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Evaluation of the Sufficiency of a Deposit Insurance Fund Based on Risk Analysis: Approach to Credit Unions

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Abstract

The main approaches to assess the sufficiency of a Deposit Insurance Fund (DIF) are based on estimating the probability of default of its insured and on the coverage of its deposits in case of discontinuity. In this context, when studying the solvency of financial institutions associated with guarantee funds, it is important to realize that there are some differences when dealing with credit unions concerning traditional commercial banks.

In Brazil, for example, about 90% of credit unions are affiliated with an umbrella organization, which act as an extra layer of support, protecting the system from image risk and promoting inter-cooperation. In addition, there are also the particularities of some types of funds considered Paybox Plus, such as the Guarantee Fund of Financial Cooperatives (FGCoop), which, through financial assistance, encourages healthy credit unions to incorporate those that may be at risk of liquidation.

Therefore, it is considered good practice to bring these specific issues about cooperative institutions to give a more in-depth view of the probability of default, as it is one of the main proxies for determining the DI fund target. Thereby, this paper has as its main goal to present a brief analysis of a dynamic regression model adequacy as a way of predicting in advance the liquidation of a Brazilian credit union, using the PEARLS system (WOCCU, 2009) as a method of attributing the explanatory variables, which as a set of financial indicators built specifically for monitoring the performance of credit unions, allows a more forward-looking view of these institutions risk reality.

Keywords: Credit Unions, Deposit Insurance, Probability of Default, Dynamic Regression, PEARLS.

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1 Introduction

The main public policy objective of a deposit insurer is to reimburse depositors if a bank goes bankrupt, with that in mind, it is considered a best practice to build protection mechanisms which have the financial capacity to ensure that these obligations are met. According to internationally accepted best practice by the International Association of Deposit Insurers (IADI), the appropriate measure of adequacy of a Deposit Insurance Fund (DIF) is the Target Fund Ratio (TFR), which is the ratio of the target fund size to estimated insured deposits in the banking system.

IADI (2009) also states that most countries use their experience with bank failure losses to determine the deposit insurance target fund size because, with sufficient information about bankruptcy costs, a deposit insurer can estimate the empirical frequency distribution of losses and use this distribution to determine the level of losses that the guarantee fund should be able to absorb. This approach to determining the target is known as the Loss Distribution Approach.

However, countries with limited experience in bank solvency will lack sufficient data to develop an accurate empirical loss distribution and may have difficulty estimating the probability of very rare events. Thus, a more forward-looking alternative is the Credit Portfolio Approach, which allows a view of banking sector risk through separate estimates of institution probability of default, correlation in defaults, insurer exposure, and losses given default. This will provide superior estimates to the Loss Distribution Approach, with fewer data prerequisites, which can be easily applied and customized to many national settings.

This approach has been used to model the target deposit insurance fund for many countries, including US (FDIC, 2017), Colombia (Fogafin, 2013), Canada (CDIC, 2011), Singapore (Oliver, Wyman & Company, 2002), Nigeria (Katata and Ogunleye, 2014) and (O'Keefe and Ufier, 2016) and Zimbabwe (O'Keefe and Ufier, 2016), supporting its use in a similar scenario for Brazil.

Therefore, for this discussion, this study has as its main goal to focus more on the calculation of one of these proxies to determine the target level of a guarantee fund, within the Credit Portfolio Approach, which is the probability of default of institutions. The aim is to present a brief analysis a dynamic regression model adequacy as a way of predicting in advance the liquidation of a Brazilian credit union.

Among the specific objectives is to obtain an intuitive risk score for these credit unions. Furthermore, as it is an analysis focused on this type of financial institution, it is important to consider some particularities, as explained below.

1.1 Particularities of Credit Unions

FDIC (2017) states in his study that the aggregate amount of losses that a deposit insurer wants to be able to absorb over a specific time horizon is a public policy choice, that is, the choice of the confidence level to obtain the DI target fund must be aligned with the market experience in which the guarantee fund is inserted. Therefore, it is worth highlighting some features of the credit unions reality, which in some countries have an extra layer of support and protection.

In Brazil, for example, credit unions can organize themselves into systems, which provides an economy of scale under a pyramidal structure, in which these systemic organizations can act by structuring, on a larger scale, the services of their affiliates, supervising their actions, encouraging operational, financial, regulatory and technological integration and promoting inter-cooperation between the financial cooperatives.

