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WAGNER EDUARDO SCHUSTER

RISK-ADJUSTED RETURN:
Banking Sector Analysis through the RAROC Model

Porto Alegre
2019

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Dissertation presented as a partial requirement to obtain a Master's Degree in Economics, by the Graduate Program in Economics of Universidade do Vale do Rio dos Sinos - UNISINOS

Advisor: Prof. Dr. Luciana de Andrade Costa

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To my best friend Mauricio (*in memoriam*).

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ABSTRACT

Bank sector scenario in Brazil nowadays is facing increasingly competitiveness and credit loans expansion. Moreover, the resources are scarce and the decision to allocate capital to a product or another represents an important trade-off for managers, what reinforces using robust decision-making tools that consider risk to maximize returns. The aim of this work was to analyze the risk-adjusted return for the banking sector through the RAROC model based on three perspectives: Regulatory, Economic and Forecasted RAROC. The database was provided by a financial institution and contains data for the two core business products (Payroll-linked and Working Capital loans) as well as macroeconomic variables. This work contributes to the literature by proposing a new approach which enables to measure profitability stratified within the institution's portfolio and furthermore to project its values. Methodologically, a Value at Risk (VaR) model with Monte Carlo Simulations was used for the Economic RAROC, a Vector Autoregressive (VAR) model for Forecasting and a historical approach for the Regulatory RAROC. Through Regulatory RAROC an *ex-post* analysis, month by month, reveals that the Payroll-linked loans returned 8.13% on average with positive and superior average market values throughout the entire period, while Working Capital presented 4.03%, but a result that varied greatly with several negative returns. Furthermore, the Economic Capital calculated for Payroll-linked was substantially lower than the Regulatory while in Working Capital was the contrary, reinforcing that the first would present a much higher return as optimizing the allocated capital (from 6.87% to 45.75% in 2019M06), highlighting the relevance of an internal model. Finally, the Forecasting RAROC enables an *ex-ante* prospective decision and the results reveals that in a 12-month future scenario the Payroll-linked would return 9.31% in average while Working Capital would present 1.29%, confirming that the first product will continue to remunerate the invested capital properly while the second has a potential for return, however without measures that change the current projected scenario, the product does not present itself as a good capital investment. To conclude, the overall tests reveal that the models had a good performance and therefore bring innovative results that satisfactory contributes to a strategic management focused on risks.

Keywords: Risk-adjusted return. RAROC. Value at Risk. Vector Autoregressive.

RESUMO

O setor bancário no Brasil enfrenta um cenário de crescente competitividade e expansão dos volumes de crédito. Além disso, os recursos são escassos e a decisão entre alocá-los em um produto ou outro representa um importante *trade-off* para os gestores, reforçando o uso de ferramentas robustas para a tomada de decisão que levem em consideração o risco para maximizar os retornos. O objetivo deste trabalho foi analisar o retorno ajustado ao risco para o setor bancário por meio do modelo RAROC baseado em três perspectivas: RAROC Regulatório, Econômico e Projetado. O banco de dados utilizado foi fornecido por uma instituição financeira e contém dados para os dois principais produtos (Crédito Consignado e Capital de Giro), bem como variáveis macroeconômicas. Este trabalho contribui à literatura ao propor uma nova abordagem que permite medir a rentabilidade estratificada no portfólio do banco e, além disso, projetar seus valores. Metodologicamente, um modelo *Value at Risk* (VaR) com Simulações de Monte Carlo foi utilizado para o RAROC Econômico, um modelo de Vetores Autoregressivos (VAR) para a Projeção e uma abordagem histórica para o Regulatório. Através do RAROC Regulatório, uma análise *ex-post*, mês a mês, revela que o Crédito Consignado teve retorno de 8,13%, em média, com valores positivos e superiores aos de mercado ao longo de todo o período, enquanto o Capital de Giro apresentou retorno de 4,03%, porém um resultado que flutuou bastante com vários pontos negativos. Além do mais, o Capital Econômico calculado para o Crédito Consignado foi substancialmente menor que o Regulatório, enquanto no Capital de Giro foi o inverso, reforçando que o primeiro apresentaria um retorno muito maior ao otimizar o capital alocado (de 6,87% para 45,75% em 2019M06), destacando a relevância de um modelo interno. Finalmente, o RAROC Projetado permite uma decisão prospectiva *ex-ante* e os resultados revelam que, em um cenário futuro de 12 meses, o Crédito Consignado retornaria 9,31% em média, enquanto o Capital de Giro apresentaria 1,29%, confirmando que o primeiro produto continuará a remunerar adequadamente o capital investido, enquanto o segundo tem potencial de retorno, porém sem medidas que alterem o cenário projetado atual, o produto não se apresenta como um bom investimento de capital. Para concluir, os testes gerais revelam que os modelos tiveram um bom desempenho e trazem resultados inovadores que contribuem satisfatoriamente para uma gestão estratégica focada em riscos.

Palavras-chave: Retorno ajustado ao risco. RAROC. Value at Risk. VAR.

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LIST OF ABBREVIATIONS

AD	Anderson-Darling test
ADF	Augmented Dickey-Fuller test
AIC	Akaike Information Criterion
AIRB	Advanced Internal-Rating Based Approach
ALLL	Allowance for Loan and Lease Losses
BACEN	Central Bank of Brazil
BCBS	Basel Committee on Banking Supervision
BRGAAP	Brazilian Generally Accepted Accounting Principles
CDI	Brazil interbank deposit rate
CM	Cramer-Von Mises test
CMN	National Monetary Council
Cofins	Social Security tax
CR5	Concentration Ratio of the 5 largest
CS	Chi-Squared test
CSLL	Social Contribution on Net Income tax
EAD	Exposure At Default
ECB	European Central Bank
ECL	Expected Credit Loss
EVA	Economic Value Added
FIRD	Foundational Internal-Rating Approach
FPE	Final Prediction Error
GDP	Gross Domestic Product
HHI	Herfindahl-Hirschman Index
HQ	Hannan-Quinn Information Criterion
IBC_BR	Economic activity index of Brazil
IBGE	Instituto Brasileiro de Geografia e Estatística
IFRS	International Financial Reporting Standards
INCC	Building index of Brazil
IPCA	Consumer Price Index of Brazil
IPI	Industrial Production Index of Brazil
IRPJ	Corporate Income tax

KS	Kolmogorov-Smirnov test
KW	Kwman test
LGD	Loss Given Default
LM	Lagrange Multiplier
LR	Likelihood Ratio
MLE	Maximum Likelihood Estimation
MME	Moment Matching Estimation
NPL	Nonperforming Loans
OLS	Ordinary Least Squares Estimation
Pasep	Civil Servant Heritage Formation Program tax
PCL	Provision for Credit Losses
PD	Probability of Default
PIS	Social Integration Program tax
PP	Phillips-Perron tax
R^2	Coefficient of Determination
RAROC	Risk Adjusted Return on Capital
RFB	Brazilian Internal Revenue Service
ROE	Return on Equity
RWA	Risk-Weighted Assets
SA	Standard Approach
SC	Schwarz Information Criterion
SFN	National Financial System
VaR	Value at Risk
VAR	Vector Auto-Regressive Model
VEC	Vector Error Correction Model
WO	Webel and Ollech test

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1 INTRODUCTION

After the implementation of the “Plano Real” in 1994 and the end of hyperinflation, Brazil began to experience a period of economic stability. This economic environment allowed banks’ profitability to result more directly from credit rather than from funding exclusively (SOARES, 2002). Along with the technological innovations of the period, a new scenario had emerged with the reduction of inflationary losses, the increase in bank spreads and the growth of credit loans (SANTOS; FAMÁ, 2007). These factors challenged financial institutions to speed up credit approvals process while maintaining the risk of operations at acceptable levels. In the Brazilian banking market, the percentage of credit volume relative to the Gross Domestic Product (GDP) jumped from 36% in 1995 to over 47% in 2019, and this level exceeded 50% between 2013 and 2016 (BACEN, 2019c). Even after the Brazilian economic crisis from 2014, which affected the banks’ credit offer, according to BACEN (2017) the percentage of credit volume relative to GDP returned to increase, reflecting a banking market that consistently evolved after the crisis.

In this context of credit growth, financial institutions need to develop increasingly robust tools to manage their portfolios and improve the return to their shareholders, like any other for-profit firm. Therefore, banks’ executives are responsible for developing strategies to increase banks’ profitability and consequently investors’ returns (BASTOS, 2000).

Nowadays, the most widely used measure used to analyze the performance of financial institutions is the Return on Equity (ROE), which is calculated by dividing net income for the period by equity. However, this measure does not consider all the risks incurred, generating a limited view of the real return on financial institutions as the banking activity faces several risks. Given the proportional relationship between risk and return, not considering risks may be a serious limitation, because the results, at least in the short term, could be artificially boosted as institutions take more risk in their activities (KLAASSEN; VAN EEGHEN, 2015).

The main role of a commercial bank is being a financial intermediary between borrowers and lenders, working primarily with third party capital for their loans. As a result, financial institutions usually have higher leverage ratios than other sectors (MARINHO; DE CASTRO, 2018) and consequently they absorb the risks of this intermediation. Thus, banks face various types of risks, such as interest rate risk, market risk, foreign exchange risk, credit risk, operational risk, among others, which may lead to bank insolvency (SAUNDERS, 2000).

As a consequence, the leaders of the main central banks in the world created the Basel Committee on Banking Supervision (BCBS) in order to monitor and supervise the banks, being responsible for recommending to central banks measures to ensure the soundness of these institutions and international financial stability (BCBS, 2014). These measures, known as the Basel Accords, include establishing minimum required capital and adopting procedures to maintain the stability of the financial system.

In the context of risk management, a methodology that has been gaining ground is the Risk Adjusted Return on Capital (RAROC). RAROC was further developed in the 1970s as a measure of economic and financial performance and represents the risk-adjusted return on capital, aiming to measure banks' portfolio risk and to assess the amount of equity needed to face depositor exposures (ENOMOTO, 2002). Regulatory institutions – such as the United States regulators and the Basel Committee - advise banks to use robust models and data to calculate business-related risks, including credit risk and the allocation of required capital (JAMESON, 2001). RAROC models are the most widely applied in this regard as it takes into account economic returns as a result of risks (MILNE; ONORATO, 2009; ECB, 2010).

By analyzing the RAROC, the institution will have a clearer view of its investments, once the return, in this view, is weighted against the risk incurred, unlike ROE. Especially in this increasingly competitive market and given the relevant risks faced by the banking segment, it is important for financial institutions to consider decision-making tools that take risk into account to maximize their returns.

Although widely used and studied, most of RAROC models found in the literature are used extensively for comparison between banks only (CASTRO JUNIOR, 2011; LIMA et al., 2014; ASSIS, 2017; DING; FENG; LIANG, 2018). However, this methodology could be developed internally by comparing, within the same institution, which products generate the most business value. When doing a breakdown by product, as RAROC measures a bank's risk-adjusted return, which products are bringing the highest return, that is, which products are adding more value to the institution and generating more return to the shareholders?

Furthermore, studies found in the literature are concerned with calculating the RAROC for a given base date and some address past periods to measure the robustness of the model (CASTRO JUNIOR, 2011; LIMA et al., 2014; KLAASSEN AND VAN EEGHEN, 2015; ASSIS, 2017; DING; FENG; LIANG, 2018). However, what would be the trend of these products in the future? It would be interesting to be able to project these values, allowing simulations with different parameters, to know what would happen to these portfolios if, for example, the interest rate charged on a product changed? Do fluctuations in macroeconomic variables, such as GDP, tend to affect credit's offer affecting the growth and/or profitability of each product? How would the profitability of these products behave in a hypothetical adverse economic situation? And how would they behave in an optimistic scenario?

Thus, this paper aims to suggest a new approach to profitability analysis for credit operations of a financial institution through the RAROC methodology. With this methodology, based on the assessment of risk-adjusted return, it will be possible to measure profitability stratified within the institution's portfolio of credit operations and will also be able to project its values for a relevant future, enabling the analysis of the return on each risk-adjusted loans in a static as well as prospective manner, allowing product comparison and active portfolio management, assisting managers' decision-making to prioritize operations that truly add value to the institution. For this purpose, a credit institution's databases will be used and three different models are created: Regulatory, Economic and Forecasted RAROC.

The RAROC models are already widespread in the banking market. However, this study innovates when this model is adapted to a level of openness by product and no longer in the grouping of the total portfolio of the institution and when it is prospectively viewed, i.e. projected the value of your indicators for the future. The formula for the RAROC model is relatively simple, the greatest complexity lies in defining some of the parameters required to calculate these components at an open level per product as well as defining econometric models to be used for forecasting.

In order to achieve the main objective, the work is divided into two secondary objectives. The first one is to analyze the database provided by the institution to identify the necessary items that are part of the scope of the RAROC methodology and the disaggregation of the RAROC components to a product level. The second objective is the analysis of a historical period of the main variables involved in order to make projections of these values for the future through econometric models.

From an economics perspective, although there are disagreements about causality, the financial system is unanimously pointed out as fundamental for economic growth and development (PAGANO, 1993). However, there is an interesting discussion about the relationship between the degree of competition in the banking sector and the risk taken by financial institutions and the system as a whole, where some authors argue that the greater the competition the lower the risk (BOYD; DE NICOLÓ, 2005) while others argue the opposite (KEELEY, 1990; ALLEN; GALE, 2000). In Brazil, when compared to other countries, there is still a huge potential for credit growth and increased competitiveness in the sector. Brazil has credit volume to GDP ratios substantially lower than developed countries – such as the United States, Australia, France and Italy – and even lower than in some developing countries - such as China, South Africa and Chile (WORLD BANK, 2018). In addition, the Central Bank of Brazil (2018) estimates a 7.2% growth in the credit balance for 2019. As for concentration, in Brazil the banking segment is highly concentrated, especially compared to countries such as Germany, United States and Japan (BACEN, 2018). Recently, however, the Central Bank of Brazil (BACEN) has been taking measures aiming at greater competition in the sector, especially the “BC+ agenda” and the regulation of *fintech* activity (BANCEN, 2019b).

Within this economic context, financial institutions are facing an increasingly competitive scenario where resources – in this case, especially the issue of required capital – are scarce and the decision to choose between allocating these resources to a particular product or another represents an important trade-off for managers. In this sense, companies need as much information as possible to support their decision making, and the RAROC model emerges as an important tool for assisting managers of financial institutions in the decision making process, as it enables the ranking of products according to their return.

Thus, given the current context of: i) increasing relevance of the risk management process in financial institutions – especially after the third Basel Accord; ii) the importance of the financial system for economic growth and development; iii) the expected scenario for Brazil in the coming years of increased credit volume and competition in the sector; and iv) the relationship between competition in the banking sector and risk. This work is justified both from an academic and financial market points of view.

The proposed model may be used by market players – both financial institutions (to improve their risk management and support decision making) and regulators (to assess risk in the banking sector and the system as a whole), as well as investors themselves that will get a better assessment of the risk involved in their investments. In addition, the study has academics relevance, as the work makes it possible to foster discussion about the importance of the financial system, its relationship between competition and risk, and the decision-making process in competitive environments, as there is a gap in the literature regarding the use of the RAROC model prospectively and disaggregated by product.

In addition to this introduction, this dissertation is structured in four chapters. The next chapter presents the theoretical framework and a literature review on the main topics to be addressed. In the third chapter the methodology to perform the calculation of the RAROC model is presented as well as the database structure used. In the fourth chapter, the results are presented and discussed, both for the proposed models (their results and tests) and for the RAROC model itself. In the final chapter concluding remarks and directions for future research are made.

2 THEORETICAL FRAMEWORK

The theoretical framework aims to present definitions, concepts and methodologies, as well as a literature review on the subject, in order to provide a better understanding of the RAROC methodology, which is the object of this research. Prior to this, however, given that RAROC is the study of risk-adjusted returns, it is necessary to conceptualize risk in the banking system, in particular credit risk. Afterwards, a literature review is presented discussing the relationship of the financial system and economic growth as well as the relationship between sector competition and risk. In addition, concepts of risk management in financial institutions are addressed, including a brief discussion on capital management and the role of the Basel Committee, presenting some of the main risk measurement models.

Additionally, the RAROC methodology is introduced as well as the definition of the concepts of the main variables used in the model. Finally, a literature review is presented addressing empirical studies that used this model. The aim of this literature review is to serve as a reference for the construction of the methodology, especially about the RAROC model, which is the main research problem.

2.1 DEFINITION AND CONCEPT OF RISK IN FINANCIAL INSTITUTIONS

In finance, all actions taken involve a certain degree of uncertainty and risk can be defined as a measure of this uncertainty, i.e. when uncertainty can be measured quantitatively, there is risk (GITMAN, 2004). Risk may also be defined as the probability of financial loss and may be measured by comparing the variability between observed returns and expected returns on a given investment (JORION, 2007).

Risk is inherently associated with bank's operation, since the main purpose of a financial institution is to intermediate resources between surplus and deficit agents, i.e. between creditors and borrowers. Therefore, banks have an obligation to meet the demand of their creditors regarding the liquidity and profitability of the funds invested and also to meet the financing needs of their borrowing customers (LEÃO, 2012). Thus, as banks are debtors to investors and creditors to borrowers, it is usual for a financial institution to eventually absorb the risks of this intermediation, which makes them subject to various risks such as interest rate variation risks, market risk, foreign exchange risk, credit risk, operational risk, among others, which, in the extreme, may lead these institutions to insolvency (SAUNDERS, 2000).

Once the approach of this dissertation regards to credit operations, the main risk faced in this case is the credit risk, which, accordingly to Saunders (2000), may be the most relevant among all the risks incurred by a financial institution. Credit risk is defined as the risk of loss, i.e. the risk of not receiving the payment or flow of payments determined in the loan agreement (SECURATO, 2012).

Altman, Caouete and Narayanan (2000) define credit risk as the probability of the creditors not receiving from the debtor within the agreed time and conditions. Sicsú (2010) defines credit risk as a probability of loss not acceptable to the lender. Referring to the likelihood of loss, credit risk may be defined by the losses generated in the event of deterioration in the quality of loans granted. This deterioration, in turn, occurs not only when there are losses by the financial institution, but also when the probability of loss increases, for example, when signs of possible insolvency are observed (BRITO; ASSAF NETO, 2008a). Also in this sense, Linardi and Ferreira (2008) state that credit risk can be defined as a reduction in the value of a loan portfolio due to changes in credit quality.

Therefore, default or the probability of default is directly related to credit risk. According to the Bank Economy and Credit Report (BACEN, 2018), a survey on the main risks to financial stability conducted by the Central Bank of Brazil, regarding credit risk, default is the most cited internal factor. Hoggarth, Sorensen and Zicchino (2005) also state that the most commonly used way to measure credit risk is to assess default or its probability in a particular credit portfolio. In this sense, Santos and Famá (2007) argue that to minimize this risk, credit risk management stands out, based on subjective (case-by-case analysis) or objective (statistical analysis) procedures such as default risk monitoring. As mentioned, the issue of the insolvency of organizations or their risk has been investigated for several years with relevant studies in Brazil (ALTMAN; BAIDYA; DIAS, 1979; BRITO; ASSAF NETO, 2008a; KANITZ, 1978) and worldwide (ALTMAN, 1968; BEAVER, 1966; CAPON, 1982; DURAND, 1941; FISHER, 1936; OHLSON, 1980).

