

Determinants of credit risk: A multiple linear regression analysis of Peruvian municipal savings banks**Valentín J. Calderon-Contreras^{a*}, Jhony Ostos^a, Wilmer Florez-Garcia^b and Harold D. Angulo-Bustanza^c**^aUniversidad ESAN, Peru^bUniversidad Nacional de San Antonio Abad del Cusco, Peru^cUniversidad Continental, Peru**HRONICLE***Article history:*

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*Keywords:**Credit risk**Delinquency**Municipal savings banks**Macroeconomic variables***ABSTRACT**

In order to identify the determinants that influence the credit risk of Peruvian municipal savings banks, this quantitative research uses a nonexperimental design and a longitudinal sample to analyze monthly data corresponding to macroeconomic variables and microfinance institutions' internal variables from 2011 to 2020. Using multiple linear regression, the results show that the interest rate, unemployment rate, and liquidity ratio positively influence the credit risk of Peruvian municipal savings banks; the study also shows that gross domestic product, efficiency of administrative expenses, solvency, and coverage of provisions exert a negative influence on credit risk. It is concluded that seven of the eight independent variables studied influence the credit risk of Peruvian municipal savings banks; only the inflation variable does not significantly influence credit risk.

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1. Introduction

Liu and Sun (2018) found that the greatest difficulty faced by small and micro-enterprises is the lack of financing. In addition, it is important to note that, through the removal of financial barriers, microcredit almost always reduces poverty (Ahlin & Jiang, 2008). Along these lines, Durango-Gutiérrez et al. (2021) found that microcredit financial institutions have contributed to financial inclusion, sustainable economic development, and the fight against poverty. Microcredit programs are thus an effective tool for improving the well-being of the most vulnerable social groups within economies. In this regard, according to the Superintendence of Banking, Insurance, and Pension Fund Managers (known as the SBS, its acronym in Spanish), Peruvian municipal savings banks constitute the main financial intermediaries in the microfinance market, playing a central role in the formalization, development, and sustainability of Peruvian small and micro enterprises (SBS, 2021). Fig. 1 shows that, between 1998 and 2020, the number of municipal savings banks in Peru fell by 26.7%, from 15 to 11 municipal savings banks; in contrast, in the same period, the number of direct credits granted by municipal savings banks increased by 22.7% on average per year, reaching 26.455 billion Peruvian nuevos soles (PEN) by December 2020 (SBS, 2021). Peruvian municipal savings banks are those entities that carry out the process of financial intermediation, collecting deposits and granting credits, mainly to small and micro enterprises (SBS, 2021). In this sense, municipal savings banks are the main financial intermediaries that contribute to the financing of the operations of small and medium enterprises (SMEs) in Peru, as well as to their acquisition of inputs or goods to increase their productive and commercial activity.

In this study, accounting arrears are considered a credit risk: the accounting arrears ratio is defined as the percentage of direct credits that have fallen into arrears. It is determined by dividing the overdue portfolio by the total direct credits. In

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this case, the overdue portfolio includes overdue credits and credits in judicial collection (SBS, 2015). Credit risk is inherent to microfinance institutions and constitutes the main type of risk they face.

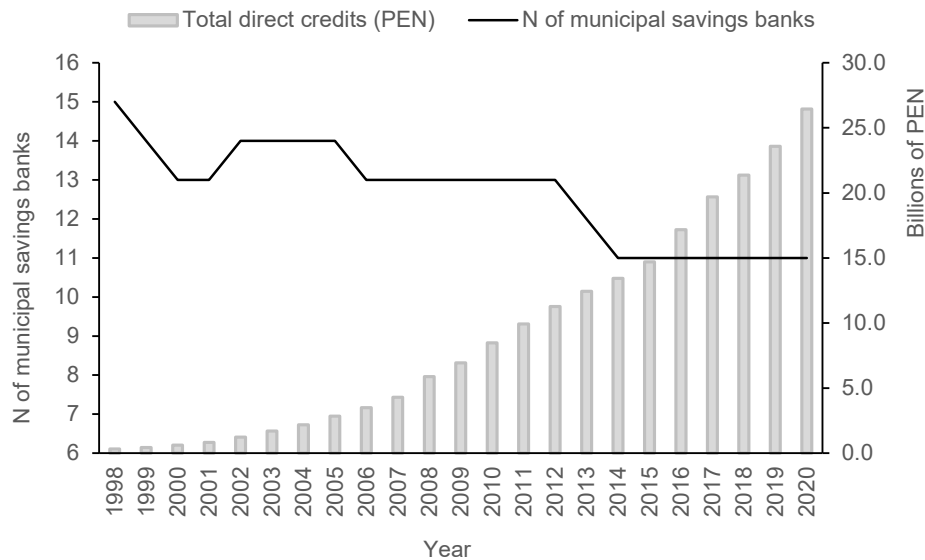


Fig. 1. The number of municipal savings banks in Peru and the number of direct credits (1998-2020).
Note: Based on SBS data (2021).