In addition, it is known that many guarantee funds have more than one type of financial institution as associated, but it is not uncommon to find deposit insurers that have only credit unions as members, such as in Canada (AMF), Colombia (Fogacoop), Germany (BVR), Italy (FGD), Japan (SIC), Mexico (Focoop) and Brazil (FGCoop). Thus, it is also worth noting the existence of particularities of some types of funds considered Paybox Plus, like FGCoop in Brazil, which, through financial assistance, encourages healthy credit unions to incorporate those that may be at risk of liquidation.

Given the above, it appears as another specific objective of this article, the use of the PEARLS system (WOCCU, 2009) as a method of attributing the list of to be tested by the model, which, because it is a set of financial indicators built specifically for monitoring the performance of credit unions, allows a more forward-looking view of these institutions risk reality.

2 Methodology

2.1 Components of the Credit Portfolio Model

The Credit Portfolio Approach employs a Merton-Vasicek based model to estimate deposit insurance losses, models of this type describe the expected losses as expressed by equation 1.

$$Expected\ Losses_t = PD_t * EAD_t * LGD_t, \tag{1}$$

where,

PD = Probability of Default. Probability of an institution being liquidated, undergoing intervention, or being unable to honor its obligations within a given time horizon;

- In this approach, the model creates a potential contagion effect on bank failures, by estimating the correlation of these settlements, thus creating a fourth proxy that correlates the individual PD with that of other institutions, allowing regulators to estimate a more realistic distribution of defaults.

EAD = Exposure at Default. How much the DIF will pay in the event of a liquidation.

LGD = Loss Given Default. Loss after the event of default, as a percentage of exposure.

This model will generate failures based on these measures, using a Monte Carlo simulation to produce total expected losses, and as a result, it will find a fund size needed to cover these losses defined by cutting into this estimated distribution, with the confidence given by the choice of severity by the insurer.

As mentioned earlier, the focus of this study is on calculating the Probability of Default (PD), which will be dealt with in the next sessions.

2.2 Probability of Default (PD)

Many insolvency analyzes have been carried out in the banking sector in different parts of the world since the failure of banking institutions can have more harmful consequences for the economy than the failure of companies not belonging to the financial sector. In this sense, when evaluating studies on this topic, the three most common approaches are observed to estimate the probability of bank liquidation:

1. Statistical Methods;
2. Rating Agency-based Forecasts of Bank Failure; and
3. Actuarial Bank Failure Rates (specialists).

The focus of this article is on approach 1, which involves estimation using financial statements through a statistical model based on the PEARLS system. This approach has as an outcome the temporal modeling of the Equity Representativeness Index Y_t, defined by:

$$Y_t = \frac{Equity_t + Income_t}{Total\ Asset_t}. \tag{2}$$

The default in this scenario is synonymous with insolvency or liquidation of a credit union, which are assumed to default when their equity or total asset value falls below that of their outstanding liabilities, which occurs when y_t, given by equation 2, it reaches zero.

In this context, the study proposes to define a risk score as the probability of a credit union being liquidated in a future horizon of h months, i.e.,

$$RS_t = P_t(Y_{t+h} \leq 0), \tag{3}$$

where, Y_{t+h} is a random variable representing the value of the Equity Representativeness Index h months ahead and P_t represents the conditioned probability function on observations $y_1, \ldots, y_t$. In this work, it is assumed that Y_{t+h} follows a normal distribution with mean, $\hat{y}_{t+h}$, estimated by a Dynamic Regression Model, described in the next session.

Figure 1 illustrates the procedure for obtaining the risk score (for $h = 12$) and its behavior over time.

