OPTIMIZING CAPITAL ALLOCATION: BANKING SECTOR ANALYSIS THROUGH THE RAROC MODEL

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ABSTRACT

The Basel Accords have increasingly required financial institutions to allocate more and higher-quality capital to cover unexpected losses. As a result, choosing to allocate capital to one product over another poses a significant trade-off for managers, underscoring the need for robust decision-making tools that incorporate risk to maximize returns. This paper proposes an empirical approach to serve as an internal model for calculating economic capital, utilizing the RAROC (Risk-Adjusted Return on Capital) methodology to analyze its impact on the profitability of a bank's credit portfolio, which is segmented by credit product. Moreover, it compares these findings with those derived from standardized regulatory capital models. The dataset used in this analysis, provided by a financial institution, covers its two core business products—Payroll-linked loans and Working Capital loans—from January 2011 to June 2019. For the internal model, we employed Value at Risk (VaR) models with Monte Carlo Simulations. The results show that Payroll-linked loans outperform Working Capital loans in terms of RAROC, whether regulatory or economic capital is used, making them a more attractive option for capital investment. Additionally, the adoption of the proposed internal models would significantly enhance the RAROC for Payroll-linked loans, increasing from 5.76% to 38.37% as of June 2019, thereby improving capital optimization. In conclusion, the overall tests indicate that the proposed models performed well and could be effectively employed by financial institutions, offering innovative insights that contribute substantially to strategic, risk-focused management.

Keywords: Finance. Risk-Adjusted Return. RAROC. Value At Risk. Economic Capital.

OTIMIZANDO A ALOCAÇÃO DE CAPITAL: ANÁLISE DO SETOR BANCÁRIO POR MEIO DO MODELO RAROC

RESUMO

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Os Acordos de Basileia têm exigido, de forma crescente, que as instituições financeiras aloquem mais capital e de maior qualidade para cobrir perdas inesperadas. Como resultado, a decisão de alocar capital em um produto em detrimento de outro representa um trade-off significativo para os gestores, ressaltando a necessidade de ferramentas robustas de tomada de decisão que incorporem o risco para maximizar os retornos. Este artigo propõe uma abordagem empírica para servir como um modelo interno de cálculo de capital econômico, utilizando a metodologia RAROC (Retorno Ajustado ao Risco sobre o Capital) para analisar seu impacto na rentabilidade da carteira de crédito de um banco, segmentada por produto de crédito. Além disso, compara esses resultados com aqueles obtidos a partir de modelos regulatórios padronizados de capital. O conjunto de dados utilizado nesta análise, fornecido por uma instituição financeira, cobre seus dois principais produtos de negócio — empréstimos consignados e empréstimos de capital de giro — no período de janeiro de 2011 a junho de 2019. Para o modelo interno, empregamos modelos de Valor em Risco (VaR) com Simulações de Monte Carlo. Os resultados mostram que os empréstimos consignados superam os empréstimos de capital de giro em termos de RAROC, independentemente de ser utilizado capital regulatório ou econômico, tornando-os uma opção mais atraente para investimento de capital. Além disso, a adoção dos modelos internos propostos aumentaria significativamente o RAROC dos empréstimos consignados, passando de 5,76% para 38,37% em junho de 2019, melhorando assim a otimização do capital. Em conclusão, os testes gerais indicam que os modelos propostos tiveram um bom desempenho e poderiam ser empregados de forma eficaz pelas instituições financeiras, oferecendo insights inovadores que contribuem substancialmente para a gestão estratégica focada em riscos.

Palavras-chave: Finanças. Retorno Ajustado ao Risco. RAROC. Valor em Risco. Capital Econômico.

1 INTRODUCTION

The primary function of a commercial bank is to serve as a financial intermediary between borrowers and lenders, predominantly relying on third-party capital for their lending operations. Consequently, financial institutions typically operate with higher leverage ratios compared to other sectors (Marinho & de Castro, 2018). These institutions are exposed to a variety of risks, including interest rate, market, foreign exchange, credit, and operational risks, among others. Saunders (2000) observed that such risks could potentially lead to bank insolvency.

In response to these challenges, the leaders of major central banks globally established the Basel Committee on Banking Supervision (BCBS), which is responsible for overseeing the regulation and supervision of financial institutions. The BCBS also recommends measures aimed at ensuring the stability and soundness of these institutions, with a view to promoting international financial stability, including the establishment of minimum capital requirements (BCBS, 2014).

The Basel Accords (I, II, and III) have progressively imposed more stringent capital requirements on financial institutions, both in terms of quantity and quality, to cover unexpected losses, particularly in relation to credit risk. As a result, the allocation of capital to specific products has become a critical decision-making challenge for managers. Furthermore, since the introduction of Basel II, banks have been encouraged to develop internal models for capital calculation. These models are expected to be more sophisticated than standardized approaches and better aligned with the specific risk exposures of each institution. Nonetheless, in the context of credit risk, it is important to note that the majority of Brazilian and Latin American banks continue to rely primarily on standardized models. This underscores the importance of developing methodologies for internal models to calculate economic capital, particularly for credit risk.

In this increasingly competitive environment, financial institutions must employ more robust tools for portfolio management. One such tool that has gained considerable prominence is the Risk-Adjusted Return on Capital (RAROC). Originally developed in the 1970s by Bankers Trust, RAROC has recently achieved widespread recognition and adoption among financial institutions. By employing RAROC, institutions can obtain a clearer understanding of their investments, as this metric accounts for both expected and unexpected risks, in contrast to other measures such as Return on Equity (ROE), which only consider expected losses.

Although RAROC models are frequently used and extensively examined in the literature, their primary utility has been in the comparative assessment of banks at a broad level, often without delving into portfolio-specific analyses (Castro Junior, 2011; Lima et al., 2014; Klaassen & van Eeghen, 2015; Assis, 2017; Ding et al., 2018). This study proposes a novel approach that can be adapted for portfolio comparisons within a single institution, enabling the ranking of products based on their return on capital. This facilitates active portfolio management and supports managers in prioritizing operations that add the most value to the institution.