According to the SBS (2017), credit risk is defined as the possibility of losses due to the fact that debtors do not have the will or the capacity to make the stipulated payments on time or due to the breach of contractual obligation by issuers, counterparties, or debtors. In this regard, over the years, the financial system has experienced a series of financial crises linked to credit risk, which have affected the financial health of municipal savings banks. In this context, studies by Chen et al. (2021) show that, from 2007 to 2009, during the subprime mortgage crisis, financial institutions that came away with less favorable results in terms of their liquidity indicators, return on assets (ROA), net interest margin, and high provisioning costs were those with lower capital ratios and a higher credit risk. Along these same lines, Castro (2013) found that, during the European financial crisis, banks' credit risk increased substantially in the countries of Greece, Ireland, Portugal, Spain, and Italy.

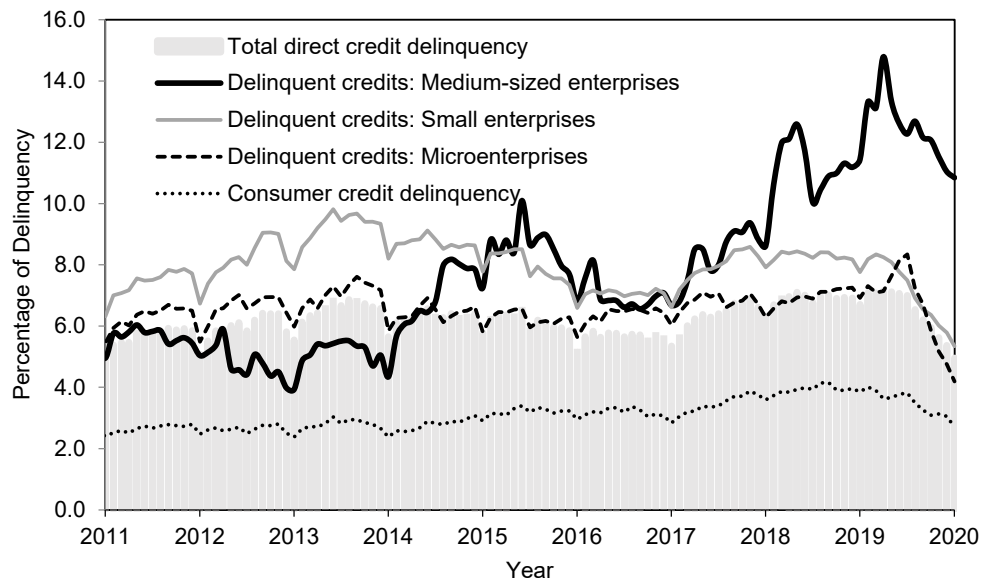


Fig. 2. Municipal savings banks' monthly arrears by type of credit (%)
Note: Based on SBS data (2021).

In addition, Forgione and Migliardo (2019) show that companies experiencing difficult financial situations make extensive use of commercial credit, affecting their suppliers, which increases the probability of undergoing debt restructuring with their banks. In this way, when financial institutions' credit portfolios deteriorate due to default, those banks assume a higher credit risk, affecting their credit portfolios, with a consequent increase in arrears. In this regard, as illustrated in Fig. 2,

between 2011 and 2019, the accounting arrears ratio of Peruvian municipal savings banks showed an obvious upward trend, especially among the arrears of loans to medium-sized enterprises, small enterprises, and micro-enterprises that, in March 2020, reached historical arrears ratios of 14.8%, 8.2%, and 7.1%, respectively (SBS, 2021).