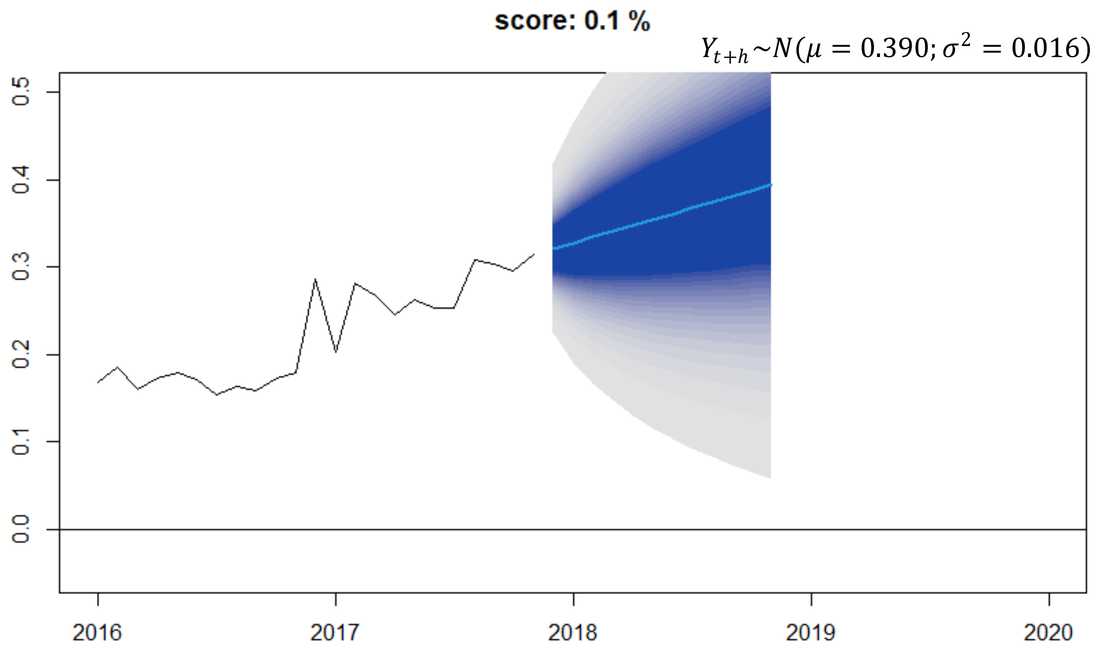

Figure 1. Illustration of the calculation of the Risk Score ($h = 12$). The light blue line represents the predictive value $\hat{y}_{t+h}$ with its respective 99% confidence interval (gray).

2.2.1 Dynamic Regression Model

In this work, the insolvency probabilities of credit unions are estimated using a Dynamic Regression model, which appears as an extension of the traditional regression models, which, when applied to time series, often have some assumptions violated.

In the multiple linear regression models commonly studied in the literature, it is assumed that the errors "generated" by the model have some characteristics such as: zero mean, constant variance, normal distribution and independence, assuming, therefore, the absence of serial correlation.

According to Dias (2008) one of the main problems when trying to model a time series through a traditional regression model is that the hypothesis of noise independence is not realistic and, therefore, the tests and results derived from the model are no longer valid. Thus, the consequences of the autocorrelation of residuals imply the need to look for procedures to deal with this problem, since ignoring them generally leads to wrong conclusions.

One of the possible solutions is exactly the use of dynamic regression models, given that the hypothesis of error independence is not realistic in the context of time series. These models consider, in addition to the variable of interest and its lagged values, also the effect of explanatory variables (causal or exogenous) and their lagged values.

It should also be noted that the word "dynamics" does not indicate that the model parameters evolve over time, it means a regression model in which the dependence structure of a time series was included (ZANINI, 2000).

With this, the Dynamic Regression (DM) or ARMAX models can be described by the following equation:

$$y_t = \beta_0 + \beta_1 x_1, t + \beta_2 x_2, t + \cdots + \beta_k x_k, t, t + \eta_t \qquad (4)$$

$$\eta_t = \varphi_1 \eta_t - 1 + \cdots + \varphi_p \eta_t - p + \varepsilon_t + \theta_1 \varepsilon_t - 1 + \cdots + \theta_q \varepsilon t - q$$

where,

- y_t is the response variable;
- $x_t = (x_{1,t}, \ldots, x_{k,t})$ is the vector of explanatory variables;
- $\{\eta_t\}$ is a process $ARMA(p, q)$;
- $\{\varepsilon_t\}$ is an i.i.d process with zero mean and constant variance;
- $\beta = (\beta_0, \beta_1, \ldots, \beta_k)' \in R_k + 1$ is the vector of regressor parameters;
- $(\varphi_1, \ldots, \varphi_p)'$ is the vector of the self-regressor parameters; and
- $(\theta_1, \ldots, \theta_q)'$ is the vector of moving average parameters.

In practice, the strategy usually used to build a dynamic regression model is a forward strategy, i.e., a simple model is initially considered to later improve it and include new variables until an appropriate model is found, with significant and coherent parameters, and also with the inclusion of explanatory variables and their lags to the extent necessary.