Moreover, the RAROC methodology offers valuable insights when comparing outcomes derived from different capital calculation methods, whether standardized or internal regulatory models. As such, this study proposes an empirical approach to be utilized as an internal model for the computation of economic capital, with comparisons made to results obtained from regulatory capital. For this methodology, Value at Risk (VaR) models were applied in conjunction with Monte Carlo simulations.

The methodology proposed in this paper can be utilized by various stakeholders — financial institutions seeking to enhance risk management and improve decision-making processes, and regulators aiming to assess risk within the banking sector and the broader financial system. Furthermore, this study holds academic significance by addressing a gap in the literature regarding the application of the RAROC model disaggregated by product, and by suggesting a streamlined approach for the computation of internal models for credit risk.

The results show that Payroll-linked loans outperform Working Capital loans in RAROC, making them a more attractive option for capital allocation. The adoption of the internal models would significantly boost the RAROC for Payroll-linked loans, enhancing capital efficiency. Overall, the proposed models prove effective for financial institutions and offer valuable insights for risk-focused management.

2 THEORETICAL FRAMEWORK

Risk is defined as the probability of loss, and risk management models must effectively incorporate and predict potential losses. In financial institutions, risk entails two types of losses: expected and unexpected (Zaik et al., 1996). Expected losses are those that institutions anticipate based on the risk levels of their operations and are considered an inherent part of business activities. Therefore, as Marshall (2001) emphasizes, an institution's revenue must at least be sufficient to cover these losses. Consequently, banks are required to account for these expected losses on their balance sheets, recording them as Allowance for Loan and Lease Losses (ALLL). Unexpected losses, by contrast, represent the maximum potential losses that could occur beyond the expected losses already provisioned. To manage such risks, banks must maintain adequate equity (capital) to absorb these unforeseen losses (Carvalho et al., 2018).

Given these risks, financial regulations require banks to maintain minimum capital reserves, particularly to address unexpected losses associated with credit risk. The objective is to ensure that banks have sufficient capital to withstand potential losses, thereby preserving the stability of the global financial system, as outlined by the Basel Committee on Banking Supervision (BCBS, 2014). The level of capital required correlates directly with the institution's risk exposure, reinforcing the importance of sound risk management practices.

To determine the capital required for credit risk, the Basel Committee established three methodologies: (i) the Standardized Approach (SA), (ii) the Foundation Internal Ratings-Based Approach (FIRD), and (iii) the Advanced Internal Ratings-Based Approach (AIRB). In Brazil, only the Standardized Approach is currently used for credit risk. This method consists of rules defined by the regulatory authorities, where capital requirements are calculated by applying a risk weight to net allowance balances (i.e., the allowance balance minus provisions). This calculation yields the Risk-Weighted Assets (RWA), and the capital required is a fixed percentage of the RWA. This regulatory capital serves as the minimum amount necessary to address risks while safeguarding the institution's solvency and protecting the interests of shareholders and third parties.

However, since the SA models are standardized across all banks, they may fail to reflect the specific risk profiles of individual institutions. For this reason, both the Central Bank and the Basel Committee (particularly since Basel II) have encouraged banks to develop their own internal models for capital calculation. As a result, since the 1990s, banks have implemented various internal models to more accurately measure their risks and determine the equity required to absorb unexpected losses (Lopez & Saidenberg, 2000). Some well-known internal models include JP Morgan's CreditMetrics, Credit Suisse's CreditRisk+, and KMV's Credit Monitor, which incorporate diverse sources of information, such as macroeconomic indicators and market values. However, these models are not without limitations, particularly in terms of access to comprehensive data, which complicates long-term projections (Jarrow & Turnbull, 2000).

Internal models reflect the concept of economic capital, which differs from the regulatory capital required by financial authorities. Both approaches aim to measure the capital needed to address unexpected losses, but internal models, by accounting for the institution's unique characteristics, are often better suited to capture the specific risks faced by individual banks.

This distinction is significant because regulatory capital requirements frequently exceed the amount of capital necessary from an economic standpoint. Consequently, adopting internal models can reduce capital charges, improving profitability and enhancing competitiveness (Allen et al., 2004). The comparison presented in this paper encourages financial institutions to invest in advanced risk management technologies to capitalize on the benefits offered by internal models.

The Basel Accords (I, II, and III) further emphasize the importance of risk management by progressively increasing both the quantity and quality of required capital. In this context, the Risk-Adjusted Return on Capital (RAROC) methodology has gained prominence in Brazil and globally. RAROC measures the financial return generated by a credit portfolio in relation to the amount of capital required to support the portfolio's associated risks. Although developed by Bankers Trust in the 1970s, RAROC has only recently become widely adopted by financial institutions, particularly in Brazil (Carollo, 2008; Enomoto, 2002). By using RAROC, institutions can gain clearer insights into their investments, as the return is weighted against both expected and unexpected risks—offering a more comprehensive perspective than traditional metrics such as Return on Equity (ROE)[3], for example.

The standard formula for RAROC, developed by Bankers Trust, is expressed as follows:

$$RAROC = \frac{Profit}{Capital} \tag{1}$$

Where profit captures the operation's overall profitability, encompassing all product revenues minus product-related costs, including provisioning expenses. Capital refers to the investor's capital, representing the amount of equity the bank must allocate to absorb unexpected losses. Consequently, this indicator reflects the return generated by a given operation in proportion to the required capital (Bastos, 2000).

Once these components have been estimated, calculating RAROC becomes straightforward, as shown in equation (1). The result provides an accurate measure of the profit that compensates shareholders for their capital investment and ensures the institution's long-term sustainability (Zaik et al., 1996). Although the formula is relatively simple, various approaches to calculating its components have emerged over time due to advancements in risk management techniques developed after the RAROC model's introduction in the 1970s.

