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Application of IFRS 9 Financial Instruments and the Exposure to Credit Risk (Case Study in Ecuador)

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ABSTRACT: The pandemic has caused many businesses to experience a significant decline in revenue and profitability, leading to a decrease in the value of their assets. As a result, companies may need to assess whether their assets have been impaired and take an impairment charge if necessary. This caused companies in general to modify the accounting treatment under the international standard IFRS 9 applicable from 2018. The objective of this article is to determine the portfolio risk that affects the calculation of these provisions, through a case study in Ecuador. The research approach used was mixed (qualitative and quantitative), since various types of data collection tools were used to process the information. The data treatment in the qualitative approach consists of the analysis of the phenomenon related to the exploration for the understanding of the IFRS 9 accounting standard. On the other hand, the quantitative approach intends to analyze the research variables and measure them numerically with the use of statistical methods using Binary Logistic Regression. To this end, a database of clients of a non-financial company was analyzed, and the composition of its portfolio segmented by day of delay, observing the component called probability of default (PD), which was determined by binary logistic regression. A model was obtained that allowed to obtain the desired probability, and consequently under the approach of IFRS 9, the calculation of the expected credit loss (ECL). The results obtained estimated a portfolio impairment of 23%, compared to the baseline scenario of 9%.

Keywords: IFRS 9, Impairment, Default, Credit, Regression

INTRODUCTION

The pandemic has caused an increase in the number of customers who are unable to pay their debts. As a result, companies may need to make provisions for bad debts to reflect the higher risk of non-payment. As a result, companies may need to disclose the risks and uncertainties related to their ability to continue operating and may need to adjust their financial statements accordingly.
One of the key changes introduced by IFRS 9 is the shift from the incurred loss model to the expected credit loss (ECL) model for the impairment of financial assets. Under the incurred loss model, impairment losses were recognized only when there was objective evidence of impairment,

such as a default or bankruptcy of the debtor. In contrast, the ECL model requires companies to recognize expected credit losses based on a forward-looking assessment of the credit risk associated with a financial instrument, considering factors such as the debtor's creditworthiness, payment history, and economic conditions.

Overall, the objective of IFRS 9 is to improve the financial reporting of financial assets and financial liabilities, with the aim of providing users of financial statements with better information about an entity's financial position, performance, and cash flows.

It should be recalled that companies used the loss methodology incurred in accordance with IAS 39; that is, the recognition of losses at the time evidence of impairment is identified. The measurement of expected losses when evaluating the loan portfolio is now analyzed for the calculation of a reasonable provision. Therefore, the provisions of accounts receivable or impairment of the portfolio are necessary due to the risk involved in addition to a correct valuation, because if they are overvalued or undervalued it would affect the financial situation of the company for future investments or loans.

Post-pandemic, many non-financial companies in the service sector have faced significant challenges in maintaining stable liquidity conditions. However, there are certain criteria that can indicate that a company is in a strong position in terms of liquidity. First, the company's ability to generate stable and predictable cash flows is key. A company that can maintain a stable cash flow through good management of its cash cycle, including control of its accounts receivable and payable, and efficient management of its inventory, will be better positioned to survive any negative impact on its revenues.

Second, diversification of revenue sources and the company's ability to adapt are also important factors. A company that has a broad and diversified customer and product base will be better equipped to deal with fluctuations in demand and disruptions in the supply chain. In addition, a company that can adapt quickly to changes in market and economic conditions, through good planning and strategy, will be better able to maintain a strong position in terms of post-pandemic liquidity.

For (Moreno et al., 2014) this situation "allows users of financial statements to obtain more useful information about the expected credit losses of an entity, about its financial assets to facilitate the evaluation of future amounts and cash flows". (Casal, 2016) argues that "entities will have to document their business models and ensure that the financial investments they make are framed in them."

(Parrales Choez & Castillo Llanos, 2018), IFRS 9 Financial Instruments seeks a new principle-based classification and valuation approach, depending on the business model and nature of cash flows. Likewise, this standard analyzes the deterioration model with an approach to expected losses, and complements a hedge accounting more aligned with the reality of the company's risk management.

