + b_3 * x_3 + \dots + b_n * x_n + \varepsilon, \text{ where:}$$

- x_i are the predictor variables;
- y is the response variable;
- b_i represents the slope parameters associated with the independent variables;
- ε represents the residue.

In order to highlight the impact of influencing factors on the rate of non-performing loans, we chose Romania as a representative country, for the period 2000-2020, with an annual frequency of the analyzed data. I will use the methodology of the multiple regression model in which I will consider as the response variable the rate of non-performing loans and as predictor variables I have chosen the unemployment rate, the inflation rate and the GDP growth rate. At the same time, I will also analyze the influencing factors on the customer's creditworthiness, considering the level of the customer's creditworthiness as the dependent variable and the gross profit, the level of credit history and the turnover as independent variables. Data were extracted from the Eurostat and World Bank database.

3. Research results

We will begin the presentation of the results of the current research by highlighting the statistical indicators that refer to the average, median, minimum value, maximum value and quartiles. The data processing was carried out by means of the Excel program.

Table 1. Statistical indicators

	Non-performing loan rate	*Unemployment rate*	*GDP growth rate*	*Inflation rate*
Average value	7.72	6.45	3.67	11.64
Median	4.09	6.81	4.19	6.19
Maximum value	21.87	8.11	10.43	43.18
Minimum value	2.59	3.91	-5.52	1.80
Quartile 1	3.78	5.90	2.34	3.75
Quartile 2	4.09	6.81	4.19	6.19
Quartile 3	11.85	7.10	5.70	15.82

Source: own processing in Excel

On average, the rate of non-performing loans recorded in Romania was 7.72%, the maximum value being 21.87%. The median coincides with the second quartile indicating that half of the values are below the 4.09% threshold and half of the values are above this threshold.

During the analyzed period, the minimum recorded unemployment rate was 3.91%, while the maximum value was 8.11%. The first quartile claims that 25% of values are less than 5.9% and 75% of values are greater than this level.

The average value of the GDP growth rate was 3.67% and the minimum value decreased to -5.52%. The third quartile indicates that 75% of the values are less than 5.7% and 25% of the analyzed data are found above this level.

Taking into account the maximum value of the inflation rate in Romania, we can say that for a certain period the phenomenon of hyperinflation was manifested, the proof being the value of 43.18%. After the implementation of the inflation targeting program in Romania, in 2005, the minimum recorded level of the inflation rate was 1.8%.

One of the stages preceding the realization of the multiple regression model is testing the stationarity of the data series. I will perform this testing by using the Augmented-Dickey-Fuller test. The null hypothesis states that the data series is non-stationary while the alternative hypothesis states that the data series is stationary.

Table 2. Stationarity of data series

Test	*Augmented-Dickey-Fuller test*	
Assumptions	I(0)	I(1)
Data series	Prob.	Prob.
GDP growth rate	0.0479	0.0002
Unemployment rate	0.6117	0.0354
Inflation rate	0.0875	0.0001
Non-performing loans rate	0.0155	0.0001

Source: own processing in Eviews 7.1.

Taking into account the values obtained from the stationarity test, it can be noted that the GDP growth rate and the non-performing loans rate are stationary data series at the level, while for the unemployment rate and the inflation rate, it is necessary to carry out the first difference to see if these series become stationary or not. After stationing the data series (first difference), both data series became stationary (no unit root). So, following this test, we can conclude that the GDP growth rate and the NPL rate have an order of integration equal to 0, and the inflation rate and the unemployment rate have an order of integration equal to 1.

Another stage prior to the realization of the multiple regression model is represented by the verification of the existing correlation at the level of the predictor variables, in the present situation, at the level of the inflation rate, the GDP growth rate and the unemployment rate.

Table 3. Correlation of predictor variables

	GDP growth rate	*Unemployment rate*	*Inflation rate*
GDP growth rate	1.000000	0.118754	-0.458752
Unemployment rate	0.118754	1.000000	-0.265960
Inflation rate	-0.458752	-0.265960	1.000000

Source: own processing in Eviews 7.1.