According to Securato (2012), the original formula developed by Bankers Trust measured capital—the denominator of the equation—as the regulatory capital required by financial authorities. However, a more recent version, developed by Bank of America and now widely used by financial institutions,

[3] Return on Equity (ROE) is the most widely used metric for evaluating the performance of financial institutions today. However, it is calculated by dividing net income for the period by equity, taking into account only expected losses.

redefines capital as risk-adjusted economic capital, calculated using the institution's internal models, typically based on the Value at Risk (VaR) methodology. This method estimates the maximum potential loss a portfolio could incur, with economic capital representing the amount needed to cover unexpected losses at a given confidence level and within a specific time horizon. Following Bank of America's approach, several scholars, including Saunders (2000), Smithson and Hayt (2001), Kraus (2013), and Prokopczuk, Rachev, and Trück (2004), have advocated for this shift, arguing that the denominator should reflect economic rather than regulatory capital.

Stoughton and Zechner (2007) further contributed to the literature by presenting a theoretical model for applying RAROC in institutions where equity issuance is infrequent, but debt capital remains readily accessible. Their work explores the economic foundations of capital budgeting mechanisms, particularly RAROC and Economic Value Added (EVA), demonstrating the alignment of these models with broader economic principles within a theoretical framework.

Building on this foundation, the methodology proposed in this paper complements Stoughton and Zechner's (2007) theoretical model by providing an empirical approach. Using real data from a Brazilian financial institution, we validate these concepts in a practical context. Specifically, our methodology applies the RAROC model to compare results derived from two distinct capital calculation methods: standardized regulatory models and internal models, as discussed by Securato (2012), Saunders (2000), Smithson and Hayt (2001), Kraus (2013), and Prokopczuk, Rachev, and Trück (2004).

Our primary focus is on credit risk, as it remains the most significant risk for banks in Brazil and across Latin America, where standardized models continue to dominate. The comparison of these methods offers practical insights into how financial institutions can enhance their capital management and optimize risk-adjusted returns.

3 METHODOLOGY

The dataset utilized in this study was provided by a financial institution and contains information on its two core business products[4]: Payroll-linked loans and Working Capital loans. Together, these products account for 40% of the bank's total portfolio and 20% of its total assets. The data are reported on a monthly basis, covering the period from January 2011 to June 2019. The variables included are Date, Product, Balance, Nonperforming Loans (NPL), Provision for Credit Losses (PCL), Interest Rate, Allocated Capital, Administrative Costs, Assets Ratio, and Write-offs. Figure 6 and Table 3 in the Appendix present graphical representations, along with detailed descriptive statistics for all variables.

[4] The actual values were multiplied by an undisclosed constant to ensure confidentiality. This adjustment does not affect the RAROC model, as it is expressed as a percentage of capital.

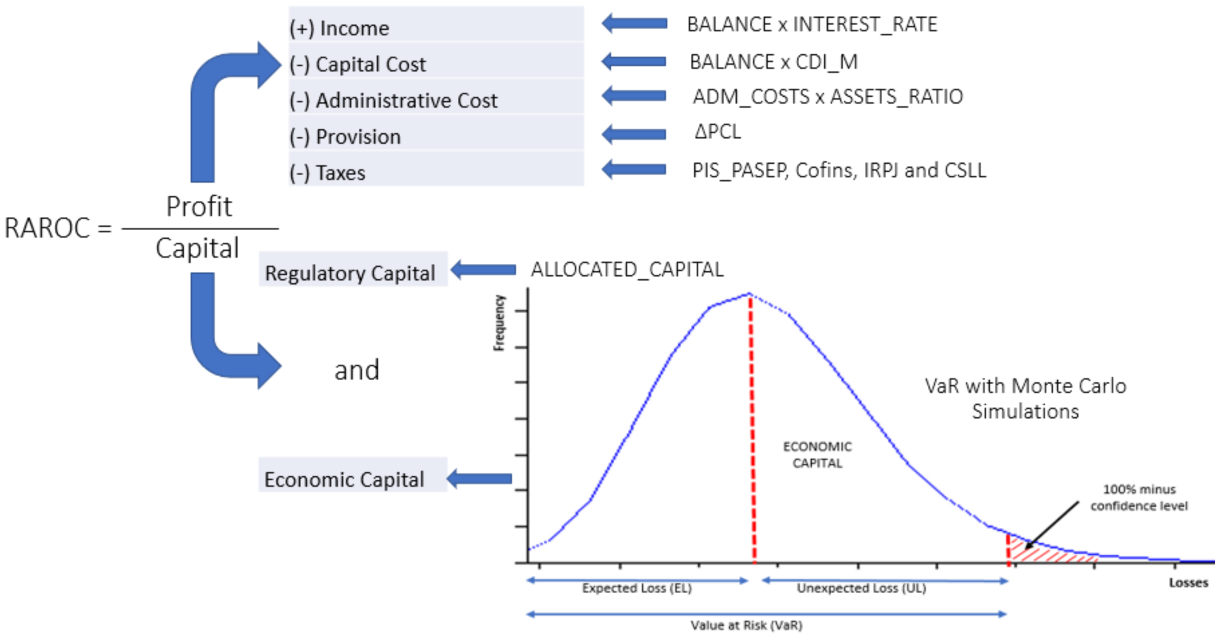

Figure 1 – RAROC model proposed
Source: authors.

To achieve the objectives of this study, we employed statistical and mathematical procedures to produce inferences based on the selected sample, utilizing R version 3.6.1 with RStudio version 1.1.338. The methodology is divided into two main parts. First, we propose a framework for calculating each variable in the RAROC model, stratified by product. Second, we introduce a straightforward approach to compute an internal model and estimate economic capital. Figure 1 presents a diagram summarizing the proposed methodology. The outcome of this process provides a risk-adjusted return for each product, allowing for a comparison from both regulatory capital and economic capital perspectives, with a focus on June 2019. The next sections provide more details regarding each part of the methodology.