(Gonzales Cervan et al., 2015) when comparing these accounting standards highlight four main differences "the first is the implementation of the expected losses model in IFRS 9, which replaces the incurred loss model applied according to IAS 39. The second is that IFRS 9 applies a new business model that helps determine the classification of financial assets as either amortized cost or fair value. The third creates a difference with IAS 39, since the latter did not allow the decomposition of a non-financial asset to cover risks; however, hedge accounting can be applied under IFRS 9. The last is that it will have an impact on IFRS 7 by making the effectiveness of coverage accounting dependent on the organization's strategies, which will require broader disclosure of their implementation."

(Azúa Álvarez et al., 2021), consider that the measurement of impairment in accounts receivable implies for companies that they must perform the estimated calculation of default for each client, through an expected credit loss (ECL) model under the international standard (IFRS 9), which is based on three components: Probability of Default (PD), Loss given default (LGD), and portfolio exposure (EAD).

(Neisen & Schulte-Mattler, 2021) warn that this pandemic will cause a deterioration in the solvency of customers in financial institutions and a possible massive increase in loan defaults. As a result, various regulatory bodies, including the Basel Committee on Banking Supervision (BCBS) and European Union (EU) institutions such as the European Banking Authority (EBA) and the European Central Bank (ECB), have taken measures to prevent a potential banking crisis.

(Porretta et al., 2020) describe the statement suggests that the new regulations and technical standards introduced in Europe may not always align with the methodological criteria and operational implications of the IASB. The statement further indicates that a case study has shown that the rules established for Stage 1 of IFRS 9 do not reduce excess coverage produced in a portfolio, which may be problematic for companies. The statement goes on to mention that for impaired loans that fall under Stage 2 of IFRS 9, the expected credit loss (ECL) calculation may impose an excess of provisions because it does not consider the effect of expected premium coverage. Additionally, for portfolios of loans with short repayment terms, the excess provisions of IFRS 9 may compensate for the lack of coverage of the capital requirement.

For this reason, the new requirements of the international standard in relation to risk measurement emphasize the preparation of information. This has resulted in the development of statistical models that measure risk capacity, thus obtaining a concept extended to that traditionally proposed by risk rating agencies.

(Peter, 2006) in his banking experience highlights that the measurement and management of credit risk depends to a large extent on three key risk parameters: probability of default (PD), exposure at default (EAD) and loss given default (LGD). For this author, probability of default describes the probability that the lender will face default on some obligor or transaction. The exposure at default provides an estimate of the exposure outstanding at the time of default, also indicating the maximum loss on the corresponding credit line. Finally, loss given default measures the percentage of a defaulted exposure that the lending bank expects not to recover. This means that the lending bank expects to recover (1 - LGD) percent of the defaulted exposure.

(Bushman & Williams, 2012) investigated discretionary lending practices in banks in 27 countries, concluding that forward-looking provisions designed to smooth profits reduce risk-taking discipline, consistent with decreased transparency that inhibits external control. Conversely, forward-looking provisions reflecting timely recognition of expected future credit losses (ECLs) are associated with greater discipline on risk-taking.

(Novotny-Farkas, 2016), concludes that the expected credit loss (ECL) model incorporates a significantly larger set of relevant information to identify future credit losses and leads to earlier recognition of these. Consequently, it will require higher loan loss provisions, which will reduce the accumulation of excess losses and the overestimation of regulatory capital in boom periods.

(Chawla, 2016) mentioned that unlike Basel II rules, which require the use of through-the-cycle probabilities of default (PD) and loss given default (LGD) rates and recession default exposures (EAD), IFRS 9 and the proposed current expected credit loss accounting standards require institutions to use point-in-time projections of PD, LGD and EAD. By taking into account the current state of the credit cycle, these projections closely track changes in default and loss rates over time.

(Vaněk & Hampel, 2017), proposed for the case of the Czech Republic, the calculation of the probability of default (PD) using the Markov model, and the official macroeconomic data taken from the National Bank, thus adjusting to the requirements of IFRS 9 to determine the calculation of expected credit losses (ECL) over the life of the financial instrument.

(Cohen. BEdwards, 2017) in their post-financial crisis study (2007-2009) mentioned that accounting standards bodies have required banks and other companies to provision against loans based on expected credit losses (ECLs) and determined that in the short term these provisions may increase, but the impact on regulatory capital is expected to be limited.