On the one hand, there is an indirect relationship between the unemployment rate and the inflation rate, the intensity being weak, and between the GDP growth rate and the unemployment rate there is a direct relationship, the intensity being still weak.

The intensity of the relationship between the inflation rate and the GDP growth rate is moderate, and the direction of the link is indirect.

As a result of this testing, we can conclude that at the level of the predictor variables there are no relationships of strong intensity, so they will all be included in the regression model.

The econometric model presented below has as a dependent variable the level of the non-performing loans rate and as independent variables we have chosen the inflation rate, the GDP growth rate and the unemployment rate.

Table 4. Results of the econometric model

Dependent Variable: RATA_CREDITELOR_NEPERFOR
Method: Least Squares
Sample: 2000 2020
Included observations: 21

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RATA_DE_CRESTERE_A_PIB	-0.210029	0.094942	-2.211962	0.0191
RATA_SOMAJULUI	1.979897	0.948081	2.088322	0.0221
RATA_INFLATIEI	-0.297722	0.093037	-3.200026	0.0052
C	-0.813666	6.062894	-0.134204	0.8948

R-squared	0.864035	Mean dependent var	7.717287
Adjusted R-squared	0.859452	S.D. dependent var	5.689164
S.E. of regression	4.517596	Akaike info criterion	6.023480
Sum squared resid	346.9474	Schwarz criterion	6.222437
Log likelihood	-59.24654	Hannan-Quinn criter.	6.066659
F-statistic	15.90615	Durbin-Watson stat	2.480002
Prob(F-statistic)	0.000030		

Source: own processing in Eviews 7.1.

NPL ratio = - 0.8136-0.21*GDP growth rate + 1.979*Unemployment rate - 0.2977*Inflation rate

The obtained results suggest that all the independent variables considered have a strong impact on the rate of non-performing loans. The value recorded by the determination ratio indicates that 86.4% of the variance in the GDP growth rate is explained by the regression model.

The Fisher test probability value that is lower than the 5% significance threshold indicates the validity of the econometric model made. In the same vein, the regression performed is not false since the value of the determination ratio does not exceed the value of the Durbin-Watson statistic.

When GDP growth increases by one percentage point, the rate of non-performing loans will decrease by 0.21 percentage points, keeping other variables constant.

When the unemployment rate increases by one percentage point, the NPL ratio will increase by 1.979 percentage points, holding other variables constant.

When the inflation rate increases by one percentage point, the non-performing loans rate will decrease by 0.2977 percentage points, keeping other variables constant.

On the one hand, there is a direct relationship between the inflation rate and the GDP growth rate, while there are indirect relationships between the GDP growth rate and the unemployment rate, respectively the non-performing loans rate.

I believe that, from a policy perspective, the results imply that policymakers should implement countercyclical policy measures aimed at reducing the potential for significant increases in non-performing loans during economic downturns, as this could slow the pace of a subsequent economic recovery over time. The authorities could look for ways to restrict the growth of long-term non-performing loans through much greater rigor in granting loans as well as stricter supervision of wages and the borrower's ability to pay. Economic growth could reduce NPLs over time, and this most likely reflects the effect of growth on jobs and business conditions, and thus the ability of borrowers to repay loans.

The analysis continues by highlighting the test of normality of errors represented by the Jarque-Bera test. In this test, the errors are normally distributed under the null hypothesis, while under the alternative hypothesis, the errors are not normally distributed. The situation of a perfectly normal distribution implies a skewness value of 0 and a kurtosis indicator value of 3.