3.1 Calculating RAROC Variables for each Product

At this stage, we propose straightforward mathematical procedures to calculate the RAROC variables for each product, utilizing the data available in the dataset. Income from financial intermediation corresponds to the interest earned by the bank on loans issued. This income can be calculated by multiplying the loan interest rate by the balance of operations (Kong et al., 2017), representing the bank's primary source of revenue. As shown in Equation (2), this income increases proportionally with an increase in either the Balance or the Interest Rate.

$$Income_t = BALANCE_t * INTEREST\_RATE_t \tag{2}$$

Conversely, Capital Cost represents the most significant expense for a financial institution, as it reflects the interest paid to depositors. This cost corresponds to the capital utilized by the bank to issue loans, commonly referred to as funding. According to the Bank Economics Report published by the Central Bank of Brazil (BACEN, 2018), funding costs are closely tied to the CDI (Brazilian Interbank Deposit) rate, which serves as a benchmark for the average funding cost of financial institutions. Therefore, as outlined in Equation (3), the Capital Cost is calculated as the product of the Balance and the CDI rate.

$$Capital\_Cost_t = BALANCE_t * CDI\_M_t \quad (3)$$

Administrative Costs encompass all expenses associated with the institution's organizational structure, including wages, data processing, communications, and rent, which are essential to support the bank's operations (Brugnera & Gientorski, 1998). The variable ADM_COST reflects the total administrative expenses for the entire bank, requiring an apportionment to allocate these costs proportionately across individual products. This allocation was performed based on the share that each product's balance represents in relation to the bank's total assets (captured by the Assets Ratio variable). Thus, the Administrative Costs attributed to each product are calculated as follows:

$$Administrative\_Cost_t = ADM\_COST_t * ASSETS\_RATIO_t \quad (4)$$

For Provision Costs, the dataset provides only the balance of the Provision for Credit Loss (PCL), requiring an adjustment to derive the relevant cost. To calculate the Provision Costs, we consider the provisioning flow, which reflects the change in the PCL balance over the month, as demonstrated in Equation (5).

$$Provision\_Cost_t = PCL_t - PCL_{t-1} \quad (5)$$

Lastly, taxes are calculated in accordance with the regulations of the Brazilian Internal Revenue Service (RFB) and follow two distinct rules based on the tax base: profit or revenue. Financial institutions in Brazil are subject to four primary taxes: Corporate Income Tax (IRPJ), Social Contribution on Net Income (CSLL), Social Security Contribution (Cofins), and social contributions to the Social Integration Program (PIS) and the Civil Servant Heritage Formation Program (Pasep). The respective tax rates are 25%, 15%, 0.65%, and 4%. The IRPJ and CSLL are levied on profit, while PIS/Pasep and Cofins are assessed on revenue. Accordingly, two separate equations (Equations 6 and 7) are used to calculate the applicable taxes.

$$Revenue\_Tax_t = (Income_t - Capital\_Cost_t) * (PIS\_PASEP + Cofins) \quad (6)$$

$$Profit\_Tax_t = (Income_t - Capital\_Cost_t - Revenue\_Tax_t - Administrative\_Cost_t - Provision\_Cost_t) * (IRPJ + CSLL) \quad (7)$$

With all variables defined, the net profit (the numerator in Equation 1) can be calculated for each product. By dividing the net profit by the corresponding capital — whether Regulatory or Economic — the RAROC for each product can be determined.

3.2 Calculating the Required Capital

The dataset provides the regulatory capital, which reflects the capital calculated according to regulatory guidelines, as outlined in Section 2. For the calculation of economic capital, we propose a Value at Risk (VaR) approach utilizing Monte Carlo simulations as a simplified internal model. As described by Gilli and Kellezi (2006) and Jorion (2007), the VaR methodology estimates the amount of capital necessary to cover potential portfolio losses over a specified time horizon, with a certain level of statistical confidence. Following the works of

Magnou (2018) and Oppong, Asamoah, and Oppong (2016), the general VaR formula is expressed as:

$$VaR_{\propto} = [F^{-1}(1-\propto) - \mu] * \sqrt{h}, \qquad \propto \in (0,1) \tag{8}$$

Assuming a random variable X with continuous distribution F, F^{-1} is defined as the inverse of the distribution F, $\propto$ is the confidence level, μ is the mean of the distribution and h is the horizon considered. Thus, the $VaR_{\propto}$ can be defined as the difference between the $(1-\propto)$ quantile of the distribution F minus the mean (μ) times the squared root of the horizon considered (h). Following the Basel II Accord approach, the confidence level $(\propto)$ is considered as 0.1% and the horizon period (h) as one year. The mean is calculated as the first moment of the distribution. It is reduced from the VaR value because it represents the expected loss already covered by the provision. Therefore, the VaR estimated here measures the sufficient capital to cover, at 99.9% confidence, the losses from a portfolio over a one-year holding period. This capital is considered the economic capital risk-adjusted of each product.

The VaR may also be determined as the volatility around the projected average expected loss, reflecting the possibility of loss in adverse situations for which institutions must have enough equity to face in order not to compromise the institution and ensure business continuity. Figure 2 illustrates this situation. Given a distribution of losses generated by VaR, they may be divided into expected loss (represents the provision) and expected loss (represents the required capital).

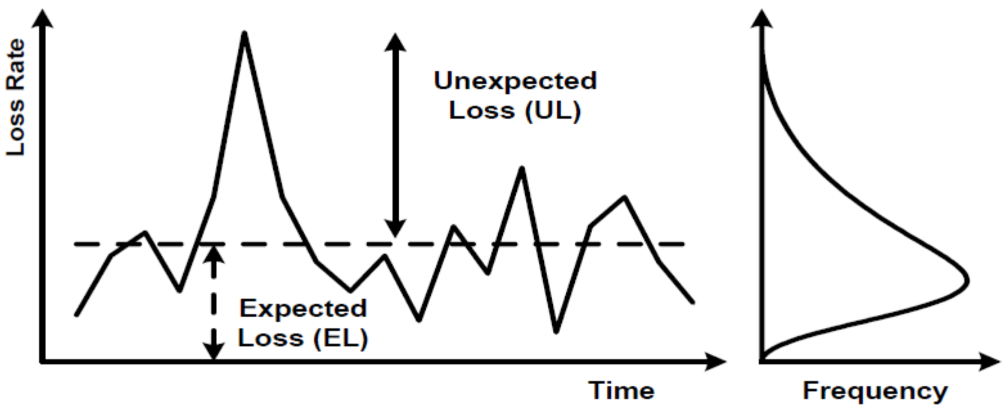

Figure 2 – The Value at Risk (VaR)
Source: BCBS (2005).