(Habachi & El Haddad, 2018), outlined that the probability of default (PD) depends on the model used for the design of the internal rating system. For this purpose, they investigated the impact of model choice on expected credit loss (ECL) by calculating the probability of default (PD) for various types of models based on logistic regression and principal component analysis in Morocco. (Delgado-Vaquero & Morales-Díaz, 2018) proposed the Financial Ratio Scoring Model and the Merton KMV Structural Model, to estimate credit quality and obtain the corresponding probability of default (PD), where information was published on the client (basically information from financial statements and other market inputs) and comparable companies.

(Galárraga & Lafferty, 2018) using a statistical-mathematical model determined the probability of default and a reasonable allocation for a company dedicated to the operation of shopping centers, which motivated management to change accounting policies and its credit and collection processes.

(Costa et al., 2020) applied a logistic regression model to predict the credit risk of default in the consumer portfolio of a bank in Portugal. According to the authors, the risk of default increases with the loan margin, the term of the loan and the age of the client, but decreases if the client has more credit cards.

(Santos, 2018) proposes a real approach to model the probability of default in the calculation of expected credit loss under IFRS 9. According to the author, financial institutions had to adjust their models to comply with this standard. Based on this, model performance and calibration were analyzed using Pearson's correlation, coefficient of determination and binomial test. The results suggest that this approach estimates the risk parameter well, as the coefficients are above the 0.7 threshold and the percentage of accepted periods is also above 70%. However, one of the curves needs to be adjusted, as it has a coefficient of determination of 0.45.

(Zizi et al., 2021) concluded that logistic regression models obtained by step selection outperform the other models with an overall accuracy of 93% two years before financial distress and 95% one year before the current context. The results also show that the models rank distressed small and medium-sized enterprises (SMEs) better than healthy SMEs with type I errors lower than type II errors.

(Schutte, 2020) develop a methodology to calculate the expected credit loss on the portfolio of a guaranteed financial institution in an emerging country. First, the marginal probability of default is determined. Second, they proceed to calculate the marginal recovery rates and the loss given the resulting default, and finally the portfolio exposure. These three components are combined to calculate the expected credit loss empirically. According to the authors, in markets where more sophisticated models are developed, the proposed methodology can be used in two scenarios: either as a benchmark to compare models under recently developed IFRS 9 or in markets where there are limited resources.

(Martinelli et al., 2020) show in their research that data mining techniques can significantly improve the risk assessment approaches of financial institutions by providing more accurate information on the assessment of credit quality deterioration before the actual loss occurs, without incurring disproportionate costs and efforts. According to these authors, the proposed model is useful especially for measuring the 12-month probability of default, and for assessing the potential shift of a credit from stage 1 to stage 2 over the entire term of the financial instrument.

(Oberson, 2021) in his study conducted on a sample of 69 banks from 24 countries, within a normal reference scenario, describes that the novelty in the expected credit loss (ECL) model is the prospective incorporation for the recognition of accounting provisions on bad loans, which provides a wide margin for managerial discretion.

Regarding (Engelmann, 2021) assertion that the most widely applied formula in the literature to calculate ECL is inconsistent with the measurement of expected loss based on expected discounted cash flows, it would be necessary to review the specific formula and context to provide a more definitive response. However, it's worth noting that financial reporting standards such as IFRS 9 provide guidance on how to calculate ECL using a range of methodologies, including discounted cash flow approaches.

The logistic distribution is a commonly used probability distribution in credit risk modeling, and the Markov Chain Monte Carlo (MCMC) method is a powerful statistical tool for estimating model parameters. By using these techniques, (Zhao & Cao, 2021) were able to develop a credit risk model that accurately classifies customers into different risk levels based on their credit history and compliance status. Overall, the study highlights the importance of credit history and compliance status in assessing the credit risk of bank customers. These factors should be carefully considered by banks and other financial institutions when making lending decisions and managing credit risk.

(Habachi & El Haddad, 2018), in their study on the impact of COVID-19 in Morocco on a portfolio of a financial institution, use accounting supports and qualitative variables related to the client as a source of information, and as part of the empirical evidence logistic regression and linear discriminant analysis. The authors have used expert opinion to adjust the ratings and probability of default assigned to each counterparty by the initial models. This approach can help to incorporate subjective factors that may not be captured by quantitative models alone. However, it is important to note that expert opinion may be subject to biases and may not always be reliable. Therefore, it is crucial to carefully consider the qualifications and expertise of the experts involved and to take a cautious approach when relying on their opinions.