For credit risk management, the assessed data, whether qualitative or quantitative, should be part of the credit granting process without predetermined ideas, ensuring a fair and equal process. Sometimes, human capacity has limitations in this process due to the number of data and variables and/or the relationship established between them. Despite the techniques applied to improve performance in credit risk assessment, the problem calls for more complex methodologies, thus emerging nonlinear probabilistic models that model human experience, offering a reduction in loan granting time, and same time, presenting a quality and equal criteria response to identical proposals from different clients (PEREIRA; CHORÃO, 2007).

2.2 FINANCIAL SYSTEM, GROWTH, COMPETITION AND RISK LITERATURE REVIEW

From the point of view of economic literature, the financial system began to be seen as important by Schumpeter (1911) in his studies of innovation. Myrdal (1968) also recognized the relevance of banks to economic development in their studies of the process of cumulative circular causation. Since then, especially since the 1980s, various economic growth models have come to include the financial system as an important factor for economic growth and development (PAGANO, 1993), especially the works of Stiglitz and Weiss (1981), Keynes (1982) and King and Levine (1993).

Even endogenous growth models, such as Romer (2006) and Lucas (1988) – which emphasize technology and agent preferences, with little relevance to the financial system – value the banking system because developed financial markets are essential to accelerate economic growth as they lower transaction costs by allocating more efficiently scarce resources (DUTRA; FEIJÓ, 2009).

In a meta-analysis study on financial development and economic growth, Valickova, Havranek and Horvath (2014) found 67 relevant studies between 1993 and 2012 that together implied a positive and significant relationship between financial development and economic growth. However, it is necessary to emphasize that the causality between economic growth and financial development is quite controversial in the economic literature[1], specially about savings. Some authors argue that there should be the formation of a prior saving that will enable investors begin the process of economic growth from there, while other authors argue that this savings will be

[1] Galeano and Feijó (2012) study brings the distinctive view that economic schools have about the relationship between the financial system and economic development, especially the different approach given to savings by each school.

generated during the process of economic expansion (GALEANO; FEIJÓ, 2012). Although there are disagreements about the causal relationship between economic growth and financial development, the economic literature is unanimous in stating that the degree of financial system development and access to credit play an important role in economic growth and development.

In Brazil, there is a great potential for credit growth, as the Central Bank of Brazil estimates a 7.2% acceleration in credit balance growth for 2019 based on the prospect of a favorable economic environment for the coming years, mainly based on the expectation of higher GDP growth (BACEN, 2018). Moreover, it is important to point out that, although the volume of credit relative to GDP has increased in Brazil, when this level is compared to developed countries, the volume of credit in Brazil still has a lot of room to grow. According to World Bank (2018) in July 2018 the ratio of credit to GDP in the United States was 179%, 142% in Australia, 95% in France and 85% in Italy, while in Brazil it was 68%[2]. Furthermore, even when compared to other developing countries it is clear that the level is low in Brazil, as this figure is 150% in China, 143% in South Africa and 109% in Chile, for example. These numbers corroborate the credit growth potential for Brazil in the coming years.

Given the importance of the financial system for economic growth, another interesting discussion regards the relationship between concentration in the banking sector and the risk to which financial institutions and the financial system as a whole are subjects. There is no consensus in the literature, as many authors – as well as most regulators – argue that excessive competition in the sector tends to increase risks for institutions, while other authors argue that it is with a system less concentrated that it will be possible to reduce the risk of the institutions and the financial system as a whole.

Among the authors who argue that greater competition between financial institutions will bring less risk to the system, the theoretical foundation is based on the work of Boyd and De Nicoló (2005). According to them, the evidence that a more concentrated system would reduce risk – as widely assumed in the literature – is at least controversial, since there is empirical evidence in both directions. The theory of

[2] It is important to point out that there are differences in the metric used by the Central Bank of Brazil and the World Bank to calculate the volume of credit in relation to each country's GDP. Because of this, for example, the percentage of credit volume to GDP for Brazil in July 2018 was calculated at 68% by the World Bank while representing 46% by the Central Bank of Brazil.

the authors is based on the idea that banks, having great market power, may charge higher interest rates to their customers, which will increase the probability of these customers defaulting, as they will have to bear very high interest rates on their loans, causing the risk of banks and the financial system as a whole to increase.

However, as a basic principle of banking supervision, the theory prevails that a banking sector with excessive competition brings greater risk to institutions (JIMÉNEZ; LOPEZ; SAURINA, 2007). This view has theoretical foundation in the works of Keeley (1990) and Allen and Gale (2000), because according to the authors in a system with excessive competition the banks would tend to relax their lending requirements, given the more competitive scenario, which would pose a greater risk to the institution and the system as a whole.

Some empirical works are found in the literature that tried to prove the evidences disposed in the theory. These include the work of Jiménez, Lopez and Saurina (2007) who tested both theories in a study of the Spanish banking system and ultimately confirmed that there is a negative relationship between banks' market power and risk. In other words, the greater the market power of banks, the lower the risk of the system. There are also more recent empirical works with the same objective of compare the result of the theories in this regard, among them the works of Tan (2016), Bushman, Hendricks and Williams (2016) and Marsh and Sengupta (2017).

Tan's paper (2016) studied the Chinese banking market where several reforms in recent years have aimed to increase competitiveness in the sector while maintaining the stability of the financial system. According to the author, no robust results could be found to confirm the theory that increasing the sector's competitiveness would bring greater risks. On the other hand, studies for the United States banking market like Bushman, Hendricks and Williams (2016) and Marsh and Sengupta (2017) found strong evidence that excessive increase in banking competition brings with it increases in risks, both individually for banks and for the system as a whole.

In Brazil, it is known that the banking sector is historically concentrated. According to the 2018 Bank Economy Report (BACEN, 2018), the commercial banking segment has an HHI of 0.1630 and a CR5 of 84.8%[3], while developed countries such as Germany, the United States, and Japan, for example, had a CR5 of 35%, 43% and

[3] The Central Bank of Brazil uses to measure the sector concentration, mainly the normalized HHI (normalized Herfindahl-Hirschman Index) and CR5 (Concentration Ratio of the 5 largest) indices. The data presented refer to the indices according to credit operations.

51%, respectively. However, the Brazilian Central Bank itself has recently been taking steps to increase competition in the sector, as, according to the entity, the greater the competition between institutions, the more efficient these institutions will become and consequently the lower the costs of services and products provided to citizens (BACEN, 2019b).

In this sense, mainly two factors have made the system has a tendency of deconcentrating and consequent increase of competitiveness. The first factor is the "BC+ agenda", which intends to facilitate the entry of foreign entities in order to increase the sector's competitiveness and reduce bank spreads (BACEN, 2018). In addition, through its Resolution No. 4,656 of April 26, 2018, the National Monetary Council (CMN, 2018) disciplined the conduct of credit operations between persons through companies based on electronic platforms. This resolution paved the way for these companies – known as *fintechs* – to operate without being linked to a conventional financial institution. Since then, there has been a growing wave of *fintechs* in both business and customer numbers, which has induced the traditional banking industry to modernize and improve profitability to remain competitive in the market (H2 VENTURES; KPMG, 2018).

Factors such the potential for credit volume growth and increased competition in the banking sector, further reinforce the relevance of risk management in financial institutions, bringing greater challenges to the decision-making process. In the case of a bank, equity may be considered the main available resource and, given its scarcity, the decision of where to allocate it becomes a trade-off inherent to a financial institution.

In the economic literature there are many models that study the decision-making process, from rational agents models to behavioral models[4]. Therefore, the model proposed in this dissertation may contributed to this discussion, since it could serve as a tool for managers of financial institutions and help them to identify and prioritize the products that have higher risk-adjusted return.

2.3 RISK MANAGEMENT IN FINANCIAL INSTITUTIONS

[4] In Gontijo and Maia (2004), it is possible to find a review of the main existing models for decision-making.

Banks operate in a dynamic, volatile, regulated and competitive market and, therefore, the management of financial institutions is directly associated with good risk management, as these will have a direct impact on the institution's economic and financial performance (ASSIS, 2017). The risk management structure in financial institutions involves the establishment of appropriate policies for the company that enable comprehensive risk mediation, pricing and control (CROUHY; GALAI; MARK, 2000).

Risk assessment and management is approached by the theory of coherent risk analysis that involves, among other factors, the development of risk management models, incorporating issues such as the optimization of invested capital (CHERNY, 2008). In addition, the development of methodologies should take into account risk management for the company as a whole, seeking integrated management of all risks in terms of unit of measure and common strategies, in order to comply with Resolution No. 4,557 of February 23, 2017. This resolution deals with the risk management structure and capital management structure of financial institutions, especially regarding integrated risk management in institutions (CMN, 2017).

Risk being defined as the probability of loss, risk management models should be able to incorporate and predict the loss. Risk in a financial institution is basically composed of two types of losses: expected losses and unexpected losses (ZAIK et al., 1996). Expected losses are represented as those losses that the institution expects to incur according to the risk levels of the operation, being accepted as part of the business. Therefore, according to Marshal (2001), the institutions' revenues must cover these losses and, consequently, the banks must make the provision of these amounts in their balance sheets, which is recorded as Allowance for Loan and Lease Losses (ALLL). Unexpected losses, on the other hand, correspond to the maximum losses that an institution may face – minus the expected losses that are already provisioned – and, therefore, banks must have enough equity to face these possible unexpected losses (DANTAS; PEREIRA; CARVALHO, 2018).

Because of those risks, there are regulations that require banks to have minimum capital requirements to account for them, in particular the portion of unexpected losses in the case of credit risk. As a consequence, the Basel Accords emerged, where the leaders of the main central banks in the world met and created the Basel Committee on Banking Supervision (BCBS) to monitor and supervise the banks, being responsible for recommending to central banks measures to ensure the soundness of these institutions and international financial stability (BCBS, 2014). These measures include establishing minimum required capital and adopting measures to maintain the stability of the financial system.

2.3.1 Basel Accords and the Definition of Equity

Following the onset of a crisis in the international financial system in 1974 caused by the insolvency of the German bank *Bankhaus Herstatt* and the unilateral decision of the United States to end the *Bretton Woods*[5] system in 1973, the world was experiencing a very fragile period in relation to the financial system. As a consequence of this context, as said before, the Basel Accords emerged.

Among the main measures recommended by this committee is the minimum capital requirement for financial institutions, given the various risks to which they are exposed. This equity requirement aims to ensure that banks will have sufficient capital to face potential financial losses that may occur, ensuring the soundness of the global financial system. Since the portion of losses that institutions already expect to lose (expected loss) is already provisioned, the required equity is intended to cover unexpected losses. It is noteworthy that the level of equity required is related to the risk taken by these institutions, reinforcing the need for sound risk management by financial institutions.

Another important point to note is that the Basel Accord itself represents only a set of recommendations, having no value from a law imposed on central banks, i.e. there is no obligation to be followed by central banks around the world. However, most central banks end up adopting the committee's recommendations and thus making the recommendations mandatory according to the legislation of each country.

The first meeting of the Basel committee took place in 1974, however the first agreement – known as Basel I – was not published until 1988. After Basel I, two other agreements were signed in 2004 and 2010, as can be seen in Figure 1, which summarizes the dates and key points addressed in each one of the existing Basel Accords.

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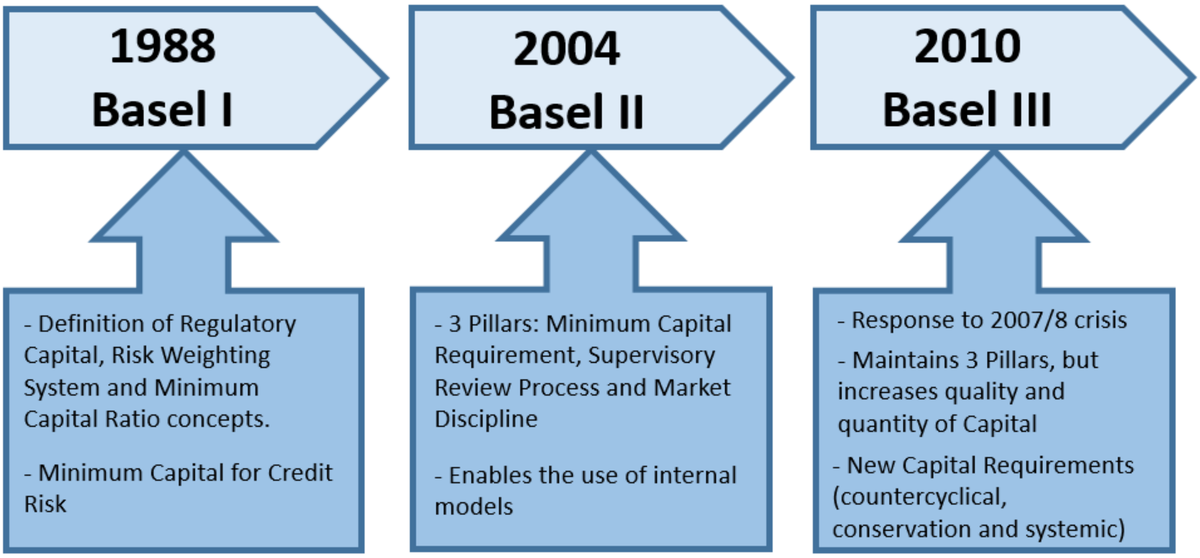
[5] The Bretton Woods system was an agreement between the world's major economies made in 1944 that defined the dollar as the international currency and stipulated a fixed exchange rate system known as the gold-dollar standard that lasted until 1973.

Figure 1 – Basel Accords



Source: elaborated by the author based on BCBS (2014)

From the first Basel Accord, the committee's concern with the determination of a minimum equity for financial institutions, defined as Regulatory Capital, is clear. In this first agreement, a minimum requirement was established only for Credit Risk[6] – which was the main concern at the time – and the following indicators were defined:

i) tier 1: is the core capital and consists of equity, common stock, reserves and retained earnings;

ii) tier *2*: is the supplementary capital and consists of hybrid fundraising instruments, such as subordinated debt.

Tier 1 capital represents the primary funding source of a Financial Institution and it is considered more reliable than Tier 2 capital, that is more difficult to accurately calculate and more difficult to liquidate.

In addition to Regulatory Capital, the Basel I agreement also defined other important concepts such as Risk-Weighted Assets (RWA) and Minimum Capital Adequacy Ratio. The concept of RWA encompasses a weight that should be applied according to the credit or borrower profile, i.e. each type of operation would have a different weight (determined by the Regulator, usually the country's Central Bank) and, consequently, different capital requirements. The concept of Minimum Capital

[6] In 1996 the Committee issued the *Market Risk Amendment to the Capital Accord*, including the minimum capital requirement for Market Risk arising from banks' exposures to foreign exchange, traded debt securities, equities, commodities and options.

Adequacy Ratio corresponded to the ratio between the institution's assets – weighted by the Weighting Factor – on Regulatory Capital, also known as the Basel Index (SECURATO, 2012).

Prior to Basel I there was no standardized regulation of supervision at the global level, that is, most countries did not even adopt minimum capital requirements – only maximum leverage ratios were set – and the few countries that adopted it did so non-standardly, resulting in a minimum standard that varied from country to country. An important factor of the Basel I agreement is that, in this first agreement, banks were not given the opportunity to create internal models for risk management and capital measurement, i.e. the expected loss and unexpected loss calculations should be performed exclusively in accordance with the standard (KAPSTEIN, 1991).

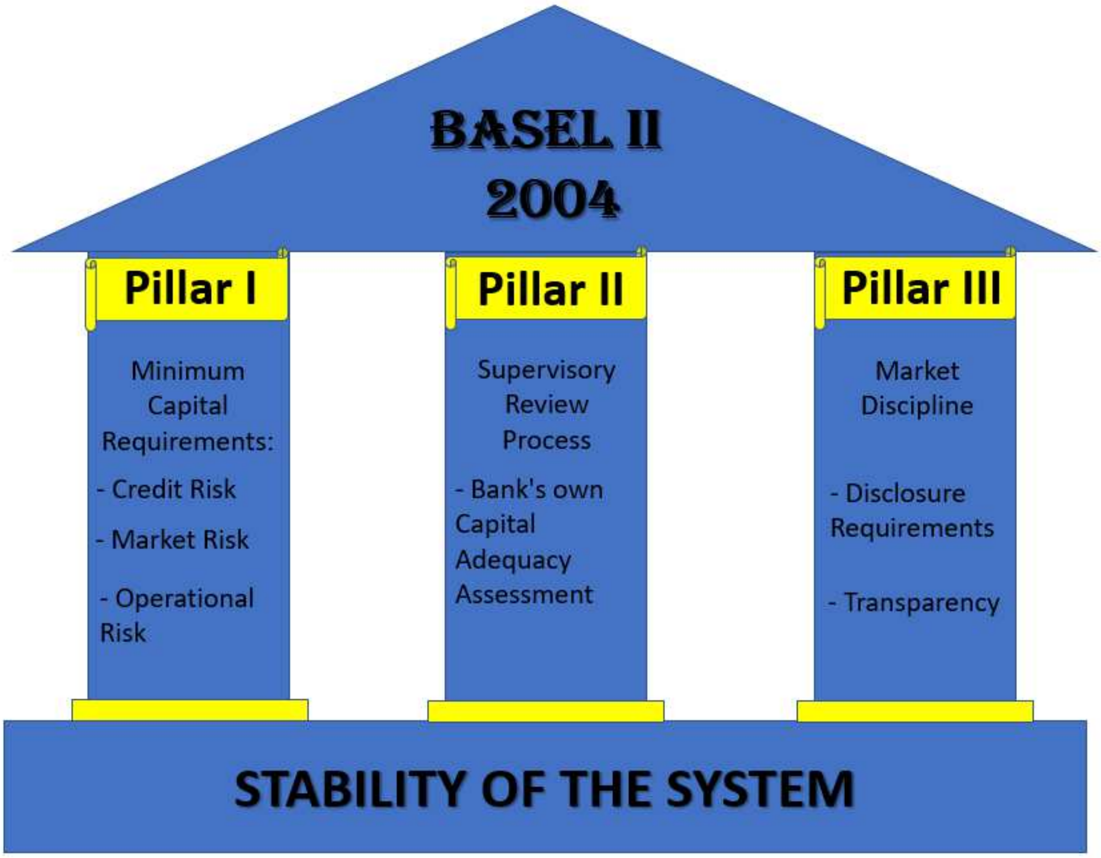
Although Basel I made significant advances in banking regulation, its definitions were not sufficient to prevent many financial institutions from becoming insolvent in the 1990s. Thus, discussions on risk and capital management continued, resulting in a second agreement signed in 2004, which became known as Basel II.