Based on Jorion (2005) and Bessis (2011), there are two primary types of VaR models: parametric and non-parametric. The parametric approach assumes that risk factors follow a normal distribution, allowing VaR to be calculated as a quantile of the distribution at a given confidence level $(\propto)$, using the volatilities and correlations among the variables. While straightforward, this method may overlook potential deviations from the underlying assumptions, as risk factor returns often do not follow a normal distribution and portfolio returns may not be linear functions of those risks.

In contrast, non-parametric models do not assume a priori that risk follows a normal distribution. Instead, VaR is calculated through simulations that generate a wide range of potential risk scenarios. There are two main approaches within non-parametric models: Historical Simulations and Monte Carlo Simulations. Historical simulations rely on past data to estimate the loss distribution, assuming that the past distribution will remain stable. In comparison, Monte Carlo simulations generate numerous random scenarios, creating a virtually unlimited set of potential outcomes and mitigating the limitations of historical data.

This study employs the non-parametric VaR approach using Monte Carlo simulations, following the methodologies of Dowd (1998) and Oppong et al. (2016). The process involves several steps: (i) estimating the parameters of a known theoretical distribution, (ii) applying statistical tests to identify the distribution that best fits the data, (iii) generating random values based on the estimated parameters, and (iv) calculating the risk measures from the simulated outcomes.

Additionally, as Allen, Boudoukh, and Saunders (2004) highlight, several assumptions are necessary to ensure the feasibility of VaR calculations. The first assumption is stationarity, meaning that the likelihood of a, for example, 1% fluctuation in losses is constant over time. The second is non-negativity, ensuring that losses cannot take negative values. The final and most critical assumption relates to the distribution of the variable—the accuracy of the selected distribution is crucial, as the simulation depends on its parameters. An inaccurate distribution could lead to underestimated risks and unreliable results.

4 EMPIRICAL RESULTS AND DISCUSSION

After calculating the RAROC variables, we estimated the profit and computed the Regulatory RAROC for each product. This calculation was performed using data from the most recent period available in the dataset—June 2019. In this period, the profit amounted to R$117.60 million for Payroll-linked loans and R$52.79 million for Working Capital loans (Table 1). By dividing the profit by the corresponding Regulatory Capital, we obtained the Regulatory RAROC for both products. The results indicate that, although Working Capital loans generated relatively higher profit, Payroll-linked loans delivered a superior RAROC, making them a more attractive option for capital allocation. This finding underscores the importance of evaluating profit relative to the capital employed.

To calculate economic capital using the VaR model, the first step involved estimating the parameters of a suitable theoretical distribution curve that fits the data. This step is crucial, as Monte Carlo simulations rely on these parameters to generate a series of potential outcomes. Each theoretical distribution curve has distinct parameters, moment-generating functions, and characteristics, such as differing measures of dispersion, central tendency, and shape. These factors influence the model's ability to represent the underlying data accurately. In this study, WRITE_OFF data for each product were used to represent the losses.[5]

[5] There are several approaches to implementing Monte Carlo simulations. However, following the methodology outlined by Brito and Assaf Neto (2008), when the available data spans a long period and provides a balanced representation of both performing and non-performing loans, the credit risk of the portfolio can be directly measured using the historical loss distribution. This is the approach adopted in this study.

Table 1
Profit and Regulatory RAROC

RAROC Variables	Payroll-linked	Working Capital
1 - Income	478.49	108.24
2 - Capital Cost	137.19	54.75
3 - Administrative Cost	42.93	17.13
4 - Provision	86.49	-54.11
5 - Taxes	94.27	37.68
6 - Profit (1 - (2 + 3 + 4 + 5))	**117.60**	**52.79**
7 - Capital (Regulatory)	2,041.63	1,094.34
8 – Regulatory RAROC (6/7)	**5.76%**	**4.82%**

Note: R$ million.
Source: authors.

The first assumption tested was stationarity. According to the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, the WRITE_OFF variables for both products were found to be stationary at the level (see Table 4 in the Appendix). The second assumption, non-negativity, is inherently satisfied, as the variable defined by the bank to represent losses is, by definition, non-negative.

With the variables confirmed as stationary and non-negative, the next step involved estimating the unknown parameters. In this study, we applied the Maximum Likelihood Estimation (MLE) method to estimate the parameters and substituted the function with the probability density function of a known distribution curve.[6] Since the appropriate distribution for the data is not known a priori, we tested four candidate distributions: Normal, Lognormal, Weibull, and Gamma. The estimated parameters for each distribution are reported in Table 5 (Appendix).

Based on the estimated parameters, the theoretical distribution curves were generated. Figure 3 presents the histograms of the WRITE_OFF data and illustrates how the fitted distribution curves align with the observed data. While visual inspection allows for a preliminary assessment of which distribution may best fit the data, statistical inference techniques are required to confirm the suitability of these distributions and identify the best fit when multiple distributions appear applicable.

For this purpose, we employed the Kolmogorov-Smirnov (KS) test, a method chosen for its simplicity and ease of interpretation.[7] The results are presented in Table 6 (Appendix). For Payroll-linked loans, only the Lognormal distribution was accepted based on the p-value. In the case of Working Capital loans, three distributions — Lognormal, Weibull, and Gamma — were accepted. However, using the D-statistic as the selection criterion, the Lognormal distribution was identified as the best fit.

[6] According to Kececioglu (2002), several methods can be used for parameter estimation, with the most common being ordinary least squares (OLS), moment matching estimation (MME), and maximum likelihood estimation (MLE). For a more comprehensive discussion on this topic, Fernandes (2013) provides valuable insights.
[7] According to Abd-Elfattah (2011), four primary statistical tests are commonly used to validate the fit of statistical distributions: Cramer-Von Mises (CM), Anderson-Darling (AD), Chi-Squared (CS), and Kolmogorov-Smirnov (KS). The purpose of these tests is to assess the hypothesis that a given random sample is drawn from a population following a specified distribution.