Peruvian municipal savings banks face different risks associated with their credit activity, such as credit risk, operating risk, market risk, and liquidity risk. Given this situation, Wagner and Winkler (2013) identified that in times of financial crisis, the financial stability of microfinance has been particularly vulnerable to these risks, especially credit risk. It is for this reason that it is necessary to define, plan for, and monitor risks in order to mitigate them in the face of the uncertainty of the national and international economic and financial environment (Gómez & Checo, 2014). In this context, according to Lassoued (2017), credit risk can be reduced through group loans and the provision of a higher level of credit to women, as well as diversification. Furthermore, according to Bülbül et al. (2019), competition obliges savings banks in Germany to make use of advanced risk management practices, and the increased concentration of the placements market stimulates the use of practices such as credit portfolio modeling and credit risk transfer.

According to Moudud-Ul-Huq et al. (2020), credit risk is the main type of risk that commercial banks engage in, and several studies indicate that the determinants of credit risk can be classified into two groups. First, there are the risk determinants specific to each individual bank and, second, there are the determinants that are influenced by the banking industry and the macroeconomic environment as a whole (Baselga et al., 2015). İncekara and Çetinkaya (2019), using a data panel model, showed that there is a significant positive relationship between credit risk and the capital adequacy index, as well as net incomes from profit sharing; on the other hand, they also found a negative and statistically significant relationship between gross domestic product (GDP) and credit risk. Along these same lines, Moudud-Ul-Huq et al. (2020), using a regression model, showed that the credit risk of Bangladesh's commercial banks responds to macroeconomic constraints: GDP, inflation rate, and interest rate, as well as bank-level variables: depositor influence, shareholder influence, liquidity, inefficiency, bank size, the insolvency risk indicator, and leverage.

Other studies support the more traditional view that high short-term interest rates increase credit risk, especially for the most indebted borrowers (González-Aguado & Suárez, 2015). On the other hand, Durango-Gutiérrez et al. (2021), using a logistic regression model and neural networks, identified that the main variables that explain loan default are the amount of the loan, the number of arrears, the guarantees provided by the borrower, the assessment of the credit analyst, and the gender of the borrower, as well as the level and trending direction of the stock exchange general index. Ocaña (2017) used a multiple linear regression model in order to identify the determinants of delinquency in the Ecuadorian banking system. He analyzed overdue portfolios, the efficiency in the granting of credits, the credit cycle, and the relationship between the growth of credit and credits with arrears, concluding that there is a causal relationship between the quality of the loan portfolio, unemployment, and the incidence of delinquency of banks. Likewise, Bai (2021), through a data panel model, showed that there is a strong positive relationship between unemployment and credit risk at the aggregate level.

Along these lines, the present study takes into account the following as determinants of Peruvian municipal savings banks' credit risk: the GDP, unemployment rate, inflation rate, interest rate, efficiency of administrative expenses, liquidity ratio, solvency, and provisions coverage. In order to gain a greater knowledge of and perspective on the management of microfinance risks, an econometric analysis must be carried out using the ordinary least squares technique in order to identify the main determinants of credit risk for Peruvian municipal savings banks. In this context, in order to achieve the study objective, the following hypotheses are proposed:

- H₁:** *GDP negatively influences the credit risk of Peruvian municipal savings banks.*
- H₂:** *The unemployment rate positively influences the credit risk of Peruvian municipal savings banks.*
- H₃:** *The inflation rate positively influences the credit risk of Peruvian municipal savings banks.*
- H₄:** *The interest rate positively influences the credit risk of Peruvian municipal savings banks.*
- H₅:** *The efficiency of administrative expenses negatively influences the credit risk of Peruvian municipal savings banks.*
- H₆:** *The liquidity ratio in PEN positively influences the credit risk of Peruvian municipal savings banks.*
- H₇:** *Solvency negatively influences the credit risk of Peruvian municipal savings banks.*
- H₈:** *Provisions coverage negatively influences the credit risk of Peruvian municipal savings banks.*

2. Methodology

This research uses a quantitative approach, a nonexperimental design, and a longitudinal sample. The study covers 10 years, from January 2011 to December 2020, and uses data that were generated on a monthly basis during said period. The unit of analysis is Peruvian municipal savings banks, and the sample size is 11, the total number of municipal savings banks present in the country, which operate in all of its 25 regions. The statistical analysis technique applied is the multiple linear regression. The dependent variable (Y_1) is municipal savings banks' Credit Risk, in other words, accounting arrears due to debtor default. As shown in Table 1, the independent variables of the econometric model used in the study are the following macroeconomic indicators: GDP (X_1), Unemployment Rate (X_2), and Inflation Rate (X_3), as well as the following variables at the internal level for each municipal savings bank: Interest Rate for SMEs (X_4), Efficiency of Administrative Expenses

(X₅), Liquidity Ratio in PEN (X₆), Solvency (X₇), and Provisions Coverage (X₈). This latter group of variables was included in the study because of the relevance assigned to them by various authors (Viphindrartin et al., 2021, Montes et al., 2021, Jumono et al., 2021), as well as by the authors of the present study.