The test equation is: JB= (n-k+1)/2 (S^2+ 〖(k-3)〗 ^2/4)

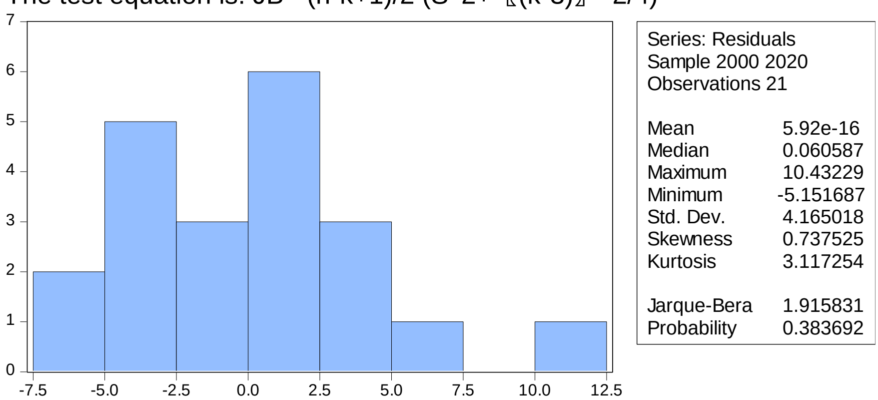

Figure 1. Testing for normality of errors

Source: own processing in Eviews 7.1.

The probability of this test, namely 0.3836, is placed above the significance threshold of 5%, which indicates the acceptance of the null hypothesis, so the phenomenon of normality at the level of errors is manifested. This statement is also supported by the values recorded by the two indicators of normal distribution, skewness and kurtosis.

The Breusch-Godfrey test I will use to test whether the errors are autocorrelated of order II or not.

The test equation is: $\hat{\varepsilon_t} = b_1 x_t + \varphi_1 \varepsilon_{t-1} + \varphi_2 \varepsilon_{t-2} + u_t$

H_0: $\varphi_1 = \varphi_2 = 0$ (no autocorrelation)

H_1: φ_i different from 0 (autocorrelation exists)

Table 5. Testing the autocorrelation of errors

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	5.244638	Prob. F(2,15)	0.2188
Obs*R-squared	8.641862	Prob. Chi-Square(2)	0.5133

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 06/09/22 Time: 15:35
Sample: 2000 2020
Included observations: 21
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RATA_DE_CRE_TERE_A_PIB	-0.024497	0.208693	-0.117384	0.9081
RATA__OMAJULUI	-0.142694	0.775905	-0.183907	0.8565
RATA_INFLATIEI	0.031717	0.076650	0.413788	0.6849
C	0.493055	4.963127	0.099344	0.9222
RESID(-1)	0.755122	0.273411	2.761862	0.5145
RESID(-2)	-0.138884	0.273905	-0.507054	0.6195

R-squared	0.411517	Mean dependent var	5.92E-16
Adjusted R-squared	0.215356	S.D. dependent var	4.165018
S.E. of regression	3.689377	Akaike info criterion	5.683749
Sum squared resid	204.1726	Schwarz criterion	5.982184
Log likelihood	-53.67936	Hannan-Quinn criter.	5.748517
F-statistic	2.097855	Durbin-Watson stat	1.778853
Prob(F-statistic)	0.122294		

Source: own processing in Eviews 7.1.

The probabilities of this test suggest that the significance threshold of 5% is exceeded, so the null hypothesis is accepted, and the presence of autocorrelation of the second order is not noted at the error level.

The next test I will apply refers to the homoscedasticity of the errors, more precisely, whether the variance of the confounding factors is constant over time. We used the Harvey test to test homoscedasticity, and the null hypothesis of this test indicates the presence of homoscedasticity at the level of errors, while the alternative hypothesis suggests the presence of heteroscedasticity at the level of disturbing factors.

The equation is: ln $\varepsilon_i^2 = c_0+c_1x_1+c_2x_2+u_i$.