The second Basel agreement encompasses a much broader view of a financial institution's risk management and innovates by allowing institutions to have the possibility to develop internal risk management models and to measure the required equity, i.e. banks could reduce the need for equity through the efficient management of their risks, encouraging the strategic use of their data and intellectual capital (ASSIS, 2017).

The Basel II agreement was established based on three fundamental concepts aimed at ensuring the stability of the international financial system. These three concepts became known as the 3 Pillars of Basel II, as can be seen in Figure 2 which illustrates the idea of Basel II and summarizes the main points addressed in each of the pillars.

Pillar 1 addressed the issues regarding the minimum capital requirement, similar to what already occurred in Basel I, but with the inclusion of the Capital Requirement for Operational Risk and, also, with the updating and refinement of the methodology for Credit Risk, resulting in a stronger equity structure compared to the first agreement. Pillar 2 addressed the incentives for adopting best risk management practices, adopting control measures and defining the monitoring methodologies of the institutions, launching the banking supervision and governance guidelines, focusing on stimulating financial institutions in the development of own management models, enabling the improvement of the supervision of the system as a whole. In Pillar 3, the intention was to reduce information asymmetry by encouraging transparency when disclosing information to the market, creating what became known as market discipline.

Figure 2 – The 3 Pillars of Basel II



Source: elaborated by the author based on BCBS (2014)

Additionally, shortly after the Basel II agreement – but still in 2004, the agency issued a review that basically incorporates the idea of Concentration Risk, which corresponds to that risk that occurs when an institution has too much exposure to a single client. This review became known as Basel II.5.

It is noteworthy that the second Basel Accord brought a much broader view of a financial institution's risk management and laid pillars that are followed to the present day. However, in 2007 the world faced a new world-wide financial crisis that became known as the *Subprime crisis*[7], prompting the members of the Basel committee to rethink some proposals of the existing agreement, which became known as Basel III.

The main objective of this third agreement is to provide greater resilience to the banking sector, as the agreement provides for a greater amount of equity for institutions and also provides rules to ensure that this capital is of better quality, increasing risk coverage.

Among the main definitions of Basel III aimed at ensuring better quality capital, stands out the separation of Tier 1 capital between Common Equity and Additional Tier 1, with only high quality assets – such as common shares and reserves profit – being eligible to make up the Common Equity. Parallel to this segregation between Common and Additional Equity, the committee now creates minimum capital ratios that are also specific to these new capital segregations, i.e. Minimum Common Equity Index and Minimum Additional Tier 1 Index. These definitions aim to strengthen the requirement on higher quality capital, because this way there is a clearer view of the capital composition of financial institutions (PINHEIRO; SAVÓIA; SECURATO, 2015).

Moreover, the Basel III Accord also created an additional capital system – beyond the Additional Tier 1 Capital – that must be composed by banks in specific situations. These additions, known as *buffers*, are a kind of reserve “cushion” designed to further strengthen the resilience of the system and are made up of three subgroups:

i) Countercyclical *buffer*, required at times of strong economic growth;

ii) Capital Conservation *buffer*, extra portion to absorb losses; and

iii) Systemically Important Capital, required from those institutions that are systemically important at a global level.

Therefore, it can be concluded that the Basel Accords, by requiring more capital and quality in capital, further underline the importance of risk management models in financial institutions. In this context, a methodology that has been gaining ground in both Brazil and the rest of the world is RAROC. Most of the world's regulatory institutions, such as the United States regulators and the Basel Committee, tell banks to use robust models and data for calculating business risks, including credit risk and also the necessary capital allocation (JAMESON, 2001) and RAROC models are the most widely applied in this regard (MILNE; ONORATO, 2009). Moreover, according to

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[7] The *Subprime Crisis* was a worldwide financial crisis triggered in 2007 that was primarily motivated by the provision of high risk mortgage lending that led several systemically important banks into insolvency, provoking an international financial crisis.

the European Central Bank (ECB, 2010) RAROC is the most relevant performance measure as it takes into account economic returns considering risks.

2.3.2 Risk Measurement Models

Since the 1990s, in parallel with the models imposed by regulators, banks have developed several internal models to measure their risks more efficiently, in order to manage their exposures subject to financial losses, as well as the equity measurement needed to cover unexpected losses (LOPEZ; SAIDENBERG, 2000).

Institutionally developed models – such as JP Morgan's *CreditMetrics*, Credit Suisse's *CreditRisk+* and KMV's *Credit Monitor* – seek to incorporate the widest array of information possible, such as the use of macroeconomic variables and market value of the institutions, for example. However, its main limitation is precisely the fact that they do not have all the necessary information, which makes the proposed models more difficult, especially in terms of longer-term projections (JARROW; TURNBULL, 2000).

When dealing with credit risk, the two main variables to be estimated correspond to the calculation of the expected loss – which constitutes the provision – and the calculation of the unexpected credit loss – which constitutes required capital.

2.3.2.1 Expected Loss or Provision

For the calculation of the expected loss (provision) currently the regulation in force in Brazil is the National Monetary Council Norm 2,682/99, which establishes the rules and guidelines for the classification and provision of credit operations to financial institutions operating within the scope of National Financial System (SFN).

According to this norm, credit operations must be ranked in ascending order of risk from AA to H, called ratings. Each of these ratings will have a corresponding level of minimum provisioning between 0% and 100% applicable to the book value of transactions, considering a maximum of delay days (DANTAS et al, 2017), as shown in Table 1. This is the way currently financial institutions authorized to operate in Brazil calculate their provisions for credit operations, which will be informed in the Balance Sheet and Income Statement (or Profit and Loss Report). Therefore, this methodology is known as BR GAAP.

Table 1 – Percentage of Provision following Resolution no. 2,682/99

Rating	Maximum delay (days)	Provision Percentage
AA	0	0.00%
A	14	0.50%
B	30	1.00%
C	60	3.00%
D	90	10.00%
E	120	30.00%
F	150	50.00%
G	180	70.00%
H	over 180	100.00%

Source: elaborated by the author based on CMN (1999)

Although BR GAAP has a conceptual basis related to expected losses, in fact this model can be considered much more as a losses incurred model, once it mainly relies on product loss history to define current provisioning levels (YANAKA, 2014; CANECA, 2015).

On the subject, Araújo (2014) also states that the standard can be considered a mixed system, as it has characteristics of both expected losses and incurred losses. The standard establishes that financial institutions must assess the risk of the borrower and the operation, but does not determine how these factors should be combined, and only some of these criteria were fixed, such as the borrower's economic and financial situation, degree indebtedness, cash flow, history, among others (VERRONE, 2007). Thus, it is up to the banks to classify the operation at the corresponding risk level, and should be based on consistent and verifiable criteria, supported by internal and external information (DANTAS et al., 2017).

In parallel to BR GAAP, financial institutions must calculate provisions based on an international model known as IAS39. However, in view of the vulnerabilities presented by this model and the fact that it has a purely backward-looking view, i.e. based only on losses incurred, from 2018 the International Financial Reporting Standards (IFRS 9) became effective, replacing IAS39 and subsequently intended to replace BR GAAP. Thus, the purpose of regulatory bodies is to standardize accounting procedures and policies across nations by providing comparison of financial statements across countries (SERASA, 2019).

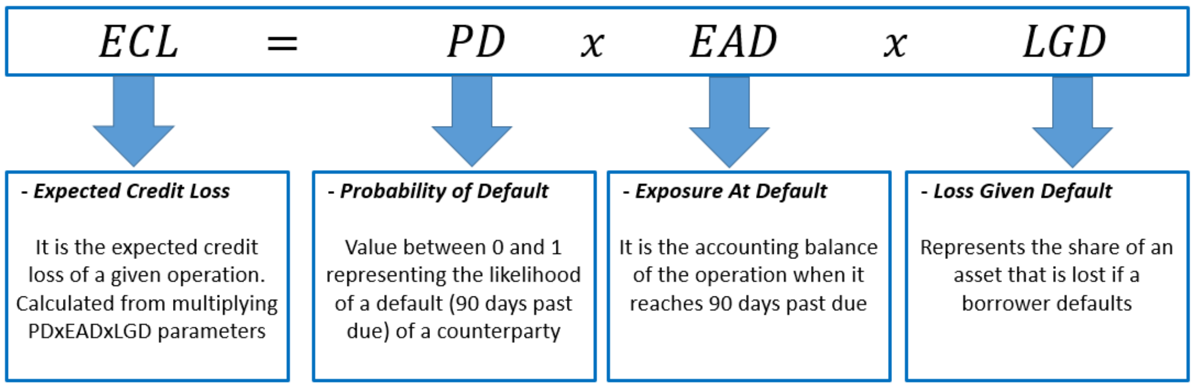
In addition, IFRS 9 assumes a substantial revision of the current impairment accounting standard, replacing the IAS39 incurred loss approach with an Expected

Credit Loss (ECL) framework. This will allow entities to recognize credit losses early and timely, better reflecting the reality of the institution's losses.

Expected credit losses should be measured considering as much information as possible. Some of the key aspects defined by IFRS 9 express that losses should represent the present value of all contractual cash flows anticipated and not received (or partially received) over the expected life of the financial instrument. In addition, loss calculation models should incorporate past, present and future information about borrowers and macroeconomic variables. Still on the macroeconomic variables, they must address more than one scenario, that is, they should reflect an amount weighted by the probabilities of a range of possible scenarios and not just one scenario (SERASA, 2019).

Consequently, the idea of expected loss calculated by the IFRS 9 model is the Expected Credit Loss (ECL) which estimation approach is based on the definition of cash flows and estimation of the parameters: Probability of Default (PD), Exposure At Default (EAD) and Loss Given Default (LGD), as shown in Figure 3:

Figure 3 – Components of ECL (PD, EAD and LGD)



Source: elaborated by the author based on KPMG (2018).

Therefore, the Expected Credit Loss will be the multiplication of these three components, each of them having its own calculation methodology, making the ECL calculation measurement process more complex compared to BR GAAP. However, it is expected that by incorporating much more factors, this would represent more accurately the reality of financial institutions' credit portfolios.

2.3.2.2 Unexpected Loss or Required Capital

As for the measurement of equity or unexpected loss, most banks currently calculate these values following regulations imposed by the Central Bank or the National Monetary Council. However, because they are standardized models, they may not reflect as well as possible the specificity of each institution and both the Central Bank itself and the Basel committee encourage banks to create their internal models for capital calculation.

There are, therefore, internal models that aim to calculate those same parameters and, as each institution creates these models internally, it is expected that they will be able to measure more precisely the risks of that institution, representing a more accurate view from the reality of each bank. The JP Morgan's CreditMetrics, Credit Suisse's CreditRisk+ and KMV's Credit Monitor are the most know examples of these models.

In the case of Equity specified by the regulator, i.e. the calculation of Regulatory Capital, the Basel Committee established three models to determine the capital requirement for credit risk: i) Standard Approach (SA); ii) Foundational Internal-Rating Approach (FIRD); and iii) Advanced Internal-Rating Based Approach (AIRB).

Nowadays in Brazil it is used the Standard Approach (SA), which consists of several rules that specify how it should be done, but succinctly the calculation involves a certain weight that will multiply the net allowance balances (the balance minus the provision). The Regulatory Capital required for an institution to operate in the financial market should be understood as the minimum necessary to address risks while preserving the integrity of the institution and thus the resources of third parties and shareholders.

In Brazil, the Resolution No. 4,192/13 from the CMN divides Regulatory Capital into: Tier I, composed of Common Equity (or Main Capital) and Additional Tier 1 (or Supplementary Capital), and Tier II Capital. However, CMN Resolution No. 4,193/13 set minimum limits to be observed in determining the various levels of capital and also considering compliance with the Additional Capital system. In addition, the regulator may request the Add-On (Additional Capital Requirement), a preventive measure adopted to cover situations that may compromise the regular operation of the institution, according to CMN Resolution No. 4,019/11.

In order to calculate the minimum capital requirements, the amount of risk-weighted assets (RWA), which corresponds to the net allowance balance multiplied by the risk weights, shall be calculated. The concept of net allowance balance means that the amount of the provision is subtracted from the book value of the operation (currently under the BR GAAP model as seen in the previous item) and the risk weights are defined by the regulator according to the type of operation, these being published in several circulars.

For institutions using the standardized approach, the calculation of minimum capital requirements corresponds to the sum of the installments related to exposures subject to credit risk, market risk and operational risk.

Therefore, the calculation of the total amount of risk-weighted assets (RWATOTAL) is based on the sum of exposure calculations for each of the risks presented, according to the methodology defined by Bacen. CMN Resolution No. 4,193/13 states that financial institutions must permanently maintain capital amounts consistent with the risks of their activities, represented by the amount of RWA, and establishes the minimum requirements for Reference Equity, Tier 1 Capital and Core Capital, considering the application of the Additional Principal Capital.

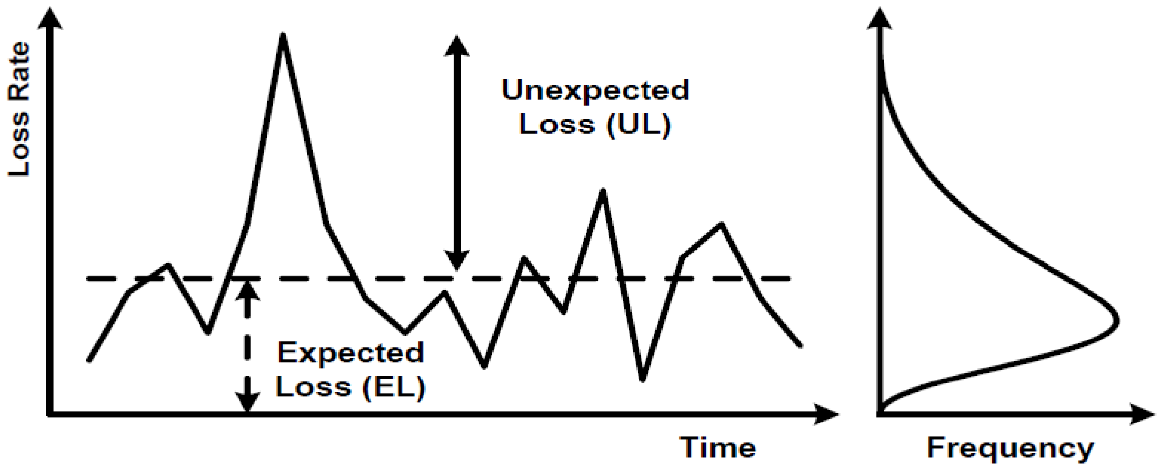
On the other hand, the internal models for capital calculation to be allocated represent an idea of economic capital, different from the idea of regulatory capital described above. Both calculations, regulatory and economic capital, have the same goal: to measure the capital to be allocated that addresses the risks inherent in the unexpected loss. However, calculation via the internal model, that is, economic capital, is expected to better represent the reality of an institution's risks covering the idiosyncratic effects inherent in each bank, unlike the standard regulatory model given by the regulator and the same for all institutions.

Moreover, as the internal models are more sophisticated than standardized, these models make capital requirements more sensitive to risk exposures. In addition, regulatory capital requirements tend to be higher than economically necessary, thus internal models could allow banks to reduce their capital charges, increasing its potential profitability and becoming more competitive. Therefore, it turns as an incentive for banks to invest in improvements in their risk measurement technology (ALLEN; BOUDOUKH; SAUNDERS, 2004).

Seeking for models to accurate measure risk and relatively inexpensive to estimate, the Value at Risk (VaR) methodology has been widely adopted specially after the Basel Committee on Banking Supervision allow – and also stimulate – the banks to calculate their capital requirements based on their own internal models. Another reason for the popularization was the creation of the *RiskMetrics* models by JP Morgan, which quickly spread this methodology (ALLEN; BOUDOUKH; SAUNDERS, 2004).

The VaR methodology represents a maximum loss that a given portfolio may incur, given a level of statistical significance and a period (JORION, 2007; MAGRO, 2008). The VaR may also be determined as the volatility around the projected average expected loss, reflecting the possibility of loss in adverse situations, which institutions must have equity to face in order not to compromise the institution and ensuring the continuity of Business. Figure 4 illustrates this situation.

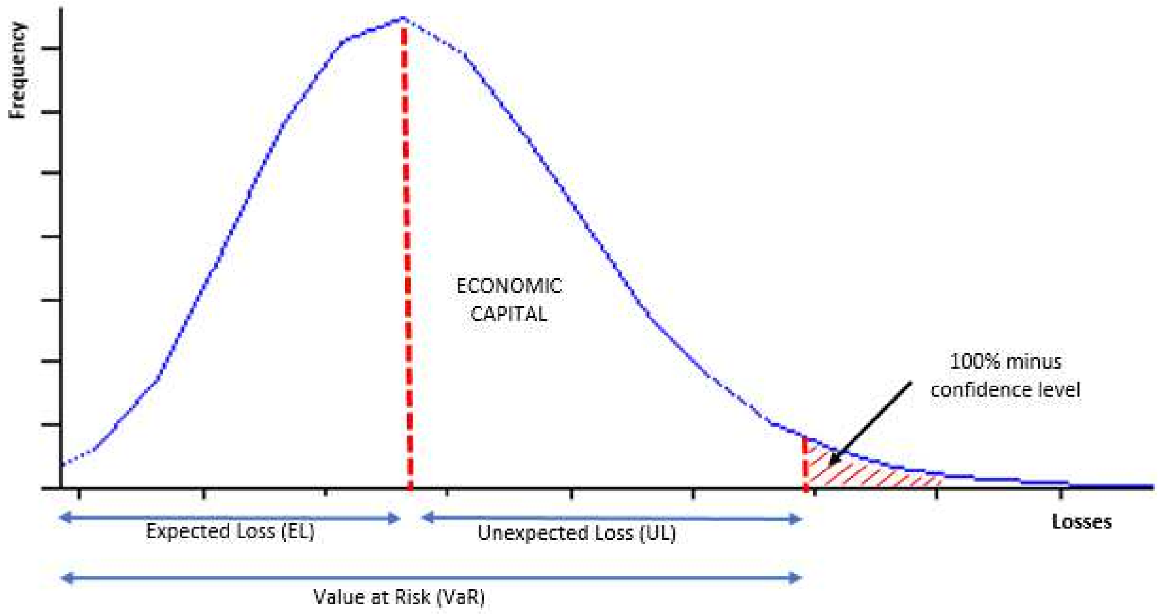
Figure 4 – The Value at Risk (VaR)



Source: BCBS (2005).

Given a distribution of losses generated by VaR, it may be divided into Expected Loss and Unexpected Loss. The Expected Loss represents the provision (either via BR GAAP or via IFRS9) and the Unexpected Loss represents the capital to be allocated (either regulatory or economic capital). Figure 5 presents the idea of loss distribution between Expected Loss and Unexpected Loss.