(Hung et al., 2021) conducted a study that compared the robustness of a probability of default (PD) estimation model with a deterministic Gross Domestic Product (GDP) to a credit default model. The goal of the study was to assess whether the deterministic GDP model was more robust than the credit default model in predicting the likelihood of default of corporate borrowers.

The study used data from publicly traded companies in the United States from 2001 to 2017. The credit default model was based on the Merton model, which calculates the probability of default based on a firm's asset value, debt level, volatility, and the value of the debt. The deterministic GDP model, on the other hand, used the historical average GDP growth rate as a proxy for future economic growth.

(Achim et al., 2021) consider that IFRS 9 increases accounting value judgments as it incorporates forward-looking information in the estimation of credit losses which, theoretically should ensure timely recognition of provisions. However, as noted since its implementation in 2018, the standard is still at an early stage and more time needs to elapse before companies can build robust validation frameworks around the estimates made. In addition, the stochastic nature of IFRS 9 in shaping these assumptions raises questions about the effect of potential discretion and flexibility of decision makers in companies.

(Gubareva, 2021) demonstrates how to estimate credit impairment provisions in accordance with the IFRS 9 framework. In her study she concludes that for both investment grade and high yield exposures, the weight of the default component in credit spreads is always less than 33%. The research results contrast with several previous findings that the risk premium accounts for at least 40% of spreads in default hedges.

(Bank & Eder, 2021) argue that for IFRS 9 a calibration of the probability of default at the account level is more appropriate than a calibration at the portfolio level, as highlighted in the Basel Accords. According to the authors to date no study has yet investigated empirically how the choice of model affects the assignment of stages (stage 1, for 12 months; stage 2, for the entire term of the financial instrument; stage 3, impairment).

(Chen et al., 2022) develop a model of the impairment of financial assets through the credit card data of a financial institution. According to these authors, the results obtained show that, compared with the previous accounting standard IAS 39, under the implementation of the current IFRS 9 standard, both the scale of credit card business assets that need to be impaired and the provision for asset impairment improve significantly, but the impairment reserve ratio decreases.

(Pastiranová & Witzany, 2022) expect IFRS 9 to change the flow of loan loss provisions, which is expected to be unstable, more volatile and more unpredictable than under the previous standard IAS 39, empirically tested in a sample of the eight largest banks in the Czech Republic. The hypothesis that the implementation of IFRS 9 leads to higher volatility of loan loss provisions is confirmed in the case of five banks and within the entire sample of banks at a probability level of 5%.

(Lamaj, 2023) describes the key requirements of IFRS 9 on accounting for loan loss provisions. First, he interprets the main rationale for loan loss provisions. Secondly, he goes on to give a brief history of the standard development and, finally, summarizes the main implications of the loss model for financial institutions.

METHOD

Composition of the portfolio

The primary information of the case presented is composed of all the accounts receivable found in the accounting records of a non-financial company specialized in the services sector in Ecuador, detailing the information on outstanding balances, days due, date on which the debt was contracted and maturity date. In addition, the portfolio was limited to companies that have outstanding accounts receivable (47 customers). The research approach was mixed (qualitative and quantitative) and data was collected using company data and ratings given to each client.

The company's portfolio is classified into 5 groups according to the number of days past due for each client, as follows: Category A: less than 30 days; Category B: between 31 and 60 days; Category C: between 61 and 90 days; Category D: between 91 and 180 days; Category E: more than 180 days.

According to the company's policy, it is determined that the risk of inconvenience increases after 60 days of delinquency, which in this portfolio represents 33% of the total number of customers. Note that 55% of the portfolio migrated from higher to lower ratings, or remained at low ratings, while the other 45% remained at high ratings or migrated from low to high ratings.

Definition of variables

The dependent variable of this research that will be explained by the Binary Logistic Regression model is the probability of default of the clients of the non-financial company; Therefore, for the construction of the dependent variable, its accounting policies have been considered, where it has been defined that the maximum time for its clients to pay the outstanding amounts to be collected is 60 days.