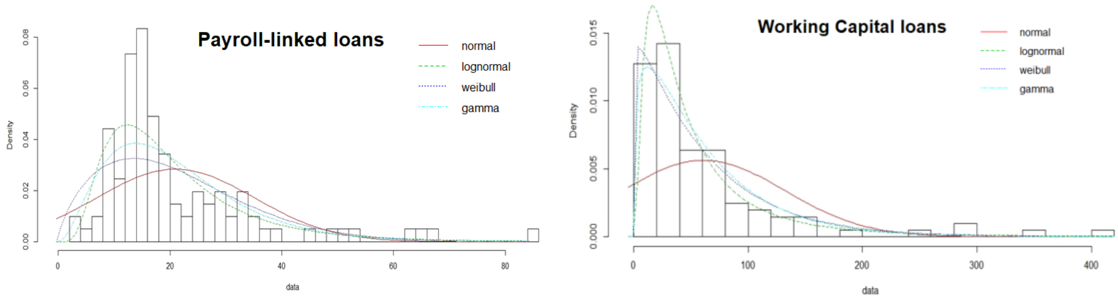

Figure 3 – Histogram and Theoretical Distributions
Source: authors.

Once the distribution is fitted, the final step involves generating a series of random numbers based on the parameters of the selected probability distribution. Following the methodology outlined by Oppong, Asamoah, and Oppong (2016), a specified number of scenarios are generated, each repeated a certain number of times. In this study, we generated 100 scenarios for each series, with 10,000 samples per scenario, resulting in 1,000,000 possible loss values for each product. This process creates a loss distribution, from which the relevant risk measures can be calculated.

More specifically, the Expected Loss (EL) and Unexpected Loss (UL) are derived from the loss distribution. As previously discussed, the EL corresponds to the first moment of the distribution (mean), while the UL is defined as the difference between the VaR and the mean, representing the economic capital required for a one-month period. The UL is then scaled to a one-year horizon by multiplying it by the square root of 12. This calculation provides the amount of capital sufficient to cover potential losses at a 99.9% confidence level over a one-year holding period, representing the risk-adjusted economic capital for each product. The results are presented in Table 2.

Table 2
VaR results

Product	monthly		one year	
	$VaR_{99.9\%}$	Unexpected Loss	$VaR_{99.9\%}$	Economic Capital
Payroll-linked	109.41	88.47	379.01	306.47
Working Capital	680.08	620.25	2,355.88	2,148.62

Note: R$ million.
Source: authors.

Finally, since the VaR measures the maximum loss of a portfolio at a 99.9% confidence level, a crucial analysis involves assessing whether the calculated Unexpected Loss (UL) — the difference between the VaR and the mean — adequately covers all observed losses (WRITE_OFF) during the period under study. Figure 4 illustrates this comparison. The graphs indicate that the Unexpected Loss estimated by the VaR model is sufficient to cover the observed losses for both products throughout the historical period, confirming the appropriateness of the calculated values. Therefore, based on the tests and results, it can be concluded that the VaR model is suitable for the dataset and that the calculated economic capital accurately reflects the required amount to manage potential losses.

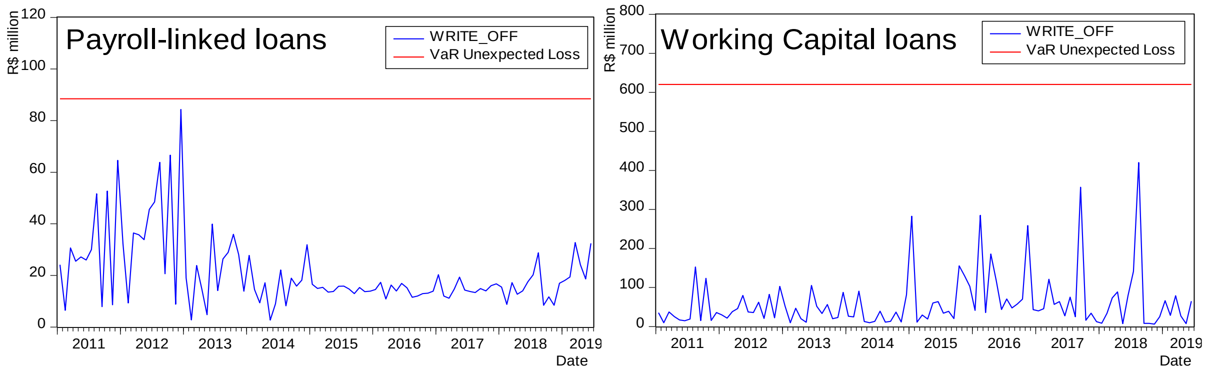

Figure 4 – Unexpected Loss vs Write-off
Source: authors.

With the economic capital confirmed as appropriate, the final step is to estimate the Economic RAROC using the same profit figures reported in Table 1 and compare the results with the Regulatory RAROC. This calculation is again based on the most recent available data: June 2019. During this period, the profit was R$117.60 million for Payroll-linked loans and R$52.79 million for Working Capital loans. By dividing the profit by the corresponding Economic and Regulatory Capital, we obtain the Economic RAROC and Regulatory RAROC for each product.

The results indicate that Payroll-linked loans exhibit a higher RAROC than Working Capital loans, regardless of whether economic or regulatory capital is applied, confirming that Payroll-linked loans are a more attractive option for capital allocation. Additionally, adopting the internal model proposed in this study would significantly increase the RAROC for Payroll-linked loans, further enhancing capital optimization. Figure 5 provides a comparative view of the Economic and Regulatory Capital and the corresponding RAROC for each product.

Building on these findings, it is important to interpret the results with a strategic perspective. While the superior performance of Payroll-linked loans suggests they are a good candidate for continued capital investment, Working Capital loans still play an essential role in the bank's product portfolio. Diversification is a key consideration, as banks typically allocate capital across multiple products to reduce concentration risk and maintain a balanced portfolio. Thus, it would not be prudent to shift all capital to Payroll-linked loans despite their higher RAROC.