Figure 5 – Loss Distribution



Source: elaborated by the author based on BCBS (2005).

VaR must be defined according to two parameters: the period and the confidence level. A one-year VaR with 99.9% confidence represents the largest possible loss within one year in 99.9% of cases. Credit VaR can also be defined for various time periods and confidence intervals, the most common being a 12 month period in accordance with the regulatory standard defined by the Basel Accords.

Once defined the VaR methodology for calculating the Economic Capital, it is important to note that there are several ways to calculate VaR, such as historical VaR, parametric VaR or even via Monte Carlo simulations (ANDO; LOPES, 2010). Further details on the VaR methodology are available in section 3.2.2.

2.4 RAROC

Among the risk measurement models, there is the Risk Adjusted Return on Capital (RAROC) methodology, which represents the financial return that a given credit portfolio offers in relation to the amount of equity that is necessary to face this credit portfolio, risk-based. This methodology was developed in the 1970s by Bankers Trust, but it was only recently that it became widespread know and used in financial institutions, especially in Brazil (CAROLLO, 2008; ENOMOTO, 2002).

Initially, RAROC was only used in aggregate form, comprising a financial indicator, from a set of indicators already adopted in the market. However, because it represents the return on risk-adjusted capital, this methodology may be used extensively, since it actually represents the opportunity cost of capital funded by a shareholder. Therefore, it is up to the institution's executives to generate strategies for sustained growth of profitability and consequent remuneration of its shareholders (BASTOS, 2000).

The standard formula for return on risk capital created by Bankers Trust is as follows:

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

where Profit is a measure of the profitability of the operation as it contains all product revenues minus product costs including provisioning expenses; Capital, on the other hand, represents the investor's capital, since it is that amount of equity that the bank needs to allocate to cope with unexpected losses. Thus, this indicator represents the return that will be obtained by the operation relative to the required capital (BASTOS, 2000).

Once those measures have been calculated, the calculation of RAROC is straightforward, as shown in equation (1). Its result indicates an accurate measure of the profit that, in fact, remunerates the capital invested by shareholders and brings sustainability to the institution (ZAIK et al., 1996). The formula is relatively simple, but over time several different approaches have been developed for the calculation of each component, due to new techniques that emerged after the development of the RAROC model in the 1970s.

According to Securato (2012), the original formula developed by Bankers Trust measured capital (denominator) as equity that the regulator requires banks to have, i.e. regulatory capital. However, a new version developed by Bank of America and used by most banks nowadays, considers equity as risk-adjusted economic capital, which is calculated by institutions' own models using the Value at Risk (VaR) methodology. This technique calculates the maximum loss that a given capital may incur, and the economic capital should be sufficient to meet the unexpected losses (since the expected losses are already covered by the provision) calculated through a certain level of statistical confidence and for a certain period of time, as seen in the VaR definition. Following the lines of Bank of America, Saunders (2000), Smithson and Hayt (2001) and Kraus (2013) have also proposed this change in the form of capital calculation stating that the denominator should encompass economic capital rather than regulatory capital. Other authors who suggested changes along the same lines were Prokopczuk, Rachev and Trück (2004) defining that economic capital should be calculated using a VaR model.

In addition to the capital calculation, the profit (numerator) calculation also changed over time. Prokopczuk, Rachev and Trück (2004) questioned the subtraction of the expected loss in profit as a risk adjustment, because, according to the authors, if the loss is already expected then there is no risk in this regard. Other authors who proposed a change in the form of the calculation was Chapelle et al. (2008), according to the authors, the numerator should be composed of economic profit or Economic Value Added (EVA). In this way the numerator could include, among other factors, an opportunity cost with profit going from accounting profit to economic profit.

Therefore, it is possible to notice that there are disagreements between the authors regarding the calculation of the RAROC components, and numerous ways of performing this calculation are presented. However, they all maintain the same pattern of assessing profitability and capital as needed and measuring return on capital, risk-adjusted.

In fact, Castro Junior (2011) conducted a study with the main Brazilian commercial banks and tested various ways of calculating the RAROC[8], making the calculation with the minimum required capital (Basel), capital by the VaR method, capital by reference equity, capital based on the normal course portfolio (Tier 1), capital related to portfolio duration and capital by the BIS IRB method. In this study, the author concluded that, although there are several ways to calculate RAROC, no significant differences were found between the methodologies.

As stated earlier, the RAROC formula is relatively simple, and the greatest difficulty is in obtaining some parameters that are part of the formula, which will be dealt with in the following sections. According to Castro Junior (2011), the main

[8] In Castro Junior (2011) it is possible to find the approaches and calculations performed with the different techniques, as well as the results found for each of the approaches.

challenges in calculating RAROC are related to the measurement of the variables that represent the Expected Loss (provision) and the Unexpected Loss (economic capital) or even the difficulty that financial institutions have to calculate revenues and expenditure disaggregated at product level given their complexity.

2.4.1 RAROC Components Definitions and Concepts

Given the possibility of several ways of calculating RAROC as previously seen, this section is necessary to conceptually define which components are used in the model proposed in this work and which formula is used to calculate these components.

i) Income

Income from financial intermediation corresponds to interest charged by banks on loans made, the income that financial institutions collect directly from credit operations and the main income from financial institutions. It can be calculated by multiplying the loan interest rate by the balance of operations (KONG; LI; YE, 2017).

ii) Capital Cost

Capital Costs expenses with financial intermediation, on the other hand, correspond to interest paid by banks to those who deposit money with the institution. These costs reflect the costs of raising money, i.e. how much banks pay their savers. According to the Central Bank's Bank Economics Report (BACEN, 2018), the funding cost is strongly linked to the CDI rate[9], although it makes the caveat that, depending on the institution's funding structure, these variables may be more or less related, since the cost of funding is an average of several funding rates. Although this warning made by the Central Bank, adopting the CDI rate as the average funding cost of financial institutions is a widely used measure.

iii) Administrative Cost

It is the expenses arising from the organizational structure of the institution, that is, the expenses with wages, data processing, communications, rent, among others, which support the company's activities (BRUGNERA; GIENTORSKI, 1998). These

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[9] CDI represents the Brazil Interbank Deposit rate and it is strongly close to SELIC (Brazil federal funds rate) which is the rate that private and public banks bases to calculate their own interest rates.

costs are recorded in the administrative expense accounts of the institution that are required to send monthly to the Central Bank of Brazil, which in turn makes this information available in the form of a “Balance Sheet / General Balance”. Among these accounts, there is the account 81700006, which represents the “Administrative Costs” (BACEN, 2019a).

iv) Taxes

According to the Brazilian Internal Revenue Service (RFB) taxes on a financial institution are as follows: Corporate Income Tax (IRPJ), Social Contribution on Net Income (CSLL), Social Security (Cofins) and social contributions to the Social Integration Program (PIS) and the Civil Servant Heritage Formation Program (Pasep) (RFB, 2019).

Those taxes have a different tax base calculation. The IRPJ and CSLL are levied on profit while PIS/Pasep and Cofins are levied on revenues, and expenses with fundraising may be discounted (RFB, 2019). Regarding the rates, RFB Normative Instruction No. 1,285 of 2012 deals with the rates of PIS/Pasep and Cofins which are currently 0.65% and 4%, respectively. RFB Normative Instruction No. 1,700 of 2017 deals with IRPJ and CSLL rates. The IRPJ tax rate is 15%, and what exceeds the result of multiplying R$ 20,000 by the number of months of the calculation period will be subject to an additional tax rate of 10%, totaling 25%. CSLL, on the other hand, has a 15% rate for financial institutions. It is important to note that this rate was 20% until December 2018 imposed by Provisional Measure 675 during the Dilma administration, which lasted for 3 years, and after this period, that is, from January 2019 onwards it would return to the 15% rate, although it may be increased again at any time via the Provisional Measure.

Table 2 summarizes the taxes to which financial institutions are exposed.

Table 2 – Taxes levied on a Financial Institution

Tax	Tax Base	Prevailing Rates	Normative
IRPJ	Profit	25%	RFB Normative Instruction No 1,285
CSLL	Profit	15%	RFB Normative Instruction No 1,285
PIS/Pasep	Revenue	0.65%	RFB Normative Instruction No 1,700
Cofins	Revenue	4%	RFB Normative Instruction No 1,700

Source: elaborated by the author based on RFB (2019).

v) Opportunity Cost

Represents the opportunity cost of the money allocated in that transaction, that is, the cost the investor has of failing to invest his money in any other asset such as government securities or even another type of security. By including this cost in the RAROC model, the product profit (numerator of the formula) becomes a function of economic profit and not just accounting, as proposed in the work of Chapelle et al. (2008). For this purpose, the average profitability of the Brazilian banking sector, which is disclosed to the market by financial institutions, may be used. However, for the sake of simplicity, this paper chose not to include the opportunity cost in the RAROC formula, and it will be used as a benchmark to evaluate the RAROC result.

vi) Provision or Expected Loss

One of the main difficulties in calculating the RAROC is the estimation of the expected loss or provision (CASTRO JUNIOR, 2011). The amounts calculated in accordance with current regulations (norm 2,682/99 of the National Monetary Council) or by the IFRS9 models could be used. Given that the IFRS9 models are still in an incipient phase worldwide, their value history turns out to be a very small sample, which would make it difficult to develop models for projecting these values to be incorporated into the projected RAROC. Thus, we chose to use the values of the current standard.

vii) Required Capital or Unexpected Loss

Another difficulty in calculating RAROC is the estimation of models that aim to measure Unexpected Loss. As with the expected loss, this value might also be obtained through regulatory calculations or through an internal model (as seen in section 2.3.2). In this case, given the relevance of the calculation of equity among the RAROC methodologies, it was decided to estimate this value via both models (regulatory and internal), allowing their comparison.

2.4.2 RAROC Applications

Several applications of the RAROC model in financial institutions are found in the literature. The RAROC model may be used both *ex-ante* and *ex-post.* As an example of the first, the model can be used to help managers defining which portfolios bring risk-adjusted returns, that is, which operations are bringing back return on invested capital. On the other hand, when used *ex-post,* the model facilitates the comparison and analysis of the performance of these portfolios in a view that prioritizes risk-adjusted invested capital, that is, it is possible to evaluate among the operations that are being granted which ones are better remunerating the shareholders' capital (CASTRO JUNIOR, 2011).

There are already several banks using this tool to control and manage their risks – especially credit risk – and investors have turned to this tool primarily to compare which institutions will bring you the highest risk-adjusted return, which is best suited to the reality. Although it was developed in the 1970s, examples of this approach are more frequently found in the literature since the 2000s, as in the cases of Milne and Onorato (2009), Silva, Ribeiro and Sheng (2011) and Castro Junior (2011). However, it is after 2010 that most studies and applications of these models in the banking system are found, as in Chlopek (2013), Lima et al. (2014), Klaassen and Van Eeghen (2015) and Assis (2017). Most of these studies focus on the Chinese banking sector, which, like China's economy as a whole, is expanding, as can be seen in the works by Bingwu and Li (2009), Xia (2017), Kong, Li and Ye (2017) and Ding, Feng and Liang (2018). Table 3 summarizes the main approaches to RAROC found in the literature.

Table 3 – Main Approaches to RAROC Model

Author	Objective/Result
Bingwu and Li (2009)	In this study the author proposed the use of a RAROC model for pricing credit operations at a bank in China. According to the author, the RAROC methodology is at the heart of modern finance theory and is the most effective management measure in both theory and practice for finance. In the paper, the author decomposes the RAROC model variables and recommends the application of the model for pricing credit operations.
Milne and Onorato (2009)	This study carried out in Finland aimed to quantify through the RAROC methodology the value creation of a given financial exposure. According to the authors, there is an asymmetry in the return of these assets, as they incur different types of risks. In conclusion, the authors state that it is not correct to use the same measurement metric for different types of risk but to adjust the RAROC methodology according to the distribution of risk incurred on that asset.
Castro Junior (2011)	The author analyzed the performance of the four largest financial institutions in Brazil in relation to risk (allocated capital) using the RAROC methodology. To this end, the author approached different calculation methodologies for the RAROC not finding significant differences between them.
Silva, Ribeiro, Sheng (2011)	In this paper the authors proposed an alternative model for lending that takes profitability into account rather than purely client risk. To this end, the authors used a RAROC model and applied it to a wholesale company in Brazil. As a result, the authors found evidence that lending for profitability is more assertive compared to lending that only takes customer risk into account.

Continue

Chłopek (2013)	Study conducted in Poland that sought to bring the advantages and limitations of using RAROC models in approaching credit risk. The study concludes that the RAROC model is quite innovative in this regard and should be increasingly employed, but bearing in mind that, as sophisticated as these methodologies may be, any approach to risk must always take into account aspects other than of these methods.
Lima et al. (2014)	Conducted in the 4 main banks in Brazil from 2004 to 2010, the authors approached different ways of calculating RAROC with the objective of validating the existence or not of significant changes in the values found depending on the methodology employed. The study concludes that the results of the different methodologies did not present significant divergences in general. Thus, it is possible to state that, regardless of the approached methodology, the RAROC method is an efficient tool.
Klaassen and Van Eeghen (2015)	It analyzed the performance of commercial banks in the United States during the period 1992-2014 using, inter alia, the RAROC indicator and concluded that this indicator, together with RoA and RoE, are crucial for the management of banking business and should be used by managers, analysts and regulators to analyze bank performance.
Xia (2017)	The work reviewed the literature on the application of RAROC models in the performance evaluation of commercial banks in China, providing examples of models that were applied in country studies between 2007 and 2011. Some of the models addressed in this article were those of Zhang et al. (2010), Guangxi Branch (2008), Wang Jiahua et al. (2011), Kongninging (2007), Fang Yi et al. (2007) and Dou Erxiang (2011). The article concludes that the applicability of the RAROC methodology to financial institutions has significantly revolutionized the economic condition in China.
Assis (2017)	In this paper, the author analyzed financial institutions in Brazil from 2010 to 2015, seeking to understand banks' economic and financial performance using the RAROC metric, through correlation analysis and multiple linear regressions.
Kong, Li and Ye (2017)	The authors proposed a RAROC model to price lending to micro and small businesses in China. The conclusion was that with the use of the RAROC model, financial institutions obtain more accurate risk information for these borrowers and thus this model can improve loan efficiency.
Ding, Feng,Liang (2018)	It analyzed 16 Chinese commercial banks using the RAROC model and concluded that the RAROC is an appropriate index to measure the performance of Chinese commercial banks that need to adapt to the increasingly internationalized financial market in China.

Source: elaborated by the author.

Among the main applications of the model, it is also highlighted the use to assist in the definition of the cut-off points for credit operations. In this case, the cutoff would be defined based on the profitability of the operations and not only by the default level, generating significant increases in revenues for institutions (BASTOS, 2000), as discussed in the work of Silva, Ribeiro and Sheng (2011). Another use is for pricing the most appropriate interest rate for each product leading to higher interest income by using financial interest rates more appropriate, as proposed in the works of Bingwu and Li (2009) and Kong, Li and Ye (2017).

According to Saunders (2000), the models currently used for lending – credit scoring models – when using certain factors considered most important, define a certain quantitative score by which customers are classified depending on their level of probability of default. In the case of financial institutions, cut-off points are usually defined based on default, i.e. institutions define a certain level of default probability accepted and, above that, clients will be denied their loans. However, this definition does not take into consideration the profitability, much less the remuneration required by the shareholder, or the opportunity cost of the invested capital. By denying credit to certain customers, one may be excluding potential high paying customers. A financial institution, like any other for-profit entity, has as its ultimate objective the remuneration of the capital invested by its shareholders and it is therefore up to the executives of the institution to generate strategies for the sustained growth of profitability and consequent remuneration of its investors (BASTOS, 2000).

Thus, an alternative methodology would be to define the cut-off based on profitability and such an alternative could be used with a RAROC model, as proposed by the authors Silva, Ribeiro and Sheng (2011). Moreover, in order to maximize the results obtained by the cut-off models through the profit curve, it is still possible to use the interest rate sensitivity. This in turn will affect the profitability of operations, making it possible to further improve the performance of these cut-off models via the profit curve.

Pricing operations according to customer risk is a practice that has been used for some time, especially in the insurance industry (PUTT, 2008). Based on the risk calculated on the client, differentiated prices or interest rates – in the case of banking institutions – are granted, with those clients presenting lower risk benefiting from lower interest rates, while those presenting higher risk have higher rates.

Operations with higher interest rates and, consequently, higher profitability may shift the cut-off point to less conservative levels. Although this procedure allows a greater number of nonperforming clients to be admitted, it yet increases the profitability of the institution, because a larger number of good payers that were previously denied by the model will offset eventually losses. Therefore, the new less conservative cut-off encompasses more customers, causing the outcome to increase (CRESPI JUNIOR; PERERA; KERR, 2017).

In a study by Stein (2005) analyzing medium-sized bank portfolios, they found an increase of US$ 1.70 million per year in these portfolios if banks use the model proposed by the author to define interest rate-adjusted cut-off points. In another study, analyzing a simulated portfolio of R$ 100 million from a financial institution Crespi Junior, Perera and Kerr (2017) found a 77.36% higher result for the institution by looking at the less conservative cut-off, making the net revenue from the company jump from R$ 10.6 million to R$ 18.8 million.

Although these applications of the RAROC model are extremely interesting, they are not in line with the goal of this paper. The objective here is to estimate risk-adjusted return by addressing the relevant issues regarding the openness of the model to product level and also prospectively. Therefore, these approaches on the RAROC model only serve as a reference for methodology applications and may be object of analysis of future works.

3 METHODOLOGY

3.1 DATABASE

The main goal of this study is to calculate and forecast a RAROC model for a credit portfolio loan of a commercial bank. For this purpose, bank-specific and macroeconomic specific variables are employed. Therefore, this paper selects data from a Financial Institution, which provides the database needed. This Financial Institution is a multiple bank and has a loan portfolio composed by several bank services such as retail, corporate, investments, mortgages and brokerage services.

Once this study focus on credit portfolio loan and the bank's portfolio is too large as well as contains multiples services, for this study is selected a data sample from the database, which covers the most relevant credit loans. Table 4 lists the bank-specific selected products from the database, which are: Product 1 (payroll-linked loan – retail), the most relevant product on the individuals portfolio and Product 2 (working capital loan – retail and corporate), the most relevant product on the corporate portfolio. Together, these products cover 40% of the total bank portfolio and cover 20% of the total bank assets. Although the actual values have been multiplied by an unreported constant in order to maintain confidentiality, this multiplication does not change the RAROC model since it is expressed as a percentage of capital.

Table 4 – List of selected Credit Products

Product	Details	Type
Product 1	Payroll-linked loan	Individuals
Product 2	Working capital loan	Corporates

Source: elaborated by the author.

The bank-specific variables are reported on a monthly basis and cover a period from 2011M01 to 2019M06, representing 102 observations for each product. Table 5 provides details about the variables, which are: Date, Product, Balance, Nonperforming Loans (NPL), Provision for Credit Losses (PCL), Interest Rate, Allocated Capital, Administrative Costs, Assets Ratio and Write Off.