Table 1

Description and abbreviation of the variables in the econometric model

Variable	Description of Variables	Notes	Abbreviation	Hypothesis and expected signs
Y ₁	Credit Risk	Portfolio in arrears/Direct credits	DELIQ	
X ₁	Gross Domestic Product	% monthly variation in GDP	GDP	H1 (-)
X ₂	Unemployment Rate	Unemployed population/EAP	UNEMP	H2 (+)
X ₃	Inflation Rate	% annual variation in CPI	INFLAT	H3 (+)
X ₄	Interest Rate	Interest rate for SMEs	INTER	H4 (+)
X ₅	Efficiency of Administrative Expenses	Administrative expenses/Total credits	EXPADM	H5 (-)
X ₆	Liquidity Ratio in PEN	Liquid assets/Short-term liabilities	LIQUA	H6 (+)
X ₇	Solvency	Total liabilities/Social capital and reserves	SOLVEN	H7 (-)
X ₈	Provisions Coverage	Provisions/Late credits	PROCOV	H8 (-)

According to Wooldridge (2010), the significance of explanatory variables in a regression model is that they explain the strength or weakness of empirical evidence, whose most useful interpretation is as follows: the “*p*-value is the probability of observing a statistic *t* as extreme as that found if the null hypothesis is true” (p. 133). Since the *p*-value represents probability, it is a number between 0 and 1. The *p*-value is the minimum probability that is established in the distribution; the null hypothesis (H₀) is rejected when its value is less than 0.05. In this way, the present paper took into account that there was a lag in the variables Unemployment Rate, Interest Rate, and Provisions Coverage, as well as in the variables Efficiency of Administrative Expenses and Liquidity Ratio in PEN, due to their influence on delinquency, which is reflected in later periods.

The multiple linear regression model is represented in equation 1, where Y₁ is the dependent variable, that is, Credit Risk; likewise, β₀ is the intercept or the ordinate at the origin, β₁, β₂ ...β₈ are the coefficients in the regression, X₁, X₂..., X₈ represent the independent variables, and μ is the difference between the observed value and the estimated value, known as the residue.

$$Y_1 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_8 X_8 + \mu \quad (1)$$

3. Results

Table 2 presents the main descriptive statistics of the significant variables at the macroeconomic level and at the internal level of Peruvian municipal savings banks from 2011 to 2020; the number of observations of the variables was 118. The accounting arrears of Peruvian municipal savings banks range between 4.89% and 7.15%; the arithmetic average was 6.16%.

Table 2

Descriptive statistics of significant variables

Variables	N	Mean	Median	Maximum	Minimum	Std. Dev.
DELIQ	118	6.16	6.18	7.15	4.89	0.56
GDP	118	0.01	0.01	0.18	-0.25	0.07
UNEMP(-1)	118	7.21	6.60	16.53	5.42	2.29
INFLAT	118	2.84	2.96	4.74	0.36	0.94
INTER(-1)	118	38.18	38.10	41.81	34.04	1.67
EXPADM(-2)	118	9.63	9.68	10.25	8.22	0.32
LIQUA(-2)	118	31.00	30.48	41.28	23.49	4.95
SOLVEN	118	7.44	7.43	8.18	7.02	0.21
PROCOV(-1)	118	136.49	134.25	180.26	123.12	9.02

Note. The data are expressed in percentage values.

Development of the econometric model

Step 1. Normality Test: The multiple regression model assumes that errors are distributed in a normal probability density function with a mean of zero and constant variance. To identify normality, the Jarque-Bera statistical test based on the Lagrange multiplier criterion is carried out. According to Wooldridge (2010), testing a hypothesis requires the sampling distribution of the ordinary least squares estimator to be normal; likewise, the residues of the samples taken from the variables must be distributed normally. In the Jarque-Bera test, the null hypothesis assumes that the distribution of the errors is normal when the probability is greater than 0.05; in the analyzed model, the probability is 0.298, so the errors are normally distributed.