In addition, several statistical tests can be used to measure the degree of adequacy of a dynamic regression model at different stages of the series modeling, tests are used in order to define the specification of the explanatory model, find the model dynamics (with the inclusion or not of lagged variables) and verify the fit of the model (DIAS, 2008). Finally, the verification of the presence or absence of self-correlations in the residues is also part of the diagnosis, usually performed using the Ljung-Box test.

2.2.2 PEARLS Method

The World Council of Credit Unions (Woccu) studied and developed a system adapted from the CAMELS method, which includes information on capital adequacy, asset quality, management capacity, results, liquidity and risk in banking institutions, for use in credit unions.

The method was named as PEARLS, an acronym for a group of economic-financial indicators for evaluating the following key operational areas of financial cooperatives:

- Protection

  It assesses the adequacy of the protection provided by the credit union by comparing the provision for credit losses with overdue credits.

- Effective financial structure

  Evaluates aspects of the structure of the assets and liabilities of credit unions.

- Assets quality

  It assesses the participation of unprofitable assets that negatively impact the profitability and solvency of the institution.

- Rates of return and costs

  It evaluates asset profitability and the cost of liabilities and capital.

- Liquidity

  It assesses the planning of cash maintenance and easy-to-perform assets, since a minimum level of liquidity is necessary, however, the maintenance of high levels can make the credit union unviable.

- Signs of growth

  It assesses whether certain equity groups or groups of results, fundamental to the evolution of a credit union, show signs of growth.

According to Bressan et al. (2011), the main goal of PEARLS is to provide monitoring of the performance of individual credit unions, helping their administrators to find solutions for deficiencies in these institutions.

Following the recommendation of Vasconcelos (2006) and based on the works of Bressan (2002), Richardson (2002), Vasconcelos (2006) and Ribeiro (2008), 100 financial accounting indicators were created within the PEARLS classification, of which eighteen were in the category protection, eighteen from the structure category, six from the asset quality category, 32 from return and costs, eleven from liquidity and fifteen from signs of growth.

3 Initial Results

The data sample used was a monthly historical series with about 26 thousand observations obtained from accounting data from all Brazilian credit unions associated with FGCoop, in the period between January 2016 and January 2022, containing all 100 financial accounting indicators within the PEARLS classification.

Initially, a first selection was made by expert analysis and then fifteen indicators were considered significant by the model. Thus, the model described by Equation 4 was adjusted considering the Y_t (Equation 2), as the response variable and the fifteen accounting indicators presented in Table 1 as explanatory variables to predict Y_{t+h}. However, this selection may still change since the work is still in progress.

Table 1- List of the fifteen indicators used for the initial adjustment of the ARMAX model

PEARLS Category	Indicator	
Protection	Concentration of Debtors	$P_{1.3} = \frac{10\%\ major\ debtors}{Reference\ Equity}$
	Portfolio Leverage Index	$P_3 = \frac{Total\ Portfolio}{Reference\ Equity}$
	Acceptable Provision Margin	$P_{7.2} = \frac{\sum stress\ of\ a\ risk\ level\ of\ loans\ overdue}{Reference\ Equity + Income}$
Effective Financial Structure	Financial Leverage Degree	$E_3 = \frac{\frac{Income}{Equity}}{\frac{Income}{Total\ Asset\ (previous\ month)}}$
	Concentration of Depositors	$E_{5.2} = \frac{10\%\ major\ depositors}{Total\ Deposits}$
	Deposit Financing	$E_6 = \frac{Total\ Deposits}{Total\ Portfolio}$
Assets Quality	Loss Index	$A_1 = \frac{Operations\ Launched\ at\ Loss\ in\ the\ last\ 12\ months}{Total\ Portfolio}$
Return and Costs	Efficiency Index	$R_{1.3} = \frac{Operational\ Income}{Administrative\ Cost}$
	Administrative Expenditure	$R_{3.1} = \frac{Administrative\ Expenditure}{Total\ Asset}$
	Operating Income	$R_{9.2} = \frac{Operating\ Revenues}{Operating\ Expenses}$
	Rate of Return	$R_{13.1} = \frac{Income}{Reference\ Equity + Income}$
Liquidity	Liquidity of Deposits	$L_{1.3} = \frac{Cash\ and\ Cash\ Equivalents}{Total\ Deposits - 10\%\ major\ depositors}$
	Centralized Deposit Liquidity	$L_3 = \frac{Cash\ and\ Cash\ Equivalents - 10\%\ major\ depositors}{0{,}3 * (Total\ Deposits - 10\%\ major\ depositors)}$
Signs of Growth	Third-Party Capital	$S_4 = \frac{Reference\ Equity - Capital}{Reference\ Equity}$
	Equity Variations	$S_6 = Monthly\ Variation\left(\frac{Reference\ Equity + Income}{Total\ Asset}\right)$