Table 6. Testing homoscedasticity of errors

Heteroskedasticity Test: Harvey

F-statistic	8.192821	Prob. F(3,17)	0.1514
Obs*R-squared	12.41382	Prob. Chi-Square(3)	0.1561
Scaled explained SS	15.20335	Prob. Chi-Square(3)	0.4217

Test Equation:
Dependent Variable: LRESID2
Method: Least Squares
Sample: 2000 2020
Included observations: 21

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-9.372449	2.344767	-3.997177	0.0009
RATA_DE_CRE_TERE_A_PIB	-0.094500	0.098093	-0.963374	0.3489
RATA__OMAJULUI	1.705403	0.366661	4.651167	0.0002
RATA_INFLATIEI	0.008670	0.035981	0.240948	0.8125

R-squared	0.591134	Mean dependent var	1.378535
Adjusted R-squared	0.518982	S.D. dependent var	2.519105
S.E. of regression	1.747138	Akaike info criterion	4.123478
Sum squared resid	51.89233	Schwarz criterion	4.322435
Log likelihood	-39.29652	Hannan-Quinn criter.	4.166657
F-statistic	8.192821	Durbin-Watson stat	1.747242
Prob(F-statistic)	0.001364		

Source: own processing in Eviews 7.1.

The three probabilities of this test exceed the significance threshold of 5%, which means that the null hypothesis is accepted, so at the level of disturbing factors the phenomenon of homoscedasticity is manifested.

The results of these tests indicate that the errors belong to a normal distribution, are homoscedastic and do not show autocorrelation of order II. Taking into account the obtained, we can conclude that the econometric model made can be used for future estimations.

The present analysis continues by highlighting the evolution of the variables considered within the multiple regression model, for the period 2000-2020.

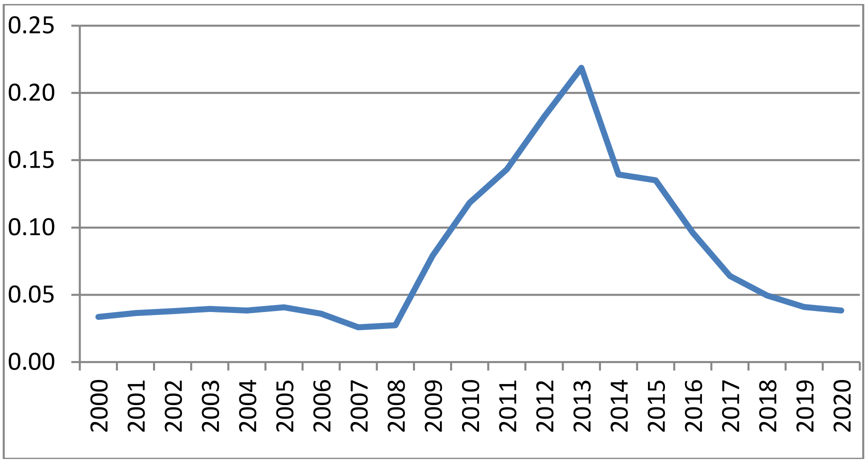

Figure 2. Evolution of the rate of non-performing loans in the period 2000-2020
Source: own processing in Excel

Throughout the analyzed period, the rate of non-performing loans fluctuated, the highest value being recorded in 2013. The beginning of the economic crisis in 2008 led to the loss of many jobs and implicitly to the disappearance of an established income from many households. These then propelled the inability to pay contracted loans and implicitly to an impressive increase in the rate of non-performing loans. After the peak reached in 2013, the rate of non-performing loans was placed on a downward trajectory until the end of the analyzed period.