Step 2. Multicollinearity test: Multicollinearity occurs when some of the explanatory variables in a regression model have a highly correlated linear relationship. When there is perfect multicollinearity, the regression coefficients of the explanatory

variables are indeterminate with infinite errors, and if multicollinearity is not perfect, the regression coefficients possess standard errors, making multicollinearity difficult to be estimated very accurately. In this regard, Table 3 shows the correlation matrix of the significant explanatory variables, whose Pearson correlation coefficients range between an absolute value of 0.00 and an absolute value of 0.66, so the presence of multicollinearity is not observed. In addition, the independent variables do not possess multicollinearity because according to the variance inflation factor test, they yield values between 1.14 and 4.21.

Table 3

Correlation matrix of explanatory variables

Variable	GDP	UNEMP (-1)	INFLAT	INTER (-1)	EXPADM (-2)	LIQUA (-2)	SOLVEN	PROCOV (-1)
GDP	1.00	0.28	-0.02	-0.08	-0.10	0.01	-0.01	0.08
UNEMP(-1)	0.28	1.00	-0.23	-0.50	-0.66	0.18	0.35	0.62
INFLAT	-0.02	-0.23	1.00	0.55	0.48	-0.32	-0.36	0.21
INTER(-1)	-0.08	-0.50	0.55	1.00	0.65	-0.19	-0.42	0.00
EXPADM(-2)	-0.10	-0.66	0.48	0.65	1.00	-0.56	-0.43	-0.29
LIQUA(-2)	0.01	0.18	-0.32	-0.19	-0.56	1.00	0.40	0.04
SOLVEN	-0.01	0.35	-0.36	-0.42	-0.43	0.40	1.00	0.40
PROCOV(-1)	0.08	0.62	0.21	0.00	-0.29	0.04	0.40	1.00

Step 3. Autocorrelation test: The linear regression model assumes that there is no autocorrelation in the errors. When there is autocorrelation, the estimators of the ordinary least squares, although linear, unbiased, and normally distributed, cease to have a minimum variance between the unbiased linear estimators. Table 4 shows the Breusch-Godfrey Serial Correlation LM test: the null hypothesis assumes that there is no autocorrelation when the probability of the F -statistic in the Breusch-Godfrey test is greater than 0.05. In the regression model, this test possesses a probability of 0.1423, which is a value greater than 0.05; in addition, Table 7 shows that the Durbin-Watson statistic is 1.675, which is a value close to 2; therefore, the presence of autocorrelation is not detected.

Table 4

Breusch-Godfrey Test Serial Correlation LM Test

F -statistic	1.985481	Prob. F (2.107)	0.1423
Obs*R-squared	4.222488	Prob. Chi-Square (2)	0.1211

Step 4. Heteroskedasticity test: Multiple linear regressions are based on the assumption of homoskedasticity, where the variance of the conditional non-observable error in the explanatory variables is constant. To justify the t and F -tests, the existence of homoskedasticity is required in the estimation of the ordinary least squares of the linear regression model (Wooldridge, 2010). In order to identify the presence of heteroskedasticity, the White test is carried out. The null hypothesis in the White test assumes that there is no heteroskedasticity problem when the probability of the F -statistic in the White test is greater than 0.05. Table 5 shows the results of the White test: a coefficient of 0.2678, which is greater than 0.05; therefore, heteroskedasticity is not present.

Table 5

White Test for Heteroskedasticity

F -statistic	1.174559	Prob. F (44.73)	0.2678
Obs*R-squared	48.91147	Prob. Chi-Square (44)	0.2824
Scaled explained SS	53.52466	Prob. Chi-Square (44)	0.1538

Step 5. Estimation of regression: After performing multiple regressions and analyzing the statistical significance of each of the eight explanatory variables using Student's t -test, Table 6 shows the following: seven variables were statistically significant ($t > 1.982$); in contrast, the inflation variable was not statistically significant ($t < 1.982$).