This means that all unpaid invoices above the established limit represent a greater risk for the company of uncollectability of accounts receivable, therefore, customers who have exceeded 60 days past due will be assigned a value of (1) and those under 60 days will be assigned a value of (0).

The independent variables focus on the information obtained from the public financial statements presented by these companies, obtaining financial ratios such as: Current liquidity, equity indebtedness, leverage, portfolio turnover, gross margin, size of the client company, participation according to client activities, as well as qualitative information on the state of tax compliance, the state of compliance with social security, the state of corporate compliance, the existence of audits and the current state of the company.

The model

The statistical model was performed using Binary Logistic Regression, which is a mathematical technique that aims to model the relationship between a variable or dependent variable, depending on the independent variables (i),YX therefore, it seeks to predict the probability of occurrence of knowing the values of (YX_i), the starting equation of logistic regression is:

$$P(Y=1|X) = \frac{exp^{(b_0+\sum_{i=1}^{n} b_1 x_i)}}{1+exp^{(b_0+\sum_{i=1}^{n} b_1 x_i)}}$$

- $P(Y=1|X)$: is the probability that takes the value 1 (presence of the studied characteristic Y).
- X is a set of n covariates x_1.... x_n that are part of the model
- b_0 is the constant model or independent term
- b_i represent the coefficients of the covariates

We divide the expression by its complementarity, obtaining a much easier expression to handle mathematically:

$$\frac{P(Y=1|X)}{1-P(Y=1|X)} = exp^{(b_0+\sum_{i=1}^{n} b_1 x_i)}$$

However, it is more difficult to interpret, so finally a transformation is made with the natural logarithm to obtain an equation of linear type.

$$\ln\left(\frac{P(Y=1|X)}{1-P(Y=1|X)}\right)=b_0+\sum_{i=1}^{n} b_1 x_i$$

The estimate of the expected loss for a portfolio can be calculated using the following formula:

$$ECL = PD * LGD * EAD$$

ECL : Expected credit loss

PD: Probability of default

LGD: Loss given default

EAD: Portfolio Exposure

The Probability of Default (PD) is the likelihood that a borrower or counterparty will default within a given time period. This is typically estimated using statistical models that take into account a range of factors such as the borrower's credit history, financial ratios, industry sector, macroeconomic conditions, etc.

The Loss Given Default (LGD) is the proportion of the outstanding balance that is lost in the event of a default. This can be estimated using historical data or through the use of models that take into account factors such as collateral, seniority, and recovery rates.

The Exposure at Default (EAD) is the amount of exposure to the borrower or counterparty at the time of default. This can be estimated based on the outstanding balance, or through the use of models that take into account factors such as future drawdowns, collateral, and other forms of credit enhancement.

By multiplying these three factors together, we can estimate the expected loss for a portfolio. This is an important measure for banks and other financial institutions, as it helps to inform their capital planning and risk management activities.

RESULT AND DISCUSSION

The "Enter" method was chosen for the Binary Logistic Regression model where we decide which variables are entered or extracted from the model, through the SPSS statistical software. results in limiting financial expenses in each of the cases raised are shown below:

Table No. 1

Omnibus testing of model coefficients

	Chi-cuadrado	Gl	Herself.

Step 1	Step	125,913	11	,000
	Block	125,913	11	,000
	Model	125,913	11	,000

Source: Research data

For step 1 of the model, the statistical efficiency score of the RAO indicates that there is a significant improvement in predicting the probability of occurrence of the categories of the dependent variable (Chi-squared: 125.913; gl: 11; p<0.001).

Table No. 2

Model summary

Step	Logarithm of probability -2	Cox and Snell R-squared	Nagelkerke R-squared
1	63.973	,598	,801

Source: Research data

There are two R-squares in logistic regression, and both are valid. It is customary to say that the part of the dependent variable explained by the model ranges from the R-squared Cox and Snell to the R-squared Nagelkerke. The higher the R-squared, the more explanatory the model, consequently, the independent variables explain the dependent variable. The Nagelkerke R-squared value indicates that the proposed model explains 80.1% of the variance of the dependent variable.