Table 5 – Description of Variables

Variable	Description
DATE	Reference date of the variables, starting on 2011M01 and ending 2019M06.
PRODUCT	Product code, as shown in Table 4.
BALANCE	Sum of the balance for each product at the reference date. R$ million.
NPL	Sum of the Nonperforming Loans (NPL) balance, represented by the credit operations in default for more than 90 days. R$ million.
PCL	Sum of the Provision for Credit Losses (PCL) balance for each product at the reference date, calculated by the current regulatory model (2.682/99). R$ million.
INTEREST_RATE	Balance-weighted average interest rate for each product.
ALLOCATED_CAPITAL	Sum of the Allocated Capital balance for each product at the reference date, calculated by the regulatory model. R$ million.
ADM_COSTS	Sum of Administrative Costs at the reference date. R$ million.
ASSETS_RATIO	Ratio of the balance to the total assets of the bank.
WRITE_OFF	Sum of the NPL that was cleared from balance sheet. Represents the loan effectively recognized as a loss for each product. R$ million.

Source: elaborated by the author.

About the macroeconomic specific data, those variables are also provided by the Financial Institution since the bank maintain a contract with a financial consulting firm, which provides several macroeconomic variables with 5 years forecasting. Those available variables are listed in Table 6 and cover a period that starts on 2011M01 until 2019M06 for the realized variables[10] and from 2019M07 to 2024M06 for the predictions. All the variables are available in a monthly basis, totaling 162 observations.

The realized variables are provided from three different sources: Banco Central do Brasil (BACEN), Instituto Brasileiro de Geografia e Estatística (IBGE) and BM&F Bovespa. In Table 6 is possible to find the code that identifies these variables in the appropriate sources.

Table 6 – Description of Macroeconomic Variables

Variable	Description	Source
GDP	Nominal GDP of Brazil. R$ million.	BACEN (4380)
IBC_BR	Economic activity index of Brazil, prior to GDP. Index 2002=100.	BACEN (24363)
IPI	Industrial Production Index of Brazil. Index 2012=100.	IBGE (PZ27)
SELIC_T	Target of Brazil’s basic interest rate.	BACEN/Copom (432)
SELIC_M	Brazil basic interest rate. Month cumulative changes.	BACEN (4390)
CDI_M	Brazil interbank deposit rate. Month cumulative changes.	BACEN (4391)

Continue

[10] The macroeconomic variables are available for the reference data 2019/08 and because of that most variables have their values realized until 2019/06 due to the regular delay of 2 months to make some data available.

EXCHANGE	Exchange rate. Month average R$/US$.	BACEN (3697)
IPCA	Consumer price index of Brazil. Month percentage.	BACEN/IBGE (433)
INCC	Building index of Brazil. Month percentage.	BACEN/FGV (192)
IBOVESPA	Brazil stock market. Points.	BM&F BOVESPA
UNEMPLOYMENT	Unemployment rate in Brazil. Labor force percentage.	IBGE/PNAD
COMMITTED	Brazil households income committed to debt.	BACEN (19881)
HOUSEHOLDS_ DEBT	Brazil households debt. Wages percentage.	BACEN (19882)
CREDIT	Financial system credit operations. GDP percentage.	BACEN (20625)
CREDIT_H	Financial system credit operations to households. GDP percentage.	BACEN (20627)
CREDIT_C	Financial system credit operations to corporates. GDP percentage.	BACEN (20626)
CREDIT_R$	Financial system credit operations. R$ billion.	BACEN (20539)
CREDIT_H_R$	Financial system credit operations to households. R$ billion.	BACEN (20541)
CREDIT_C_R$	Financial system credit operations to corporates. R$ billion.	BACEN (20540)
NPL_H	Households nonperforming loans. Percentage.	BACEN (21112)
NPL_C	Corporates nonperforming loans. Percentage.	BACEN (21086)

Source: elaborated by the author.

Based on the data, it is possible to calculate a RAROC model for each one of the products at any moment of the historical period, as well as forecasting the variables to predict the RAROC model for the next months. Next section explains the RAROC model and provides more information about the steps used to manipulate the data, create the model, tests proposed and forecast the model.

3.2 RAROC MODEL

In order to achieve the goal of this study, statistical, mathematics and econometrics procedures were implemented to produce inferences based on the selected sample. Eviews *version* 10, R version 3.6.1 (with R Studio *version* 1.1.338) and SPSS Statistics *version* 23 were the statistical software used. The focus of the model is on assessing the profitability of a financial institution's credit portfolios considering the risk. The risk to which the loan portfolio is exposed may be calculated from two perspectives: regulatory and economic. Furthermore, the model calculates these products’ profitability for both historical and forecast periods.

Therefore, the RAROC model is created following three steps: (1) calculating a regulatory and historical RAROC; (2) estimating the economic capital in order to calculate the economic RAROC; and (3) forecasting the RAROC components allowing the model prediction.

The RAROC model proposed follow a simple equation, which is:

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

where Profit is given by:

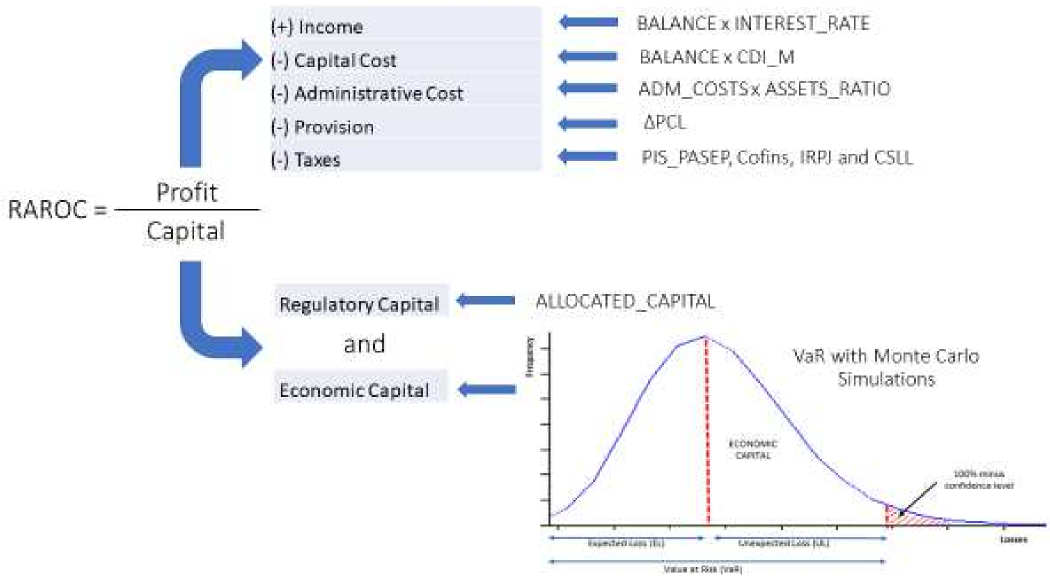
$$Profit = Income - Capital\ Cost - Adm\ Cost - Provision - Taxes \tag{2}$$

According to equation (2), the Profit is calculated by the financial income minus all expenses. The financial income is the most relevant income of the bank and is the result of the balance multiplied by the interest rate. The Capital Cost represents the cost the bank incurs to raise the funds needed to make loans, known in banking as “funding”. This cost is calculated as the result of the balance multiplied by the CDI rate, which is the Brazilian Interbank Deposit rate, used to remunerate deposits in Brazil. Administrative Costs represent several administrative expenses incurred in banking activities, such as wages and rents. The Provision is formed by the PCL flow. As the information provided by the bank is the PCL balance, the monthly variation of the provision balance is considered. Lastly, taxes are calculated according to the prevailing rates (see Section 2.4.1).

The Capital necessary, in its turn, is calculated in two different ways: Regulatory Capital and Economic Capital. This allows comparison between both and also provides a different perspective for managers. Regulatory capital is the one required by regulators and is represented by the Allocated Capital variable in the dataset. On the other hand, in order to calculate the Economic Capital, a VaR (Value at Risk) model formed by 1,000,000 Monte Carlo simulations is used. This procedure allows the creation of a vector, which contains all the loss simulated and provides the value of Economic Capital. This method is shown in Figure 5 and more details about it are described in section 3.2.2.

Figure 6 summarizes a diagram of the calculation for the RAROC model created, as well as the construction of each variable.

Figure 6 – RAROC model proposed



Source: elaborated by the author

Beyond the calculation of a Regulatory and an Economic RAROC, further important issues covered in this dissertation involve the calculation of the RAROC model for two of the most important products – instead of a single RAROC calculation for the whole bank as it is usually done – and the forecast of the model to a relevant time period – rather than just calculating for a data base or historical data. Thus, with the model proposed in this study, financial institution managers will have an important tool to assist the decision-making process.

The next three sections describe the steps used in order to create the RAROC model proposed in this work.

3.2.1 Regulatory RAROC

At this step, the objective is to calculate a Regulatory RAROC for two products in the historical period (102 months), that is, using the data provided it was calculated a RAROC model for each month providing 102 results for each product.

The main goal here is provide historical information on the products yields enabling managers to analyze from a historical point of view the products' profitability trend during the period. For this purpose, only simple mathematical procedures are required. Appendix A contains the Script used in software R in order to calculate this step and provides all the details of the mathematical procedure.

The Income is calculated by the multiplication of the Balance and the Interest Rate, as shown in Equation (3). The Income represents the most important revenue of a bank and, as can be seen from Equation (3), it increases as the Balance or Interest Rate increases.

$$Income_t = BALANCE_t * INTEREST\_RATE_t \tag{3}$$

On the other hand, the Capital Cost represents the most important expense of a financial institution once it denotes the capital required by the bank in order to make loans, known as “funding”. Equation 4 presents the Capital Costs’ formula, which is defined as the product of Balance and CDI rate (the Brazilian Interbank Deposit).

$$Capital\_Cost_t = BALANCE_t * CDI\_M_t \tag{4}$$

Administrative Costs represent all the administrative costs of the institution such as wages and rents. The variable ADM_COST regards the costs for the whole bank and an apportionment is required in order to split these values relative to each one of the products. This apportionment was made on the proportion that the balance of each product represents on the total assets of the bank (represented by the Assets Ratio variable). Therefore, the Administrative Costs for each product are expressed as:

$$Administrative\_Cost_t = ADM\_COST_t * ASSETS\_RATIO_t \tag{5}$$

Provision Costs are another important expense. However, the database provides only the balance of Provision for Credit Loss (PCL), therefore an adjustment is required. In order to calculate the Provision Costs the flow of provision is considered, it is, the change in the month’s PCL balance, as shown in Equation 6.

$$Provision\_Cost_t = PCL_t - PCL_{t-1} \tag{6}$$

Lastly, taxes are calculated considering the current rates (see Section 2.4.1) and follow two different rules according to the tax base: profit or revenue. Financial institutions in Brazil are subject to four taxes: IRPJ, CSLL, PIS/Pasep and Cofins with rates of 25%, 15%, 0.65% and 4%, respectively. The first two are charged based on profit, while PIS/Pasep and Cofins' taxes are based on revenue. Therefore, two different equations were considered (Equations 7 and 8) in order to calculate the taxes due. One important detail that required adjustment is the fact that these taxes only apply in case the bank has positive profit or revenue. Due to that, an adjustment was necessary to clear the tax amount in case profit or revenue were negatives.

$$Profit\_Tax_t = (Income_t - Capital\_Cost_t) * (PIS\_PASEP \ + Cofins) \quad (7)$$

$$Revenue\_Tax_t = (Income_t - Capital\_Cost_t - Profit\_Tax_t - Administrative\_Cost_t - Provision\_Cost_t) * (IRPJ \ + CSLL) \quad (8)$$

With all variables created, the last step is to calculate the ratio between net profit (numerator in Equation 1) and Allocated Capital (denominator in Equation 1) for each month and for each one of the products.

3.2.2 Economic RAROC

The Economic RAROC calculates capital as risk-adjusted economic capital – instead of regulatory capital, and is calculated by the institutions' own models usually using the Value at Risk (VaR) methodology. As discussed in Sections 2.3.2 and 2.4 several works suggested this change in capital calculation (PROKOPCZUK; RACHEV; TRÜCK, 2004; SAUNDERS, 2000; SMITHSON; HAYT, 2001; KRAUS, 2013) once the economic capital is expected to be more accurate than the regulatory which is standard, given by the regulator and the same for all institutions. Moreover, it should covers the idiosyncratic effects inherent in each bank.

According to Gilli and Kellezi (2006) and Jorion (2007) the VaR methodology measures the sufficient capital to cover, in most instances, losses from a portfolio over a given horizon at a given confidence level and it is commonly used to calculate the required equity to a bank. Based on Magnou (2018) and Oppong, Asamoah and Oppong (2016) a general VaR formula is given by:

$$VaR_{\propto} = \ [F^{-1}(1-\propto) - \ \mu] * \sqrt{h}, \quad \propto \in (0,1) \quad (9)$$

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 approach of the Basel II Accord and based on Magnou (2018), the confidence level $(\propto)$ is considered as 0.1% and the horizon period (h) as one year or 12 months considering that the data is monthly. The mean is calculated as the first moment of the distribution and 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% of confidence, the losses from a portfolio over a one-year holding period. This capital is considered the required economic equity risk-adjusted of each product.

Based on Jorion (2005) and Bessis (2011), there are two manly types of VaR models: parametric and non-parametric models. The parametric models assume that the risk is normally distributed and thus the VaR is calculated simply as a quantile of the distribution with a given confidence level $(\propto)$, based on the volatilities and correlations. This method is simple, however, it does not take into account some common problems that arise when we move away from the starting assumptions, either because risk factor returns do not follow a normal distribution or because portfolio returns are not a linear function of the risk.

The non-parametric models, on the other hand, do not assume the risk is normally distributed and therefore the VaR is calculated based on simulations that reproduce several possible scenarios for the risk. The fact of no presuppose *a priori* a distribution for the portfolio is very important, once according to Allen, Boudoukh and Saunders (2004) evidence shows that most loss values are not normally distributed and therefore may follow others distributions. For non-parametric models, there are two different approaches: the Historical Simulations and the Monte Carlo Simulations. The first is based on the historical values to fit the best distribution of the losses and assumes that this distribution will always be the same, while the second one is based on random scenarios, creating an infinite number of possible loss values, avoiding the use of historical values only.

The VaR methodology with Monte Carlo simulations is the model used in this study, following the previous literature (DOWD, 1998; OPPONG, ASAMOAH,OPPONG, 2016). This method uses a substantial number of possible values through a simulation algorithm and calculates the possible loss values that a capital may incur on a certain level of statistical confidence and for a certain period, as seen in the VaR definition. In order to calculate the VaR with Monte Carlo simulations some previous steps are required. In addition to these steps, according to Allen, Boudoukh and Saunders (2004, p. 8) “there are several assumptions that must be made in order to make VaR calculations tractable”.

The first assumption is about stationarity, which means that a 1% fluctuation in the losses is equally likely to occur at any point in time. In order to confirm that the variables used in the VaR model are stationary two tests for unit root are considered: Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP)[11]. Both tests have as null hypothesis that the series has a unit root, implying that it is a non-stationarity series. If the null hypothesis could not be rejected, then consecutive differences are computed in the series and the test is performed again until the null hypothesis could be rejected, i.e. the series became stationary.

Another important assumption is the non-negativity, implying that the losses cannot reach negative values. However, the variable defined as loss by the bank is, by definition, a non-negative variable.

The last and most important assumption is related to the variable’s distribution. The distribution considered must be accurate, once the values’ simulation is based on the parameters of the distribution, i.e. using a non-accurate distribution could lead to erroneous results. Four different theoretical distributions were considered in this work and the KS-test was used both to confirm if the distribution is accurate and to select which one – in case more than one is selected – fits best the data for each product.

Based on Oppong, Asamoah and Oppong (2016), Fernandes (2013), Magnou (2018) and Brito and Assaf Neto (2008b) the steps needed to calculate VaR using Monte Carlo Simulations generally are:

- Estimate the parameters of a known theoretical distribution curve;
- Apply tests to select the distribution that best fits the data;

[11] Both ADF and PP tests can be performed under the presence of intercept, trend and intercept and none. For more details see Bueno (2011).

- Generate a series of random values based on the parameters;
- Based on the chosen confidence level, calculate the risk measures.

For this purpose, some mathematical and statistical procedures are required, and Appendix B contains the Script used in software R in order to calculate these steps. Next sections describe the four stages mentioned before.

3.2.2.1 Estimating the parameters of a known theoretical distribution curve

The goal here is estimating the parameters of a known theoretical distribution curve which would fit the data used. This step is important once the Monte Carlo Simulations generate the series based precisely on the parameters estimated here and each known theoretical distribution curve has his own parameters and his own moment-generating functions.

The first challenge is choosing the loss variables to be used to estimate the parameters. Several studies apply the Monte Carlo simulations on the traditional Credit Score[12] models' data. These simulations provide innumerous scenarios for each variable of the Credit Score model and then measure possible losses combining these results. However, based on Brito and Assaf Neto (2008b), when the data available covers a large period and present an adequate balance between performing and nonperforming loans, it is possible to measure the credit risk portfolio directly from the historical portfolio's loss distribution. That is the procedure consider in this work. So the variable used is the WRITE_OFF for each product.

The next step is select the method to estimate the unknown parameters. Based on Kececioglu (2002) there are many possible methods, being the most common those three: ordinary least squares (OLS), moment matching estimation (MME) and maximum likelihood estimation (MLE)[13]. In this work, the MLE method are used. Intuitively, the MLE consists in estimating the parameters of a model using the estimates that make the observed data more likely to be from the specific sample. Mathematically, the MLE estimates parameters of a probability distribution that make

[12] Credit Score models are used by lenders and financial institutions to compute a creditworthiness note. These models use data from potential borrowers such as income and behaviors about payments for householders and cash flow, revenue and working capital for corporations, among several other factors.
[13] At Fernandes (2013) it is possible to find a rich discussion about the three methods, where the author details all the three procedures and gives examples about them.

the value of the likelihood function maximum (MYUNG, 2003). The likelihood function represents a join probability distribution of a random sample of variables $\{Y_1, Y_2, \dots, Y_n\}$ which has the individual probability distribution $f(y, \theta_1, \theta_2, \dots, \theta_n)$. This way, the likelihood function can be presented as:

$$L = \prod_{i=1}^{n} f(\,y_i;\ \theta_1, \theta_2, \dots, \theta_n), \quad i = 1,2, \dots, n \tag{10}$$

Therefore, the aim is estimate the vector of parameters $\hat{\theta}$ that maximize the probability of obtaining the specific sample. In order to do that, some differentiation techniques are required such as derivative the function and set the derivative function to zero (Equation 12), then rearrange the equation to make the parameter of interest the subject of the equation. Generally, in order to simplify the differentiation, first the natural logarithm is taken (Equation 11).

$$lnL = \sum_{i=1}^{n} ln\, f(\,y_i;\ \theta_1, \theta_2, \dots, \theta_n), \quad i = 1,2, \dots, n \tag{11}$$

$$\frac{\partial lnL}{\partial \hat{\theta}} = 0 \tag{12}$$

After that, in order to obtain the parameters of any known distribution curve, it is necessary to replace the function by the probability density function of that distribution. Once we do not know *a priori* the distribution that fits best the data, four different distributions were tested: Normal, Lognormal, Weibull and Gamma. Each distribution has different characteristics and ability to represent a series, differing in their dispersion, location and shape measurements. Next sections give some details about each one of the four distributions.