The variable with the highest incidence of Credit Risk is the GDP, with a partial regression coefficient of -1.617 ($p > 0.05$), which indicates an inverse causal relationship. The variable with the second greatest incidence of Credit Risk is the Efficiency of Administrative Expenses (EXPADM(-2)): the value of the partial regression coefficient is -0.912 ($p > 0.05$); that is, it demonstrates an inverse relationship; the third variable with the greatest impact on Credit Risk is Solvency (SOLVEN), with a coefficient of -0.550 ($p > 0.05$); the fourth variable with the greatest impact is the Interest Rate (INTER(-1)), whose partial regression coefficient is + 0.061 ($p > 0.05$), which indicates a positive relationship; the fifth variable is the Unemployment Rate (UNEMP(-1)), with a coefficient of + 0.056 ($p > 0.05$); the sixth determinant variable of Credit Risk is Provisions Coverage (PROCOV(-1)), with a negative partial regression coefficient of -0.055 ($p > 0.05$); and the seventh determining variable is the Liquidity Ratio in PEN (LIQUA(-2)), with a coefficient of + 0.029. Thus, the final model of the independent variables that explain the behavior of the accounting arrears ratio, which represents Credit Risk, is the following:

$$\text{DELIQ}_t = 22.909 - 1.617 \cdot \text{GDP} + 0.056 \cdot \text{UNEMP}(-1) + 0.061 \cdot \text{INTER}(-1) - 0.912 \cdot \text{EXPADM}(-2) + 0.029 \cdot \text{LIQUA}(-2) - 0.550 \cdot \text{SOLVEN} - 0.055 \cdot \text{PROCOV}(-1) + \varepsilon_t \quad (2)$$

Table 6

Description of the regression report

Dependent Variable: DELIQ				
Method: Least Squares				
Sample (adjusted): 2011M03 2020M12				
Included observations: 118 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	22.909	1.466	15.631	0.000
GDP	-1.617	0.320	-5.044	0.000
UNEMP(-1)	0.056	0.017	3.254	0.002
INFLAT	0.030	0.029	1.021	0.310
INTER(-1)	0.061	0.021	2.894	0.005
EXPADM(-2)	-0.912	0.127	-7.177	0.000
LIQUA(-2)	0.029	0.006	4.935	0.000
SOLVEN	-0.550	0.139	-3.963	0.000
PROCOV(-1)	-0.055	0.004	-13.338	0.000
R-squared	0.863	Mean dependent var		6.159
Adjusted R-squared	0.853	S.D. dependent var		0.556
S.E. of regression	0.213	Akaike info criterion		-0.181
Sum squared resid.	4.950	Schwarz criterion		0.031
Log likelihood	19.667	Hannan-Quinn criter.		-0.095
F-statistic	85.816	Durbin-Watson stat		1.675
Prob(F-statistic)	0.000			

Hypothesis Test

As for the hypotheses proposed, Table 7 shows that seven specific relationships have $p < 0.05$; thus, the proposed hypotheses H1, H2, H4, H5, H6, H7, and H8 are accepted, and hypothesis H3 is rejected, as its $p > 0.05$. The R-squared statistic, also called coefficient of determination, whose value is 0.863, indicates that the regression model explains 86.3% of the variation of the delinquency of Peruvian municipal savings banks. On the other hand, the F -test indicates the explanatory capacity of the model in terms of the level of precision. The F -statistic is 85.816 times greater than F in the F -distribution table (2.41); therefore, the null hypothesis of the model's insignificance is rejected: the model is significant.

Table 7

Results of the tested hypotheses for the variables in the model

Hypothesis	t	p -value	Decision
H1: GDP \rightarrow Credit Risk	-5.044	0.000	Accept H1
H2: UNEMP \rightarrow Credit Risk	3.254	0.002	Accept H2
H3: INFLAT \rightarrow Credit Risk	1.021	0.310	Reject H3
H4: INTER \rightarrow Credit Risk	2.894	0.005	Accept H4
H5: EXPADM \rightarrow Credit Risk	-7.177	0.000	Accept H5
H6: LIQUA \rightarrow Credit Risk	4.935	0.000	Accept H6
H7: SOLVEN \rightarrow Credit Risk	-3.963	0.000	Accept H7
H8: PROCOV \rightarrow Credit Risk	-13.338	0.000	Accept H8

4. Discussion

This study has found that GDP has a significant negative influence ($p < 0.05$) on the Credit Risk of Peruvian municipal savings banks, corroborating Hypothesis 1. When the GDP increases by one unit, the Credit Risk of Peruvian municipal savings banks decreases by 1.617 units. İncekara and Çetinkaya (2019) found a similar result: the inverse relationship between GDP and the credit risk of Turkish banks. They found that the increase of one unit of GDP would reduce credit risk by 0.0009; similarly, Moudud-Ul-Huq et al. (2020) found an inverse influence between GDP and the credit risk of Bangladeshi commercial banks in times of financial crisis. These findings are consistent with those of Baselga et al. (2015), who also found that GDP growth had an inverse influence on the credit risk of the banking systems in the euro area.