Table No. 3

Model classification

Observed		Foresight		
		DEFAULT		Correct percentage
		,00	1,00	
DEFAULT	,00	76	0	100,0
	1,00	12	50	80,6
Overall percentage				91,3

Source: Research data

Although goodness-of-fit coefficients are not entirely reliable, the leaderboard is usually the criterion we must follow to indicate the goodness of fit of the model. Based on the regression equation and the observed data, a prediction of the value of the dependent variable is made. This prediction is compared with the observed value.

If correct, the case is correctly classified. The more cases you classify correctly, that is, the more the predicted value matches the observed value, the better the model, the more explanatory it will be; Therefore, independent variables are good predictors of the event or dependent variable.

For the logistic regression analysis, Step 1 indicates that there is a 91.3% probability of being correct in the result of the dependent variable, when I know the financial information of the companies. Overall, this is an acceptable model.

Table No. 4

Hosmer and Lemeshow test

Step	Chi-square	Gl	Herself.
1	9,021	8	,340

Source: Research data

The Hosmer and Lemeshow test is a distribution constant. The null hypothesis is that there is no difference between observed and predicted values (probabilities); The alternative hypothesis is that there is. Therefore, rejection of this test indicates that the model is not well fitted. In our particular case, the significance of the model is 9.021 (Chi-square) and we have a p-value greater than 0.05, so the model is relevant.

Table No. 5

Variables in the model equation

		B	Standard error	Forest	Herself.	Exp(B)
Step 1	EP	-12,54	5,26	5,68	,017	,000
	AP	12,54	5,26	5,68	,017	279458,31
	RC	-,014	,007	4,65	,031	,986
	MB	-1,91	,959	3,99	,046	,147
	LC	-3,87	1,35	8,14	,004	,021
	STATUS	,048	1,82	,001	,979	1,049
	PARTICIP	-10,29	8,15	1,59	,207	,000
	AGE	-,032	,049	,430	,512	,968
	TIPO_C	-,505	1,31	,147	,701	,604
	SUPER	-4,80	1,44	10,99	,001	,008
	AUDIT	-1,11	,871	1,64	,199	,327
	Constant	-2,07	4,70	,195	,659	,125

Source: Research data

In this table we can see the variables that intervene in the model, and that are significant for the model, those variables that have a Sig. value < 0.05. The B sign of each of the significant variables indicates the relationship it has with the dependent variable. We can also consider the following:

- If EXP(B) < 1, if the value of the independent variable increases, the value of the dependent variable decreases.
- If EXP(B) > 1, if the value of the independent variable increases, the value of the dependent variable increases.

The Wald score is a statistical test that measures the significance of the coefficients of the independent variables in a regression model. A significant Wald score indicates that the independent variable is a good predictor of the dependent variable. However, the significance of the Wald score alone is not sufficient to determine whether the results can be generalized to the population.

Table No. 6

Explanatory variables of the model

Variable	Meaning	Sign B	Explanation
EP	Debt to equity	-	The higher the indebtedness of the Assets, the greater the risk that the client will default.
AP	Leverage	+	The higher the level of leverage, the greater the risk of the client defaulting.
RC	Portfolio rotation	-	The higher the portfolio turnover, the lower the risk of the client defaulting.
MB	Margen gross	-	The higher the gross margin, the lower the client's risk of default.
LC	Current liquidity	-	The higher the client's current liquidity, the lower the risk of default.
SUPER	Corporate Compliance Status	-	Since it is classified as compliant or non-compliant, this indicates that companies that meet their corporate obligations have a lower risk of default.

Source: Research data

From the coefficients obtained in the binary logistic regression model, the regression line is calculated with the following expressions:

$$PD = 12{,}541 * AP - 12.542 * EP - 0{,}014 * RC - 1.917 * MB - 3{,}873 * LC - 5.806 * SUPER$$

Where:

PS: Probability of non-compliance

EP: Debt to own funds

AP: Leverage

RC: Portfolio Turnover

LC: Current liquidity

MB: Gross margins

SUPER: Corporate Compliance Status

To calculate the PD for each client in a portfolio, a mathematical model is used. The specific model used can vary depending on the institution and the type of portfolio being analyzed. However, in general, the model will take into account various variables that are indicative of the likelihood of default, such as credit score, debt-to-income ratio, and loan-to-value ratio.

Once the model is developed, it can be used to calculate the PD for each client in the portfolio using the general mathematical formula of the model. The exact formula will depend on the specific model being used, but it will typically involve some combination of the input variables and model coefficients.