3.2.2.1.1 The Normal distribution

The Normal distribution or Gaussian distribution is the most known continuous probability distribution in statistics/probability theory. It was introduced by Carl Friedrich

Gauss (1777-1885) and graphically represents a Gaussian (or bell) curve symmetrical to the mean (LEFEBVRE, 2006). The probability density function is given by:

$$f(x|\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \quad -\infty < x < \infty, -\infty < \mu < \infty, \sigma > 0 \tag{13}$$

where:

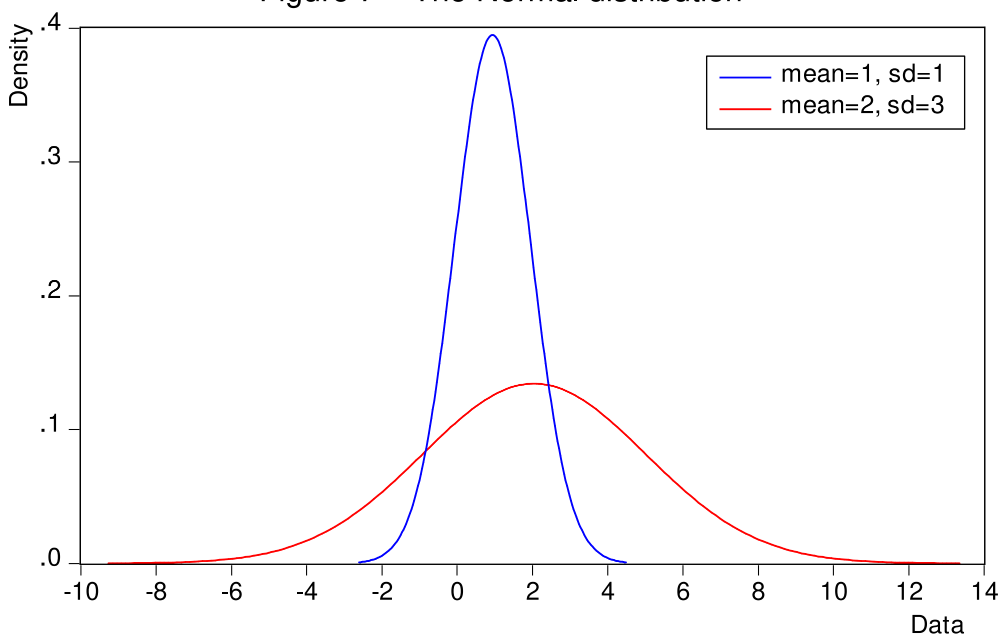
μ is the mean or expected value of the distribution;

σ is the standard deviation;

σ^2 is the variance.

Given its nature, this distribution is characteristic of loans that present defaults around a value, and its dispersion is symmetrical relative to it. The two parameters that characterize the normal distribution are the mean (μ) and standard deviation (σ). The influence of the parameters on the probability density function are observed in Figure 7. The values would be always around the mean and the smaller the standard deviation, that is, the smaller the variation between the measured values, the narrower and higher the curve becomes.

Figure 7 – The Normal distribution



Source: elaborated by the author

The first moment of a Normal distribution may be reached using the mean (μ) parameter straight, as shown in Equation 14:

$$\mu_{normal} = \mu \quad (14)$$

3.2.2.1.2 The Lognormal distribution

The Lognormal distribution was introduced by Francis Galton in 1879 and graphically represents an asymmetric curve in form of a spine. A random variable is lognormally distributed if its logarithm is normally distributed (FERNANDES, 2013). The probability density function is given by:

$$f(lnx|\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(lnx-\mu)^2}{2\sigma^2}}, \quad -\infty < x < \infty, -\infty < \mu < \infty, \sigma > 0 \quad (15)$$

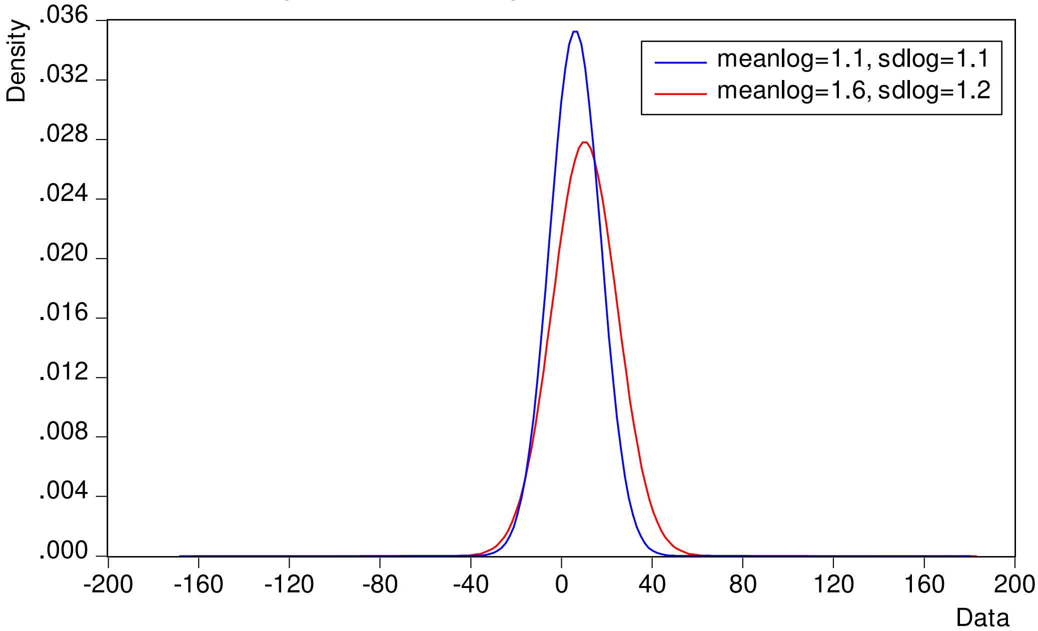
where:
μ is the log-mean or scale parameter;
σ is the log-standard deviation or shape parameter.

Unlike normal distribution, lognormal distribution is not well suited for loans that present default around a value since it presents a skew distribution with many small values and fewer large values. Therefore, the mean is usually greater than the mode. Lognormal distribution also has two parameters that characterize it, which are: the scale parameter (μ) and the shape parameter (σ). The influence of the parameters on the probability density function may be observed in Figure 8. The smaller the standard deviation, the closer the curve gets to the vertical. Regarding the mean, the smaller the logarithm of the mean, the narrower and higher the curve becomes.

The first moment for a Lognormal distribution is calculated following the Equation 16:

$$\mu_{lognormal} = e^{\mu+\frac{\sigma^2}{2}} \quad (16)$$

Figure 8 – The Lognormal distribution



Source: elaborated by the author

3.2.2.1.3 The Weibull distribution

The Weibull distribution is named after Swedish mathematician Waloddi Weibull (1951) and represents a continuous probability distribution to describe a particle size distribution. The probability density function is given by:

$$f(x|\gamma,\beta) = \frac{\gamma}{\beta} x^{\gamma-1} e^{-\frac{x\gamma}{\beta}}, \quad x > 0, \qquad \gamma,\beta > 0 \tag{17}$$

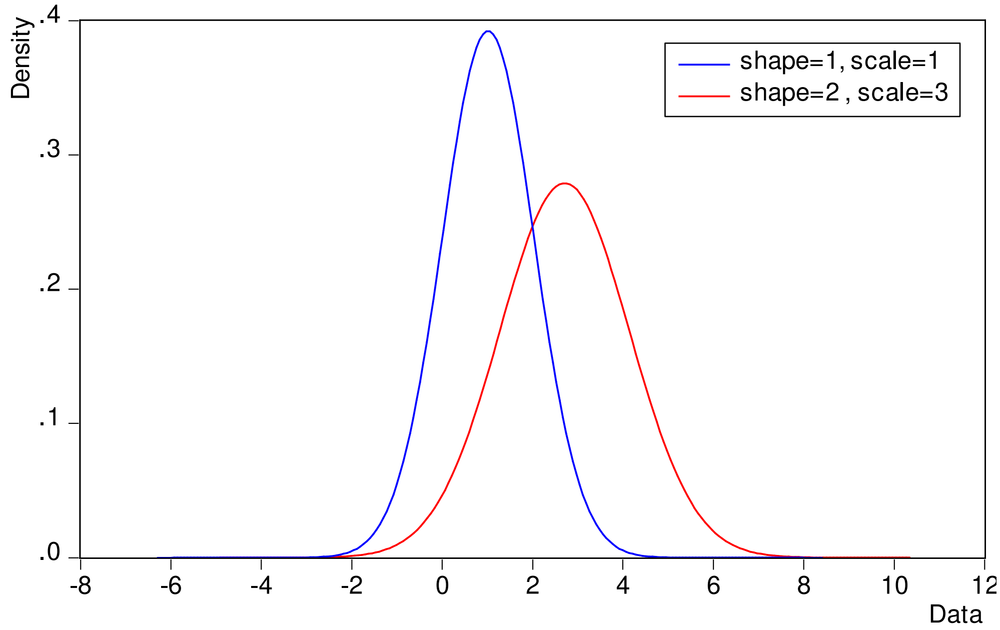
where:

γ is the scale parameter;

β is the shape parameter.

According to Jiang and Murthy (2011) the Weibull distribution gives a distribution for which, in case of credit losses, the loss rate is proportional to a power of time and has two parameters that characterize it, which are: the scale parameter (γ) and the shape parameter (β). The influence of the parameters on the probability density function may be observed in Figure 9.

Figure 9 – The Weibull distribution



Source: elaborated by the author

The first moment for a Weibull distribution is calculated following the equation 18, where Γ is the gamma function.

$$\mu_{weibull} = \beta^{\frac{1}{\gamma}}\Gamma\left(1+\frac{1}{\gamma}\right) \tag{18}$$

3.2.2.1.4 The Gamma distribution

The Gamma distribution is widely used mostly in due to its relation to a family of continuous distributions, such as exponential, chi-squared and normal distributions (LEFEBVRE, 2006). This distribution is used to predict the wait time until future events and its probability density function is given by:

$$f(x|\alpha,\beta) = \frac{1}{\Gamma(\alpha)\beta^{\alpha}}x^{\alpha-1}e^{-\frac{x}{\beta}}, \quad x>0, \qquad \alpha,\beta>0 \tag{19}$$

where:

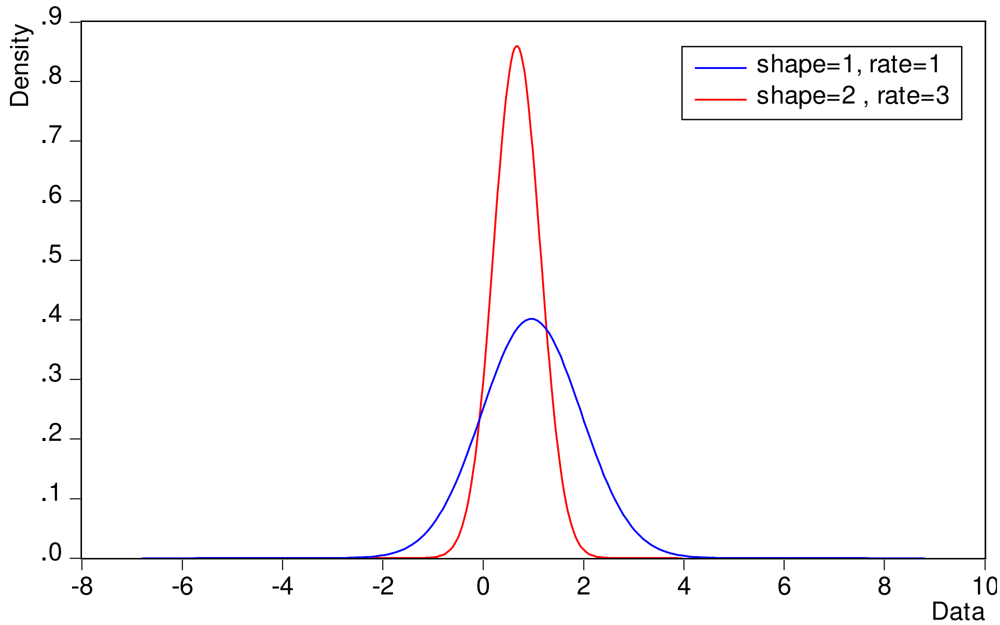
β is the rate parameter;

α is the shape parameter;

Γ is the gamma function.

The Gamma distributions is used in business models mostly to predict insurance claims and loan defaults for which the variables are always positive and the results are skewed (unbalanced). In order to compute a Gamma distribution, two parameters are required: the rate parameter (β)[14] and the shape parameter (α). The influence of the parameters on the probability density function may be observed in Figure 10.

Figure 10 – The Gamma distribution



Source: elaborated by the author

The first moment for a Gamma distribution is calculated by multiplying α by β, as shown in Equation 20.

$$\mu_{gamma} = \alpha\beta \tag{20}$$

Analyzing the graphs of the histogram of the loss series and how the theorical distribution curves created fits it, is possible to have an idea of which distribution fits best the data. However, using some technics of statistical inference, there are tests necessary to confirm if the distributions really apply to that data and to select which one fits best. Next section provides more details about it.

[14] Some authors prefer to use the scale parameter, which is the inverse of the rate parameter $\left({}^{1}/_{\beta}\right)$.

3.2.2.2 Tests to select the distribution that best fits the data

Based on Abd-Elfattah (2011) there are four main statistical tests used to validate the adjustment of statistical distributions, which are: Cramer-Von Mises (CM), Anderson-Darling (AD), Chi-Squared (CS) and Kolmogorov-Smirnov (KS). The aim of these testes is the same: test the hypothesis that a given random sample was taken from a population that follows a specified distribution.

These tests use the theory of hypothesis testing – known as null hypothesis H_0 and alternative hypothesis H_1 – to determine if the tested distribution has a good adjustment of the data. By convenience, the hypothesis always follows the rule: H_0 confirm that the tested distribution applies to the data and H_1 is the opposite, i.e. the tested distribution does not apply to the data (Equation 21). All these tests provide a statistical value and their respective p-value what allow to reject or no reject H_0.

$$H_0: T \sim F \qquad\qquad vs \qquad\qquad H_1: T \nsim F \tag{21}$$

Further then confirm – or not confirm – the use of determined distribution, another important issue provide by those testes is select which distribution best fit the data, in case of more than one distribution applies to the data. Since the four tests has the same goal, at this work only one test is used and the KS test was chosen as it is relatively simple to apply and easy to understand.

The KS fit test consists of finding the maximum distance between the expected and observed cumulative distribution function. This requires a maximum distance between the two (D_{Max}) and, subsequently, it will be confronted with a theoretical value. Only then, through this test can it be said that the distribution being tested fits the sample with determined confidence level (P-Value). Moreover, using the D_{Max} value is possible to compare and select which distribution fits best the sample.

3.2.2.3 Generating series of random values and calculating the risk measures

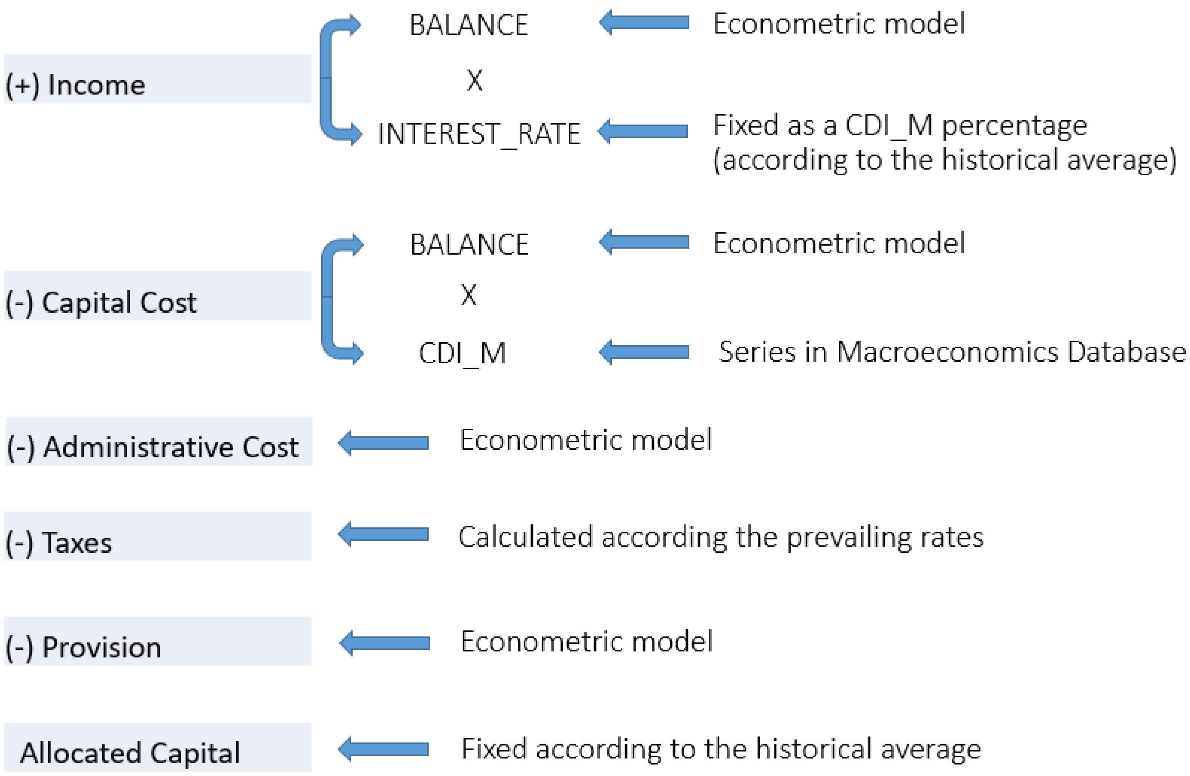
This step consists of estimating a series of random numbers based on the probability distribution parameters. According to OPPONG, ASAMOAH, OPPONG (2016) a determined number of samples (scenarios) are generated in a determined number of times (repetitions). For this work, following the authors, we decided to generate 100 scenarios to each series as well as 10,000 samples. This procedure allows the creation of 1,000,000 possible values of loss to each product.