On the other hand, it was found that Unemployment has a significant positive influence ($p < 0.05$) on the Credit Risk of Peruvian municipal savings banks, confirming Hypothesis 2. When Unemployment rises by one unit, Credit Risk increases by 0.056 units. Bai (2021) indicated that companies in the industries with the highest unemployment rates tend to have a higher credit risk; that is, the relationship between unemployment and credit risk is strong and positive, which is also what the present study has found. These results differ from what Baselga et al. (2015) found for the euro area, that unemployment does not significantly influence bank risk (as measured by the delinquency rate). However, according to Louzis et al. (2012), following the financial crisis in Europe, the increase in late payments was largely due to the increase in unemployment in Italy and in Greece. Furthermore, according to the results of the study, Inflation does not significantly influence ($p > 0.05$) the Credit Risk of Peruvian municipal savings banks: Hypothesis 3 is rejected. This conclusion coincides with the results of Viphindrartin et al. (2021), who researched the influence of the inflation variable on the level of short-term delinquency

in the Indonesian financial system; however, in the long term, according to these authors, these variables were positively related at a rate of 0.39959.

Interest Rate significantly influences ($p < 0.05$) the Credit Risk of Peruvian municipal savings banks, corroborating Hypothesis 4. When the Interest Rate increases by one unit, the Credit Risk rises by 0.061 units. This finding is in line with that of González-Aguado and Suárez (2015), who claimed that high short-term interest rates increased credit risk in the US financial market. In addition, Zheng et al. (2019) found that the active interest rate has a positive significant relationship with the credit risk of Pakistani banks. Additionally, the findings of Kodongo and Kendi (2013) and Beg and Bashir (2017) coincide with the present research, as they found that high interest rates in the financial market contributed to an increase in creditor delinquency in Kenya and in India, respectively.

The results of the study show that the Efficiency of Administrative Expenses has a significant negative influence ($p < 0.05$) on the Credit Risk of Peruvian municipal savings banks, corroborating Hypothesis 5. When the level of Efficiency of Administrative Expenses increases by one unit, Credit Risk decreases by 0.912 units. This finding coincides with what was found by Beg and Bashir (2017), who showed that the cost of labor is negatively associated with credit risk in the Seemandhra region of India. The Liquidity Ratio has a significant positive influence ($p < 0.05$) on the Credit Risk of Peruvian municipal savings banks, confirming Hypothesis 6. When the level of Liquidity increases by one unit, the level of Credit Risk increases by 0.029 units. This result differs from that found by Baselga et al. (2015), who identified a significant negative relationship between liquidity and banking risk in Europe in a context of financial crisis.

In this study, it was found that Solvency presents a significant negative influence ($p < 0.05$) on the Credit Risk of Peruvian municipal savings banks, verifying Hypothesis 7. In other words, if Solvency increases by one unit, Credit Risk decreases by 0.550 units. Finally, the results of this research show that Provisions Coverage has a significant inverse influence ($p < 0.05$) on the Credit Risk of Peruvian municipal savings banks, corroborating Hypothesis 8. If Provisions Coverage increases by one unit, Credit Risk is reduced by 0.055 units.

5. Conclusions

The econometric analysis carried out leads to the conclusion that there are seven variables that determine the credit risk of Peruvian municipal savings banks. Three of these variables directly, positively, and significantly influence Credit Risk: the Unemployment Rate, Interest Rate, and Liquidity Ratio in PEN. Also, four variables exert a significant negative influence: GDP, Efficiency of Administrative Expenses, Solvency, and the Coverage of Provisions. The variable with the greatest negative impact on the Credit Risk of Peruvian municipal savings banks is the Coverage of Provisions, and the variable with the greatest positive impact is the Liquidity Ratio in PEN. In contrast, the variable with the least impact on the Credit Risk of Peruvian municipal savings banks is the Interest Rate for SMEs. This article contributes evidence on the main factors that determine the credit risk and, consequently, the sustainability of Peruvian municipal savings banks. The conclusions of the study serve the micro-financial institutions that grant loans by providing them with information that could allow them to implement measures to control and mitigate credit risk.

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