Comparing the regulatory and economic RAROC, the internal model proposed in this study yields higher returns, especially for Payroll-linked loans. Although the RAROC for Working Capital loans decreases from 4.82% to 2.46%, the RAROC for Payroll-linked loans increases dramatically from 5.76% to 38.37%. As a result, the combined return from both products under the internal model rises to 6.94%, compared to 5.43% under the regulatory model—representing a potential 27.73% improvement. Furthermore, the Economic Capital calculated for both products was R$ 680.88 million lower than the Regulatory Capital, supporting Allen, Boudoukh, and Saunders (2004) in their argument that regulatory capital tends to be conservative and exceeds the economic capital required.

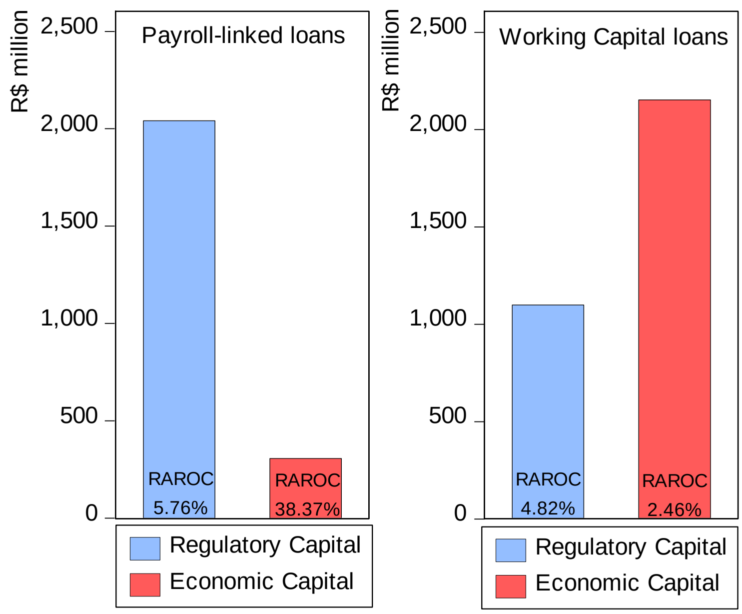

Figure 5 – Regulatory versus Economic Capital
Source: authors.

The key advantage of using internal models lies in more efficient capital allocation, allowing banks to reduce capital charges and enhance profitability. Given the scarcity of capital, better allocation would enable managers to optimize decision-making, resulting in higher returns on allocated capital compared to regulatory standards and boosting the bank's competitiveness. Additionally, the release of excess capital could be reinvested in new loans, expanding the customer base and generating further returns.

The observed differences in economic capital between the two products reflect their distinct characteristics, captured by the internal model. Payroll-linked loans exhibit lower default rates than Working Capital loans, resulting in smaller associated losses. In contrast, higher delinquency rates in Working Capital loans lead to larger losses, influencing the calculation of economic capital. Since the model aims to cover unexpected losses, products with higher and more volatile losses require greater capital reserves. For instance, the average loss for Working Capital loans was R$ 60.94 million, with a standard deviation of R$ 71.15 million, whereas Payroll-linked loans reported an average loss of R$ 20.99 million, with a standard deviation of R$ 14.14 million.

Lastly, it is essential to highlight that internal models are more sophisticated and sensitive to the unique attributes of each product, particularly default rates. To gain a more comprehensive understanding of the methodology's performance, future research should include a broader range of financial products and extend the analysis to a dynamic framework, as the results presented here are based solely on a one-period analysis.

5 CONCLUSION

This study aimed to analyze the risk-adjusted return in the banking sector, stratified by credit product, and propose an approach to measure unexpected losses. Using the RAROC model, the results presented here contribute to strategic management and capital optimization with a risk-focused perspective, maximizing the profitability analysis of credit operations in financial institutions. To achieve this, a methodology was developed to adapt the RAROC model for product-level analysis and propose an approach for calculating internal credit risk models through Value at Risk (VaR) models with Monte Carlo simulations.

The proposed methodology was applied to two credit products from a financial institution. The results demonstrate that Payroll-linked loans exhibit a superior RAROC, whether using regulatory capital or the internal model (economic capital), making them a more attractive option for capital allocation than Working Capital loans. Furthermore, adopting the suggested internal model would significantly increase the RAROC for Payroll-linked loans — from 5.76% to 38.37% in June 2019 — enhancing the potential for capital optimization.

The Economic Capital calculated for both products totaled R$ 2.46 billion, which was R$ 680.88 million, or 27.73%, lower than the Regulatory Capital, supporting the findings of Allen, Boudoukh, and Saunders (2004), who argue that regulatory capital is often more conservative than economically necessary. This underscores the main advantage of internal models—better capital allocation—enabling banks to reduce capital charges and increase potential profitability. These findings may also encourage managers to adopt internal models, which have been promoted since the introduction of Basel II. Currently, banks operating in Brazil rely exclusively on the Standardized Approach (SA) for credit risk.

However, it is essential to acknowledge the limitations of the internal model methodology proposed here. Financial institutions seeking to replace regulatory models with internal models for credit risk capital must undergo a rigorous approval process by regulatory authorities. This process requires demonstrating the model's robustness, submitting a comprehensive application, undergoing independent validation, continuous monitoring, and periodic reviews. Additionally, under Basel III, institutions using internal models are required to maintain a Capital Floor, a minimum capital level relative to standardized models. This floor is typically set at 72.5%, though it may vary depending on the risk profile of the underlying assets. It is important to note that the model proposed in this study is simplified and does not attempt to capture the full complexity of individual institutions' specific characteristics.

Our tests indicate that the proposed models performed well, providing innovative and valuable insights for risk-focused strategic management. However, given the complexity of the approach, certain simplifications were necessary — such as focusing on two banking products, which represent 40% of the portfolio, and basing the model calculations on a single reference period (June 2019). It is important to acknowledge that the results could vary if applied to different products or time periods.