These 1,000,000 possible values generate a vector of losses with which is possible to calculate the risk measures needed at this work. More precisely, with this loss distribution the Expected (EL) and Unexpected Loss (UL) are created. As discussed before, the EL is the mean of the distribution and the UL is the difference between the VaR minus the mean, measuring the sufficient capital to cover, at 99.9% of confidence, the losses from a portfolio over a one-year holding period and this capital are considered the required economic equity risk-adjusted of each product.

3.2.3 Forecasting RAROC Model

The goal here is forecasting the RAROC model providing an alternative view for managers, allowing to evaluate the possible trend in the coming periods. In order to achieve that goal, an econometric model is created using the software Eviews. This model predicts the most important variables of the RAROC equation. The remainder variables are calculated by simple mathematical procedures. This econometric model is mostly based on Levieuge (2015). According to the author, studies that forecast bank-related variables usually focus on lending rates or interest rate spreads, neglecting the bank loans, which is one of the most important variables at the RAROC model suggested here. This model is going to forecast three variables for each product: BALANCE, PCL and ADM_COSTS. With those variables' prediction, only straightforward mathematical procedures are required to forecast the remainder variables from the RAROC model. Figure 11 summarizes the procedures taken in order to forecast all the variables of the RAROC model.

Figure 11 – RAROC Forecasting model



Source: elaborated by the author

The method discussed in Levieuge (2015) is based on multivariate autoregressive models, such as Vector Auto-Regressive (VAR) and Vector Error Correction Model (VECM) models. These models, according to Bueno (2011), allow to estimate parameters based on the lags of the own variable (autoregressive), other lagged variables and yet exogenous variables, all together in a system. Therefore, these models are recommended to estimate parameters of series that are related to each other (contemporary or lagged), allowing these series to be estimated in the same model.

Thus, the model proposed on Levieuge (2015) suits very well the objective for the forecasting RAROC model, once the multivariate models are proven to be a good model to project credit variables as well as projecting the most important variables into one model. The horizon of prediction for the model, also based on Levieuge (2015), is 12 months ahead, once predicting for more than 12 months extremely deteriorates the predictive power of those models. Therefore, the follow dynamic model is proposed:

$$X_t = \Psi_0 + \sum_{i=1}^{p} \Psi_i W_{t-i} + \Theta D_t + E_t \tag{22}$$

Where X is a vector that includes the endogenous variables from bank-specific data. These variables are supposed to be highly interconnected and to characterize the main RAROC variables. The vector W contains lagged endogenous variables and additionally includes exogenous variables from the macroeconomic data. These variables are supposed to explain several conditions applied to the endogenous variables. The vector D contains determinist variables. These variables – dummies – were created to suit outliers, breakpoints or seasonality issues. Finally, E is the vector of the residuals.

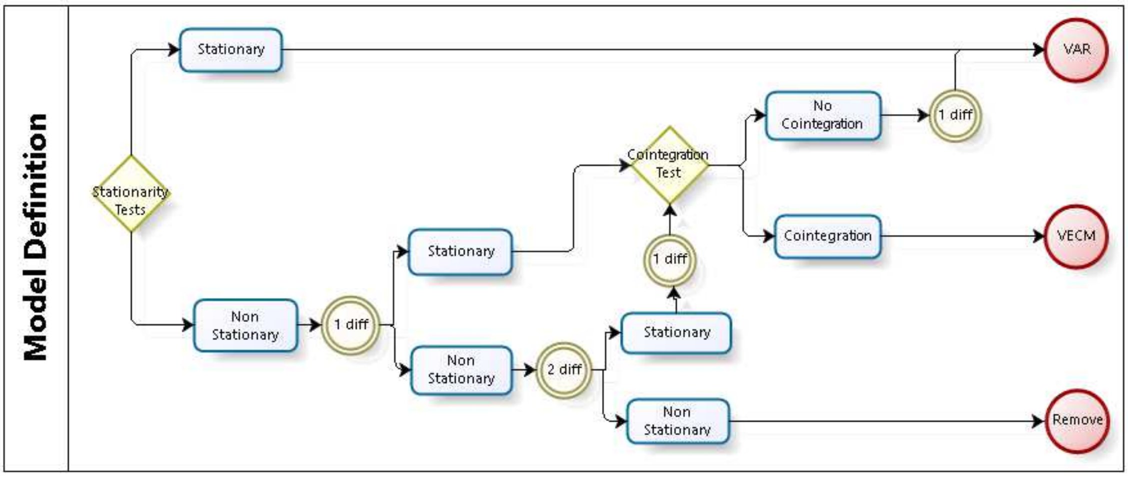
The vectors X and W were selected according to the characteristics of each product, resulting in distinct models for Payroll-linked and Working Capital loans. As endogenous variables, considering that those variables are supposed to be highly interconnected and characterize the main RAROC variables, three series were used: BALANCE, PCL and ADM_COSTS. All the macroeconomic data were tested as exogenous, maintaining the most relevant variables to the model. The macroeconomic data were also tested in lags, once the effects of the macroeconomic variables could occur with a delay. Because of that, those variables were tested until 12 lags. The dummy variables were also tested. Both macroeconomics and dummy variables were chosen according to the theoretical relevance and analyzing the t-statistic, maintain the ones that were more relevant and significative.

After choosing the most relevant variables for each model, a range of statistic tests was used to assess the validity of the model. These tests includes unit root, breakpoints, seasonality, outliers, information criterions, cointegration and causality and also a number of tests related to the residuals, such as normality, autocorrelation and heteroskedasticity. Besides that, it also important check the robustness of the model. For that, it was checked the inverse roots of the autoregressive characteristic polynomial, the coefficient of determination, the variance decomposition, the impulse response function and some graph analysis of the fitted versus the actual values.

The first tests considered were about stationarity and cointegration, because those two tests are fundamental in order to define if the model is a Vector Autoregressive (VAR) or a Vector Error Correction Model (VECM). First, testing the assumption of stationarity, the unit root tests were used. At this step, we considered the same tests used for the variable WRITE_OFF in the VaR model. Therefore, Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) were tested. Both tests have as null hypothesis that the series has a unit root, implying the series is non-stationary.

If the series are stationary, we decide to use a VAR model. Otherwise, the differences between consecutive observations are computed until the series became stationary (maximum two). However, differencing series eliminates valuable information about the relationship among integrated series. For that reason, the VECM model is an important alternative. The procedure required to define the model as a VECM, involves the cointegration tests. Figure 12 summarizes this procedure.

Figure 12 – VAR/VEC Model Definition



Source: elaborated by the author

At this work, we use the Johansen cointegration tests. This test is a multidimensional test for cointegration that defines not only if there is cointegration, but also the number of cointegration between *n* series[15]. It is important to say that, if there are *d* series, is possible to have *d – 1* cointegrating relationships. Furthermore, the cointegrating equations, similarly to a simple series, may have intercepts and deterministic trends. Thus, in order to carry out the Johansen test it is necessary to determine whether the series has a determinist trend (linear or quadratic) and whether the series has intercept. If the Johansen test confirms that the series are cointegrated,

[15] The Johansen cointegration test uses the Likelihood Ratio (LR) with two types of statistics: trace statistics and maximum eigenvalue statistics. More details about these statistics can be found in Bueno (2011).

a VECM model is suitable. In case of no cointegrating relationships, the differences are computed and the model should be a VAR.

Another important test related to the series is about breakpoints. For this purpose, the Bai-Perron test (BAI, PERRON, 2003) was used on the bank data, which tests l globally optimized breaks against the null of no structural breaks. This test employs a F-statistic to evaluate the hypothesis. Therefore, the test provides not only whether there are any breakpoints, but also what is the likely number of breaks (based on the maximum of the F-statistic) and in which period they are located. In cases that the test suggests one or more breakpoints in the series, dummy variables are created.

For seasonality, we used a test proposed by Webel and Ollech (2017) which consists in combining results for two different seasonality tests. The WO-test combines the results of the QS-test and the kwman-test (KW), both calculated on the residuals of an automatic non-seasonal ARIMA model. If the p-value of the QS-test is below 0.01 or the p-value of the kwman-test is below 0.002, the WO-test classifies the corresponding time series as seasonal. Those variables identified with seasonality by the test are treated by the Census X-13 method.

One last important test about the series is the one that investigates the existence of outliers. Although the Census X-13 method also provides a treatment for that, for the bank data we decide to use the boxplot graphs to test for outliers. The reason for this is to reinforce the robustness of the econometric model to be used, since these variables are endogenous in the model and, for that reason, a more careful analysis is required. Dummy variables were created in case of outliers in order to be tested in the econometric models.

After the variables are tested and treated, some tests about the model are required. First one, it should be defined the optimal number of lags to be included in the model. For this purpose the information criterions were considered. Based on five criterions (Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC) and Hannan-Quinn Information Criterion (HQ)) the optimal lag order for the model is selected.

Once defined the optimal lag order, causality tests should be run. In the context of vector models, test the causality is important to ordering the endogenous variables in the model, among other reasons. The correct ordering of the variables influences, mainly, the impulse response function and on the variance decomposition, which is discussed later.

According to Bueno (2011), it is known that vector models do not allow identifying all parameters of the structural form, unless some additional constraints are imposed and the model is computed in its reduced form, for later recovery of the structural parameters. For this, Cholesky's decomposition procedure is used, which forces the imposition of constraints, assuming that some matrix coefficients are equal to zero. In this case, since the decomposition occurs in a triangular form, zero is imposed on the coefficients located in the upper diagonal portion of the matrix. This is why the ordering of variables in the matrix model is important: it defines the shape of constraints, so that different ordering generates different constraints (BUENO, 2011).

In order to test causality the Granger Causality are used. This test use a conventional F-test to check the null hypothesis that a variable y does not Granger cause a variable x in determined number of lags. Therefore, the first variable in the model is the one variable that causes the most variables and the last one is that variable which are caused by the most variables.

After those tests, the model is computed and some tests about the stability of the model are also required. These tests are done in the residuals and the first assumption considers that they are normally distributed. In order to confirm that, the Jarque-Bera test is used. This test consists in verifying if the moments of the residual are equal to the moments of a normal distribution, under the null hypothesis that the distribution is normal. The Jarque-Bera test whether the series is normally distributed measuring the difference of the skewness and kurtosis (third and fourth central moments of a distribution, respectively) of the series with those from the normal distribution. In order to do that in a multivariate model there are different methods of orthogonalization. At this paper, three different methods are used: Cholesky of covariance (proposed by Lutkepohl), Square root of correlation (proposed by Doornik-Hansen) and Square root of covariance (proposed by Urzua).

Another important issue about residuals is testing if there is serial correlation. In presence of serial correlation, the estimated coefficients are biased and inconsistent due the presence of a higher lagged dependency. In order to test it, the Breusch-Godfrey test – also known as Lagrange Multiplier (LM) – is used. This test has as null the hypothesis of no serial correlation in the residuals up to the specified order. Finally, it is also assumed that the variance of the residuals is constant. Whether positive, the error is said to be homoscedastic, otherwise, they have heteroskedasticity. White test is used, with the null of homoscedasticity residuals.

Finally, once the model computed and the residuals tested, the last step is to check the robustness of the model. So, the first item analyzed was the inverse roots of the characteristic polynomial. If all roots lie inside the unit circle, i.e. present modulus values less than one, the estimated model is stable or stationary. Otherwise, several results are inconsistent, such as the impulse response function and the coefficient's standard errors (LÜTKEPOHL, 2005).

In addition, to analyze the impacts of shocks between variables, the impulse response function is used, which shows how a model variable reacts when a shock is attributed, for example, from one or two standard deviation, in another related variable. In this way, the amplitude of the shock response and the time taken for the shock effects to dissipate and the series to return to their original trajectory can be analyzed (BUENO, 2011).

Another analysis of VAR model results is possible by variance decomposition, which consists in verifying the percentage that each variable contributes to the variance of the forecast error, analyzing the influence level between the model variables (BUENO, 2011).

Lastly, the coefficient of determination (R^2) and the adjusted coefficient of determination (Adjusted R^2) are analyzed. These coefficients measures the proportion of the variance in the dependent variable that is predictable from the independent variables, in a range from 0 to 1. The difference between R^2 and adjusted R^2 is that the second compensates for the addition of variables and only increases if these new variables enhances the predictability of the model, otherwise, addition of variables should just decrease the Adjusted R^2.

With all these testes, the last step is a graphical analysis from the fitted values of the model versus the actual values of each variable forecasted, in order to examine whether the model predicts properly the data.

4 EMPIRICAL RESULTS AND DISCUSSION

This chapter begins with the descriptive statistics analysis presentation for both bank and macroeconomic variables. Then, it presents the outcomes and evaluations from the series and from the models suggested here. To conclude, the RAROC results are presented and discussed.

4.1 DESCRIPTIVE STATISTICS ANALYSIS

Firstly, Table 7 shows the descriptive statistics for the Payroll-linked and Working Capital loans. This table summarizes the information of the bank-related variables: BALANCE, NPL, PCL, INTEREST_RATE, ALLOCATED_CAPITAL, ADM_COSTS, ASSETS_RATIO and WRITE_OFF.

Table 7 – Descriptive statistics for bank-specific variables

Payroll-linked						
Series	**Mean**	**Std Dev.**	**Min**	**Max**	**Skewness**	**Kurtosis**
BALANCE	16,130.20	5,012.45	10,249.20	29,190.30	1.11	0.19
NPL	185.56	32.27	137.10	255.60	0.34	-1.09
PCL	325.43	77.78	245.20	597.60	1.34	1.49
INTEREST_RATE	1.96	0.12	1.64	2.12	-0.77	-0.31
ALLOCATED_CAPITAL	1,277.57	354.60	824.00	2,173.50	1.15	0.18
ADM_COSTS	31.06	11.56	11.10	69.80	0.50	-0.04
ASSETS_RATIO	0.09	0.01	0.07	0.12	0.86	-0.30
WRITE_OFF	20.99	14.14	2.70	84.30	2.08	5.14
Working Capital						
Series	**Mean**	**Std Dev.**	**Min**	**Max**	**Skewness**	**Kurtosis**
BALANCE	16,232.15	2,982.35	11,400.10	20,641.90	-0.28	-1.45
NPL	589.07	291.64	189.50	1,346.20	0.37	-0.85
PCL	1,275.07	304.45	741.70	2,466.20	0.37	0.64
INTEREST_RATE	1.52	0.42	0.93	2.31	0.69	-0.64
ALLOCATED_CAPITAL	1,492.59	299.72	1,021.00	1,901.20	-0.26	-1.50
ADM_COSTS	31.04	8.80	14.30	57.30	0.37	-0.40
ASSETS_RATIO	0.10	0.03	0.05	0.14	-0.23	-1.34
WRITE_OFF	60.94	71.15	6.10	419.80	2.90	9.78

Notes: period 2011M01 - 2019M06, number of observations: 102, R$ million.

Source: elaborated by the author

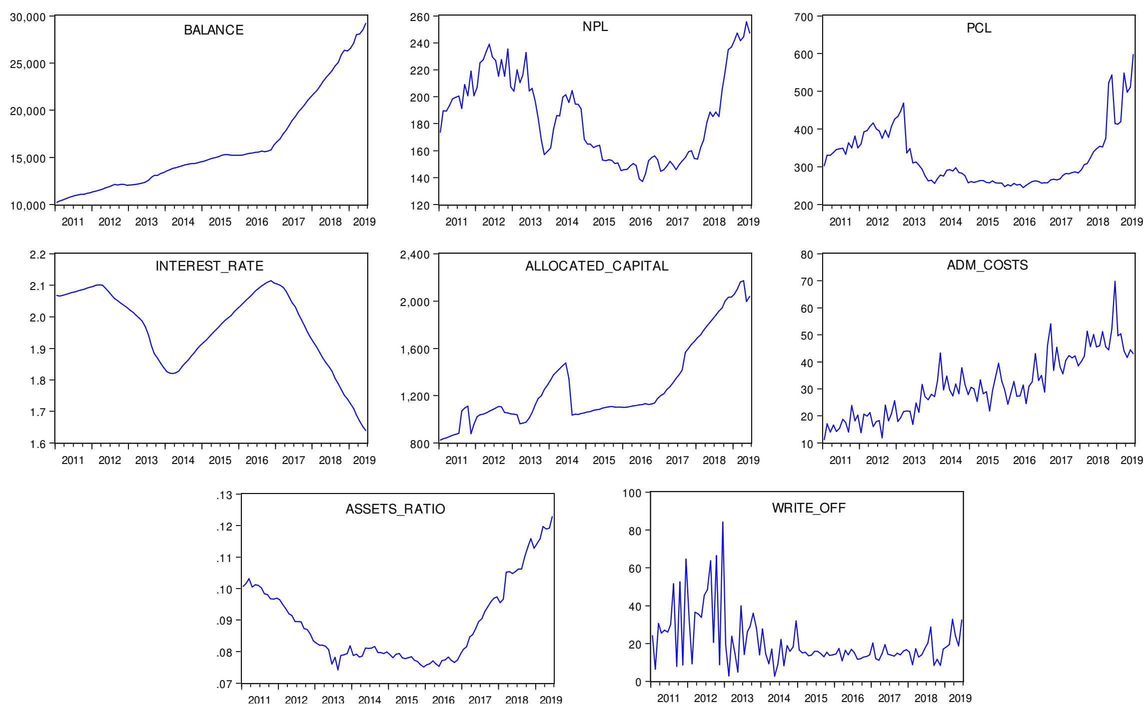
It is noteworthy that both products had a very similar average balance during the period analyzed, with Payroll-linked loans reaching R$ 16.13 billion while Working

Capital attained R$ 16.23 billion. However, it is noted through the variable NPL that Working Capital delinquency is much higher than that of Payroll loans, since while the first had an average of R$ 185 million, the latter was more than 3 times higher, reaching R$ 589 million on average, very similar to what happens, consequently, with the PCL variable.

Regarding the interest rate, Payroll-linked loans were higher than Working Capital on average, 1.96% and 1.52%, respectively. However, Working Capital has a larger standard deviation, i.e. the interest rate had a greater variation in this product, which can be confirmed by the maximum and minimum values that the rate fluctuated between 0.93% and 2.31%, while in Payroll loans the minimum rate was 1.64% and the maximum was 2.12%. The allocated capital, administrative costs and assets ratio variables presented very similar descriptive statistics for both products. Lastly, the write off variable will be analyzed later.

Figure 13 shows the graphs from Payroll-linked loans series: BALANCE, NPL, PCL, INTEREST RATE, ALLOCATED CAPITAL, ADM COSTS, ASSETS RATIO and WRITE OFF over the period 2011M01 to 2019M06.