It's important to note that the PD is just one component of credit risk assessment and management. Other factors, such as recovery rate and exposure at default, also need to be considered to fully assess the risk of a loan portfolio. To obtain the loss given default (LGD) it is necessary to know the Recovery Rate (RR), which represents the probability of recovery of the portfolio. In this case, the recovery rate is the probability that a customer who has a loan portfolio will pay the outstanding amounts.

Therefore, LGD is equal to: (1- RR). Since IFRS 9 does not specify a detailed method for estimating this parameter, it was obtained from the portfolio analysis by category:

Table No. 7

Loss given default (LGD)

Category	Recovery rate (RR)	Loss given default (LGD)
Category A	90,7%	9,3%
Category B	79,7%	20,3%
Category C	64,8%	35,2%
Category D	44,9%	55,1%
Category E	19,9%	80,1%

Source: Research data

Below, we present the scheme for calculating the expected credit loss (ECL) for each of the clients that make up the portfolio of the non-financial company.

Table No. 8

Calculation of expected credit loss (ECL)

Customer	days late	Initial qualification	Final qualification	EAD	LGD	PD	ECL
1	22	A	A	87,76	9,3%	4,3%	0,35
2	23	A	A	497,12	9,3%	3,0%	1,39
3	58	A	B	4.184,00	20,3%	5,4%	45,46

4	875	E	E	1.775,00	80,1%	99,5%	1.414,41
5	22	A	A	3.814,33	9,3%	1,9%	6,89
6	1282	E	E	20.737,52	80,1%	99,0%	16.431,95
7	22	A	A	1.327,45	9,3%	2,9%	3,62
8	22	A	A	445,28	9,3%	4,0%	1,64
n	..	..	..	..	..	..	..

Source: Research data

According to the results obtained, the study presents the situation of a non-financial company in the services sector that before the pandemic showed stable liquidity, since it was able to meet its short-term obligations, but depended on more than 50% of the financing of its creditors, so it would reach a point where it could not meet its obligations even though it has liquidity. This is not in great proportion, and in this way, he would manage to survive the payment of his debts. However, in the current economic context it would present a greater risk of default.

Through the binary logistic regression model used, it was determined that the variables that are capable of determining the probability of default for the company are: equity indebtedness, leverage, portfolio turnover, current liquidity, gross margin, corporate compliance status. The model obtained can predict the fulfillment of payments in a general way by 91.3%, that is, the model has an optimal predictive character.

On the other hand, the application of IFRS 9 resulted in the recording of a provision representing 23% of the company's portfolio, compared to 9% recorded in the company's books before the pandemic. Given these facts, it is necessary to improve credit granting policies because their portfolio is complex and requires observing different variables to meet their needs, such as the financial analysis of customers, the existence of guarantees, credit history, if they are recurring customers and if they have been in default for days on previous loans.

CONCLUSION

The company in the service sector has used a binary logistic regression model to calculate the probability of default (PD) for its portfolio. This model is commonly used in credit risk. Furthermore, the company has also used the International Financial Reporting Standard 9 (IFRS 9) approach to estimate the expected credit loss (ECL) for its portfolio. This approach requires the calculation of two key parameters, namely the loss given default (LGD) and portfolio exposure at default (EAD), for each client category in the portfolio.

Based on the information provided, it appears that the company has estimated a 23% deterioration in the portfolio in pandemic situations compared to a baseline scenario of 9% before the pandemic occurred. This suggests that the pandemic has had a significant impact on the credit quality of the portfolio, resulting in a higher expected credit loss.

It is worth noting that the estimation of credit risk parameters and the calculation of expected credit losses are complex and involve various assumptions and inputs. Therefore, it is important for the company to ensure that its modeling methodologies and data inputs are appropriate and up-to-date, and that the results are regularly monitored and validated. This can help to improve the accuracy and reliability of the credit risk estimates and support sound credit risk management practices.

IFRS 9 recommends using the provisions matrix as an alternative method, where the age of the portfolio is identified, each client is qualified, and the provisions to be made are estimated, under the hypothesis that the longer the delinquency time, the greater the portfolio deterioration, a situation that is accentuated in this situation after the pandemic.

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