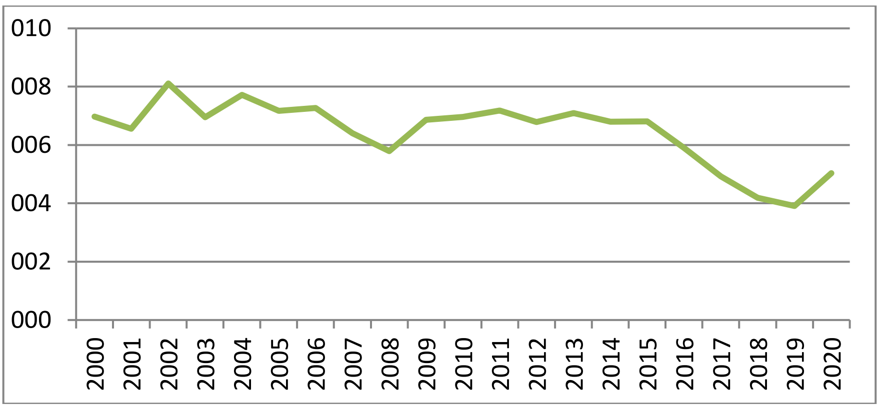

Figure 3. Evolution of the unemployment rate for the period 2000-2020
Source: own processing in Excel

In the period 2000-2020, the unemployment rate for Romania had both increasing and decreasing periods, placing itself on a downward trend from 2014 to 2019. With the emergence of the health crisis in 2020, the unemployment rate increased against the background of the closure of the activities of certain key sectors of the economy but also through the lens of the large number of illnesses caused by the COVID-19 virus. The increase in the number of unemployed at the level of the economy also had effects on their lending behavior, as many of them turned to the possibilities of deferring the payment of installments proposed by the government and adopted by the banks. This measure aimed to support households in a period in which their incomes decreased considerably.

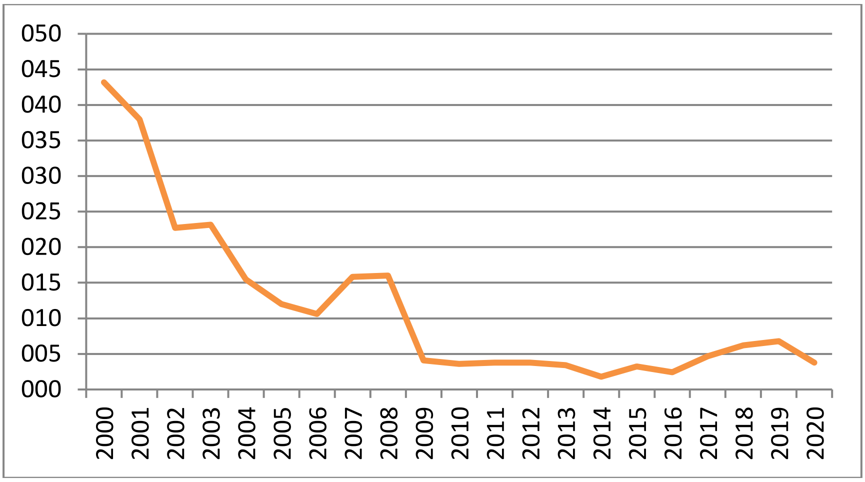

Figure 4. Evolution of the inflation rate for the period 2000-2020
Source: own processing in Excel

At the beginning of the analyzed period, the inflation rate in Romania registered a very high value compared to the rest of the considered values, of approximately 45%. The phenomenon of galloping inflation came to an end in 2005, when the inflation targeting program was implemented in Romania, which tried to keep the inflation rate below 10%. Immediately after implementation, the inflation rate exceeded this threshold, the main reason being the global economic crisis that broke out in 2008. After the effects of the crisis began to be absorbed in the economy, the inflation rate remained below 5% until 2018, when this value was slightly exceeded.

The inflation rate can be beneficial for the evolution of the economy, but only if it is kept at low values that can be sustainable for citizens.