The risk score proposed in this work was calculated for a specific financial cooperative selected from all the individual credit unions in Brazil associated with FGCoop and considering the indicators presented in Table 1. Figure 1 presents the behavior of the historical series of the response variable observations (2) as well as the risk score (3) obtained after adjusting the model (4). Here, the risk score was obtained considering a future window of $h = 12$ months.

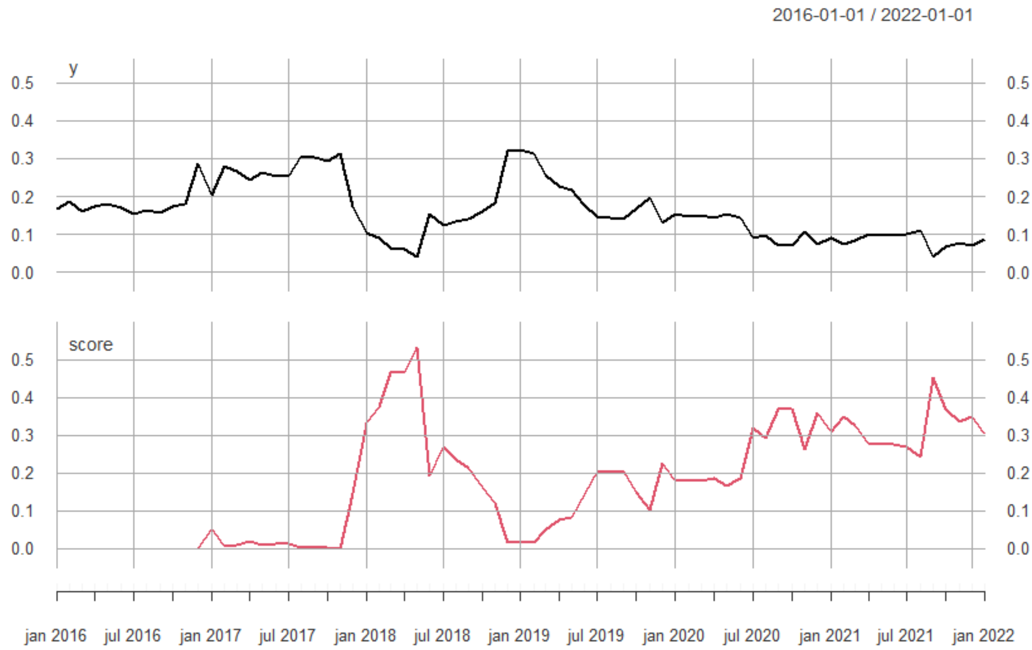

Figure 1 – Historical series of Y_t observed and Risk Score estimated according to the ARMAX model.

The proposed risk score proved to be adequate in identifying the change in risk in unexpected situations, such as seasonality or non-standard movements that may have a great impact on the behavior of the response variable, such as capital injections into the credit union or even expense reversals (Figure 1).

4 Final Considerations

This article aimed to fill a gap with regard to the construction of statistical models for forecasting and monitoring the probability of insolvency of financial institutions, as one of the main proxies for calculating the target level of a deposit insurance, with focus on credit unions.

From the point of view of an analysis related to prevention for the guarantee fund, the study provides a path (prognosis) for monitoring institutions, in which, after detecting an increase in risk, all indicators constructed through the PEARLS method, even if not are present in the adjusted ARMAX model, they can be analyzed by specialists in order to diagnose what motivated this increase.

Having calculated the risk scores, the next steps consist of estimating the other three parameters that make up the Credit Portfolio model, as discussed in the previous sessions, namely: the correlation of the institutions' default, the exposure to default and the loss given default. At the end, the value that will serve as a target for the ratio of the fund's equity to the total volume of covered deposits, will be based on the ratio of the fund size obtained on the eligible deposits for guarantee.

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