In conclusion, this study introduced a novel approach to employing the RAROC model in financial institutions, with the results demonstrating satisfactory and practical outcomes. These findings offer potential applications for other products or institutions. For future research, it would be valuable to analyze additional credit products beyond those examined here and expand the methodology to a dynamic framework. This would be especially relevant for products such as mortgages or rural credit, which involve long-term contracts and distinct payment flows. Additionally, future research aims to implement copula models to integrate credit, market, and operational risks, enabling the exploration of risk interdependencies and fostering a more comprehensive and holistic risk management framework.

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APPENDIX

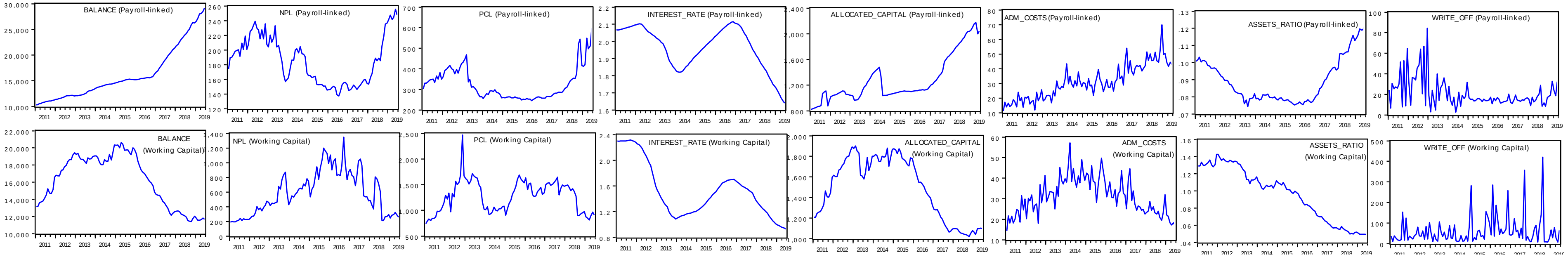

Figure 6 – Macroeconomic and Bank-specific series
Source: authors.

Table 3
Details and Descriptive Statistics of the Variables

Variable	Details	Product	Mean	Std Dev.	Min	Max	Skewness	Kurtosis
BALANCE	Sum of the balance for each product at the reference date.	Payroll-linked	16.130,20	5.012,45	10.249,20	29.190,30	1,11	0,19
		Working Cap	16.232,15	2.982,35	11.400,10	20.641,90	-0,28	-1,45
NPL	Sum of Nonperforming Loans (credit operations in default for more than 90 days)	Payroll-linked	185,56	32,27	137,10	255,60	0,34	-1,09
		Working Cap	589,07	291,64	189,50	1.346,20	0,37	-0,85
PCL	Sum of Provision for Credit Losses balance, calculated by regulatory model (2.682/99).	Payroll-linked	325,43	77,78	245,20	597,60	1,34	1,49
		Working Cap	1.275,07	304,45	741,70	2.466,20	0,37	0,64
INTEREST RATE	Balance-weighted average interest rate for each product.	Payroll-linked	1,96	0,12	1,64	2,12	-0,77	-0,31
		Working Cap	1,52	0,42	0,93	2,31	0,69	-0,64
ALLOCATED CAPITAL	Sum of the Allocated Capital balance, calculated by the regulatory model.	Payroll-linked	1.277,57	354,60	824,00	2.173,50	1,15	0,18
		Working Cap	1.492,59	299,72	1.021,00	1.901,20	-0,26	-1,50
ADM COSTS	Sum of Administrative Costs at the reference date.	Payroll-linked	31,06	11,56	11,10	69,80	0,50	-0,04
		Working Cap	31,04	8,80	14,30	57,30	0,37	-0,40
ASSETS RATIO	Ratio of the balance to the total assets of the bank.	Payroll-linked	0,09	0,01	0,07	0,12	0,86	-0,30
		Working Cap	0,10	0,03	0,05	0,14	-0,23	-1,34
WRITE OFF	Sum of the NPL that was cleared from balance sheet.	Payroll-linked	20,99	14,14	2,70	84,30	2,08	5,14
		Working Cap	60,94	71,15	6,10	419,80	2,90	9,78

Note: statistics over period 2011M01 - 2019M06 (102 observations). R$ million.
Source: authors.

Table 4
Unit Root Tests for the Write-Off Variables

Series	test	T-stat with intercept	T-stat with trend and intercept	T-stat with none	I
WRITE_OFF (Payroll-linked)	ADF	-2.6342*	-3.2938*	-0.984434	I(0)
	PP	-10.4358***	-11.1831***	-4.2111***	
WRITE_OFF (Working Capital)	ADF	-10.0036***	-10.2894***	-3.7343***	I(0)
	PP	-10.0036***	-10.3307***	-7.3346***	

Note: *, **, *** indicate rejection H0 (unit root) at 10%, 5% and 1%, respectively.
Source: authors.

Table 5
Estimated parameters for the distributions

Estimated Parameters: Payroll-linked (by MLE method)							
NORMAL		LOG-NORMAL		WEIBULL		GAMMA	
mean	20.984	ln means	2.866	shape	1.650	shape	2.968
std dev.	14.069	ln std dev.	0.593	scale	23.667	rate	0.141
Estimated Parameters: Working Capital (by MLE method)							
NORMAL		LOG_NORMAL		WEIBULL		GAMMA	
mean	60.942	ln means	3.655	shape	1.047	shape	1.240
std dev.	70.803	ln std dev.	0.934	scale	62.264	rate	0.020

Source: authors.

Table 6
KS-test

KS-test Payroll-linked				
	KS_NORMAL	KS_LOG_NORMAL	KS_WEIBULL	KS_GAMMA
D-Stat	0.2117689	0.1003988	0.1535301	0.1418863
P-Value	0.0002127	0.2553159	0.0163187	0.0329182
KS-test Working Capital				
	KS_NORMAL	KS_LOG_NORMAL	KS_WEIBULL	KS_GAMMA
D-Stat	0.2192559	0.0385487	0.0892345	0.1014957
P-Value	0.0001101	0.9981211	0.3910457	0.2441037

Source: authors.