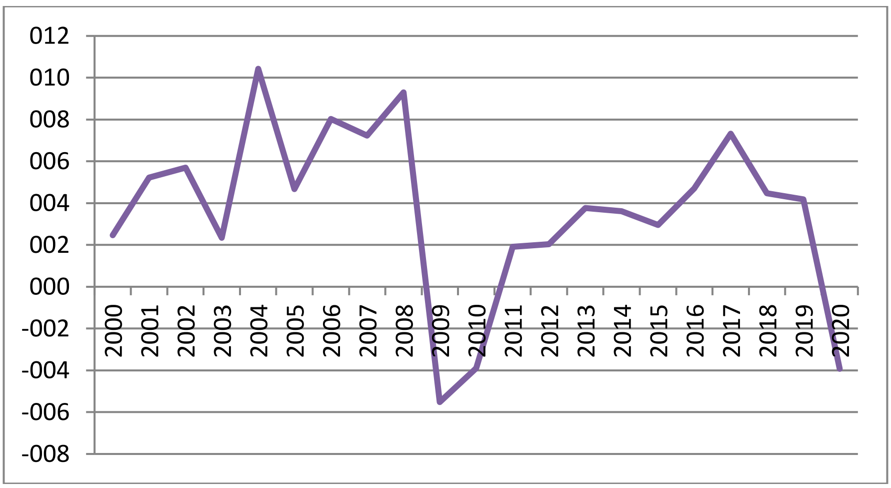

Figure 5. Evolution of the GDP growth rate in the period 2000-2020
Source: own processing in Excel

As for the GDP growth rate, in the adjacent graph it can be seen that there were both sudden increases and decreases, especially during the two crises included in the analysis, the economic crisis of 2008 and the health crisis of 2020. Although there were periods when the GDP growth rate for Romania even exceeded the 10% level, these increases are not sustainable as they are based on population consumption and not on investments both from the population and from abroad.

The period of economic decline also coincided with the period in which the rate of non-performing loans registered a considerable increase simultaneously with the unemployment rate, all of which had a significant impact on the lending behavior of the population, the latter being much more cautious when engages in contracting one or more loans.

We will also create a multiple regression model in which I will highlight the impact that the level of deposits granted to households, the level of the average salary, the monetary policy interest rate and the inflation rate have an impact on the level of loans granted to households.

Table 7. Results of the multiple regression model

Dependent Variable: CREDITE
Method: Least Squares
Sample: 2007M01 2022M02
Included observations: 182

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DEPOZITE	0.836334	0.018835	44.40254	0.0000
RATA_DOBANZII_DE_POLITIC	-0.021065	0.001261	-16.70489	0.0000
RATA_INFLATIEI	-0.015380	0.003669	-4.191955	0.0022
C	1.146577	0.157769	7.267441	0.0000

R-squared	0.851573	Mean dependent var	8.032579
Adjusted R-squared	0.850757	S.D. dependent var	0.112292
S.E. of regression	0.024918	Akaike info criterion	-4.524687
Sum squared resid	0.110525	Schwarz criterion	-4.454269
Log likelihood	415.7465	Hannan-Quinn criter.	-4.496141
F-statistic	1165.880	Durbin-Watson stat	2.179508
Prob(F-statistic)	0.000000		

Source: own processing in Eviews 7.1.

Following the application of the multiple regression model, it was demonstrated that the level of loans granted to the population is influenced by the level of deposits granted to the population, by the level of the monetary policy interest rate and also by the level of the inflation rate.

The determination ratio indicates that 85.15% of the credit variance is explained by the multiple regression model. The Fisher test probability suggests that the constructed model is valid.

When the level of deposits increases by 100,000 lei, the level of loans will increase by 83,000 lei, if the rest of the factors do not change. This relationship indicates that once more deposits are attracted from the population, more loans will be granted, as the funds are sufficient, taking into account the customer's creditworthiness as well as his repayment history.

When the monetary policy interest rate is increased by 1 percentage point, the level of deposits will decrease by 20,000 lei, if the rest of the factors remain constant. The National Bank calls for an increase in the monetary policy interest rate when there is a high level of inflation on the market but also a high level of interest applied to loans. The level of loans will decrease, and the population will be more reluctant to contract new loans.

When the inflation rate increases by one percentage point, the level of loans will decrease slightly, more precisely by 15,000 lei, if the rest of the factors remain constant. The decrease in purchasing power generated by high inflation suppresses the idea of indebtedness of the population and they will be more careful when they decide that it is time to take out a new loan.

Credit analysis is a major step in the financial decision-making process. Financial decision making includes examining the financial problems facing the organization and choosing the decision to be made. Financial knowledge is the most important aspect in credit analysis and is the procedure by which individuals improve their knowledge of factors, administrations, services and ideas so that they are able to settle on educated decisions, maintain a strategic distance from pitfalls (Cole and Shastry, 2008).

Creditworthiness is how a bank or financial institution checks whether you will default or that you are so qualified to get a new loan. The customer's creditworthiness is what lenders look at before confirming any new credit. Creditworthiness is dictated by several elements, including repayment history and credit score. Some credit companies consider the client's assets and the extent of their liabilities when deciding the probability of default (Dezfouli, 2014). Credit tells a lender exactly how reasonable the customer is for the loan or credit card application they are applying for. The decision the organization makes depends on how the credit was handled before. To do this, they look at several unique factors such as qualitative, quantitative and risk factors. Eg; overall credit report, credit score and installment history.

Creditworthiness is the ability of a natural person or legal entity to pay off financial obligations over time. Creditworthiness is a synonym of solvency (the latter concept is much more commonly used in the scientific literature).

The credit report highlights how much debt customers carry, large balances, credit facilities customers have and the outstanding balance of each record. It will also highlight any vital data for the potential loan specialist including whether you have had outstanding amounts, any defaults, liquidations, as well as collection matters. Creditworthiness is estimated by your credit score, which rates you on a numerical scale based on your credit report. A high credit score means that the creditworthiness of the customer is high. Alternatively, poor credit comes from a lower credit score. Additionally, payment history is a major key in deciding creditworthiness. Banks do not extend credit to someone whose history shows late installments, missed installments and defaulted contracts (Thomas, 2000).

Customer creditworthiness is also measured by the credit score, which measures on a numerical scale based on the credit report. A high credit score means that creditworthiness is high. Conversely, low creditworthiness comes from a lower credit score.

Payment history also plays a key role in determining creditworthiness. Lenders generally do not extend credit to someone whose history demonstrates late payments, missed payments, and general financial irresponsibility. If your payments have been made on time, your payment history on your credit report should reflect this. Payment history counts for 35% of your credit score, so it's a good idea to stay bring the level of payments under control.

The more creditworthy a customer is, the better it is for them in the long run, as it normally means better interest rates, fewer fees and better terms and conditions for a credit card or loan, which means more money in your pocket. It also affects eligibility for employment, insurance premiums, business financing, and professional certifications or licenses.

The research technique used in this study is that of the multiple regression model, as in the case of the analysis above. We chose as the dependent variable the level of the client's creditworthiness and as independent variables we considered the level of the bank's gross profit, the level of credit history and turnover. The analysis was carried out for the Romanian Commercial Bank, over a period of 15 years (2005-2022), within the limits of the available data.

The results obtained from the regression model are presented in the table below.

Table 8. Results of the regression model

Variables	*Coefficient*	*Probability*
Constant	2.188	0.0005
Gross profit	0.134	0.0001
Turnover	0.0966	0.0000
Credit history level	-0.0510	0.0010

Source: own processing in Eviews 7.1

Customer creditworthiness = 2.188 + 0.134*Gross profit + 0.0966*Turnover - 0.051*Historical credit level.

When gross profit increases by one unit, the customer's creditworthiness will increase by 0.134 units, ceteris paribus. When turnover increases by one unit, the customer's creditworthiness will increase by 0.0966 units, ceteris paribus. When the credit history is negative, the customer's creditworthiness will decrease by 0.134 units, ceteris paribus.

4. Conclusions

Banks should follow the most effective methods like credit scoring to conduct creditworthiness analysis to make effective decisions. Analysts should consider the most effective factors in the analysis process and should not neglect other factors. Quantitative factors have a large impact on creditworthiness; therefore, it is mandatory to request the customer's source of income and current liabilities for the bank to ensure that the customers have sufficient funds to cover the loan granted. Using this credit analysis study, banks can check the risk associated with each profile and therefore minimize losses.

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