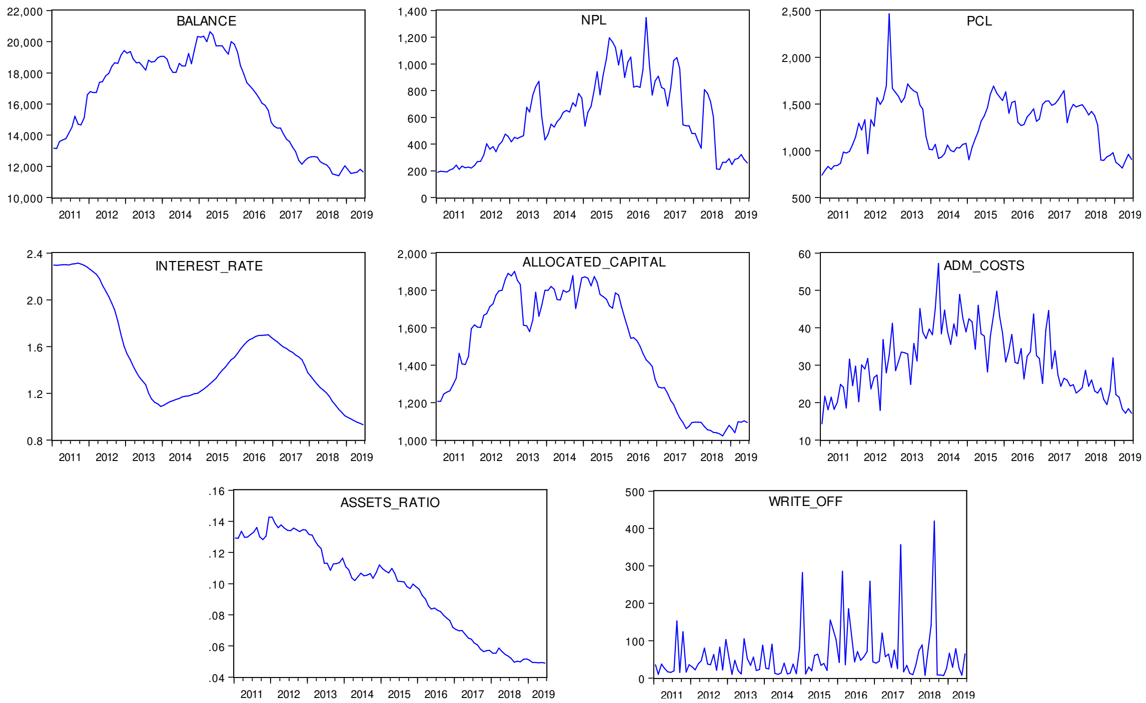
Figure 13 – Payroll-linked series



Source: elaborated by the author

Moreover, Figure 14 shows the graphs from Working Capital loans series.

Figure 14 – Working Capital series



Source: elaborated by the author

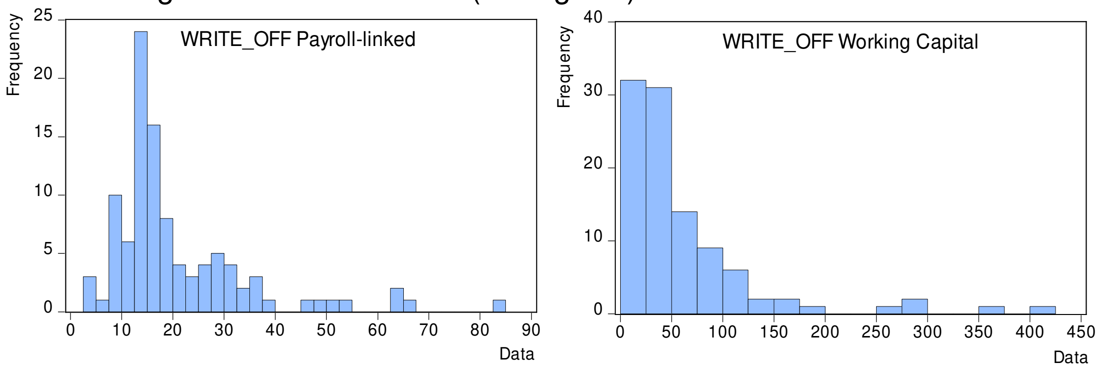
The graphs show that the balances of both Payroll and Working Capital products increased until 2015. However, after this period, Payroll continues to grow (including with a greater slope from 2017) while Working Capital has a deep decline causing the balance to shrink at least until 2019. Thus, although both products had similar average balance during the period, there is a reversal of trend, as the Payroll's balance continued to grow while Working Capital is declining or stagnant. As a result, it can be observed in the assets ratio variable that the representativeness of Working Capital in the bank's assets as a whole fell sharply in the period, from 12.94% in 2011M01 to 4.90% in 2019M06.

Another highlight is the variables NPL, PCL and ALLOCATED_CAPITAL because the three present a similar trajectory to the BALANCE of each product, showing to be much interconnected with the products' balance. Finally, another fact is the interest rate has a very similar format for both products although it has different level and inclinations.

As for the write-offs, it stands out first in relation to its descriptive statistics (Table 7) that the average presented by Working Capital is almost three times higher than the Payroll, indicating that the former has considerably higher losses. Another highlight is related to the standard deviation, since Working Capital has a larger standard deviation, indicating larger variations in the loss balances, which reached values of up to R$ 420 million.

Finally, another interesting statistic regarding write-offs is skewness and kurtosis. For both products, a high kurtosis value is noted, indicating that possibly the series is not normally distributed. As for the skewness, once again both series have high and positive values, which suggests that they are right tailed. Figure 15 shows the distribution (histogram) of losses for both products.

Figure 15 – Distribution (Histogram) for the Write-Off series



Source: elaborated by the author

Finally, the descriptive statistics for the macroeconomic variables are presented in Table 8. There are 21 variables for a period between 2011M01 to 2024M06, comprising 162 observations. Further details on each variable are found in Table 6. An important factor to note is that the period from 2019M07 to 2020M06 refers to the forecasted variables. Macroeconomic variables are considered in the econometric models used to project the variables of the RAROC model, since it is believed that there should be a relationship between the variables of the products and the functioning of the economy as a whole.

Table 8 – Descriptive Statistics for the macroeconomic data

Series	Mean	Std Dev.	Min	Max	Skewness	Kurtosis
CDI_M	0.70	0.22	0.34	1.21	0.52	-0.78
COMMITTED	21.65	0.87	19.82	23.05	-0.69	-0.62
CREDIT	27.07	1.52	23.65	29.53	-0.78	-0.31
CREDIT_C	12.84	0.98	10.80	14.68	-0.41	-0.72
CREDIT_H	14.23	0.94	12.67	15.88	0.22	-1.02
CREDIT_R$	3,204.48	722.84	1,718.71	4,583.14	-0.06	-0.54

Continue

CREDIT_R$_C	1,503.66	228.88	933.47	1,970.74	-0.38	0.16
CREDIT_R$_H	1,700.82	519.70	785.24	2,612.40	0.07	-1.05
EXCHANGE	3.19	0.81	1.56	4.12	-0.72	-1.06
GDP	589,124.21	162,271.24	333,330.50	984,783.47	0.65	-0.43
HOUSEHOLDS_DEBT	44.50	1.92	39.92	47.01	-0.43	-1.10
IBC_BR	143.45	7.55	128.43	164.99	0.39	-0.30
IBOVESPA	80,668.25	28,226.03	40,405.99	139,971.20	0.52	-0.95
INCC	0.50	0.42	-0.02	2.94	2.68	9.80
IPCA	0.42	0.27	-0.23	1.32	0.95	1.68
IPI	94.52	9.01	75.80	112.60	-0.02	-0.68
NPL_C	3.54	0.84	2.50	5.94	1.09	0.20
NPL_H	5.29	0.93	4.10	7.20	0.40	-1.06
SELIC_M	0.71	0.22	0.36	1.22	0.54	-0.79
SELIC_T	9.02	2.82	5.25	14.25	0.55	-0.92
UNEPLOYMENT	10.12	2.19	6.62	13.11	-0.46	-1.53

Note: statistics over period 2018M01 - 2024M06. Number of observations: 162.

Source: elaborated by the author

Graphs for macroeconomic variables may be found in Figure 35 in Appendix C.

4.2 SERIES AND MODELS EVALUATION

This section presents the results for series and models evaluations. It starts with the series' tests, such as stationarity, seasonality and outliers. Then, the tests regarding the models created are presented, which are divided between the tests related to the Value at Risk (VaR) model and the ones related to the Vector Autoregressive (VAR/VEC) model.

4.2.1 Series

The first test to the series is about stationarity. For this purpose, two tests were used: Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP). The results for Payroll-linked are in Table 9.

Table 9 – Stationarity tests for Payroll-linked loans

Series	test	T-stat with intercept	T-stat with trend and intercept	T-stat with none	
BALANCE	ADF	2.2771	0.7247	1.8446	
	PP	5.5269	1.9316	6.4275	
NPL	ADF	-0.8779	-0.6530	0.6099	
	PP	-0.8733	-0.5029	0.6099	
PCL	ADF	-0.4857	-0.4373	0.8124	
	PP	-0.0932	0.3317	1.1935	
INTEREST_RATE	ADF	-2.3922	-3.0855	-0.8922	
	PP	0.0177	-0.6649	-1.3299	
ALLOCATED_CAPITAL	ADF	-0.1683	-1.3486	1.6116	
	PP	-0.0421	-1.2250	1.8456	
WRITE_OFF	ADF	-2.6342*	-3.2938*	-0.984434	I(0)
	PP	-10.4358***	-11.1831***	-4.2111***	
ADM_COSTS	ADF	-1.9601	-7.1952***	0.9529	
	PP	-2.6040*	-7.2365***	-0.0695	

Series	test	T-stat with intercept	T-stat with trend and intercept	T-stat with none	
ΔBALANCE	ADF	-0.9766	-2.3201	-0.0499	
	PP	-4.0723***	-6.2498***	-1.6837*	
ΔNPL	ADF	-11.3093***	-11.4417***	-11.3168***	I(1)
	PP	-11.2347***	-11.4417***	-11.2408***	
ΔPCL	ADF	-10.4618***	-8.6653***	-10.4319***	I(1)
	PP	-10.6231***	-11.0314***	-10.5431***	
ΔINTEREST_RATE	ADF	-1.4249	-1.6033	-1.2469	
	PP	-1.5859	-1.7648	-1.4090	
ΔALLOCATED_CAPITAL	ADF	-8.1396***	-8.1640***	-7.8781***	I(1)
	PP	-8.1451***	-8.1709***	-7.8495***	
ΔADM_COSTS	ADF	-8.5363***	-8.5005***	-8.3719***	I(1)
	PP	-36.6940***	-34.7296***	-23.7200***	

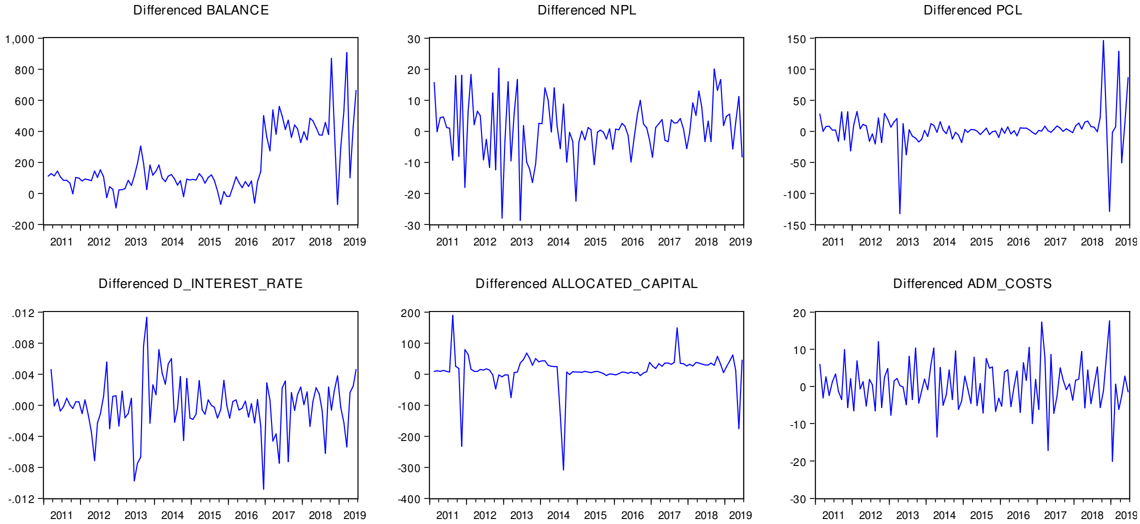
Series	test	T-stat with intercept	T-stat with trend and intercept	T-stat with none	
ΔΔBALANCE	ADF	-3.6124***	-3.6658**	-3.5377***	I(2)
	PP	-24.1178***	-27.2977***	-22.4210***	
ΔΔINTEREST_RATE	ADF	-8.4398***	-8.3830***	-8.4696***	I(2)
	PP	-8.4478***	-8.3914***	-8.4696***	

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

Source: elaborated by the author

Based on the tests, only the variable WRITE_OFF is stationary on level. For those that are not stationary in level, the first difference of the series was computed and then tested again. After that, if the series continues not stationary, the second difference was taken and the stationarity test were performed one more time. Figure 16 shows these data on first difference:

Figure 16 – Series from Payroll-linked loans on first difference



Source: elaborated by the author

Based on the tests and looking the graphs is possible to confirm that the variables NPL, PCL, ALLOCATED_CAPITAL and ADM_COSTS are actually I(1), which means they are stationary on first difference. The variables BALANCE and INTEREST_RATE, however, fail in rejecting the unit root even in their first difference, which implies that these variables are I(2). Nevertheless, looking to the graph of these variables on first difference, it appears that there are breakpoints on these series and the Bai-Perron test was computed.

The same procedures was taken for the Working Capital loans. Table 10 shows the results from the stationarity tests.

Table 10 – Stationarity tests for Working Capital loans

Series	test	T-stat with intercept	T-stat with trend and intercept	T-stat with none	
BALANCE	ADF	-0.15756	-2.30975	-0.40685	
	PP	-0.65744	-2.24124	-0.37014	
NPL	ADF	-2.25363	-2.00856	-0.92463	
	PP	-2.20639	-1.91561	0.87049	
PCL	ADF	-2.8790**	-2.80387	-0.38454	
	PP	-2.7709*	-2.63455	-0.39505	
INTEREST_RATE	ADF	-1.39796	-1.68243	-0.31391	
	PP	-1.28641	-1.71944	-0.60511	
ALLOCATED_CAPITAL	ADF	-0.64001	-2.46009	-0.33304	
	PP	-0.72843	-2.48857	-0.33464	
WRITE_OFF	ADF	-10.0036***	-10.2894***	-3.7343***	I(0)
	PP	-10.0036***	-10.3307***	-7.3346***	
ADM_COSTS	ADF	-2.5276	-2.6580	-0.3351	
	PP	-4.0686***	-4.0917***	-0.8220	

Continue

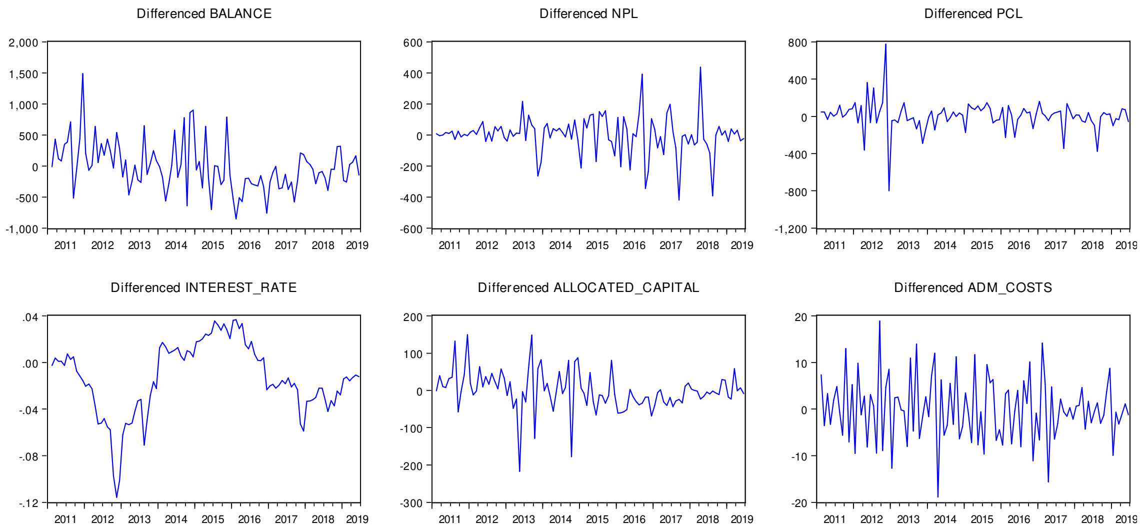
Series	test	T-stat with intercept	T-stat with trend and intercept	T-stat with none	
ΔBALANCE	ADF	-7.715979***	-8.537946***	-7.745607***	I(1)
	PP	-8.069830***	-8.546601***	-8.101240***	
ΔNPL	ADF	-9.879693***	-6.548261***	-9.929757***	I(1)
	PP	-11.89467***	-16.44674***	-11.93119***	
ΔPCL	ADF	-12.92625***	-13.01918***	-12.99079***	I(1)
	PP	-12.99005***	-13.03801***	-13.05572***	
ΔINTEREST_RATE	ADF	-3.267099***	-3.247775*	-3.288193***	I(1)
	PP	-7.224913***	-7.191376***	-7.252568***	
ΔALLOCATED_CAPITAL	ADF	-9.692267***	-10.17256***	-9.737338***	I(1)
	PP	-9.716129***	-10.17256***	-9.759773***	
ΔADM_COSTS	ADF	-8.4326***	-8.9137***	-8.4781***	I(1)
	PP	-22.7236***	-39.8174***	-22.8442***	

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

Source: elaborated by the author

As for Payroll-linked loans, in Working Capital only the WRITE_OFF is considered stationary in level. However, based on the tests and looking to the graphs on Figure 17, all the remaining variables are I(1). Even then, the breakpoint test for Working Capital loans was also taken in order to create dummies whether necessary.

Figure 17 – Series from Working Capital loans on first difference



Source: elaborated by the author

In order to confirm the breakpoints on both products, the Bai-Perron test for multiple breakpoints tests were used and the results are in Table 11.

Table 11 – Multiple breakpoints tests

Multiple breakpoint tests
Bai-Perron tests (Econometric Journal, 2003) of 1 to M globally determined breaks

	Payroll-linked				Working Capital			
Series	Breaks	Scaled F-statistic	Weighted F-statistic	Estimated break dates	Breaks	Scaled F-statistic	Weighted F-statistic	Estimated break dates
ΔBALANCE	**1 ***	**209.3562**	**209.3562**	**2016M12**	**1 ***	**20.9484**	**20.9484**	**2015M05**
	2 *	108.4299	128.8544		2 *	14.3764	17.0845	
	3 *	73.3917	105.6545		3 *	12.9451	18.6357	
	4 *	54.8038	94.2317		4 *	10.5852	18.2006	
	5 *	43.6443	95.7719		5 *	6.8755	15.0875	
ΔNPL	1	5.4183	5.4183		1	3.6700	3.6700	
	2	4.9859	5.9251		2	2.4359	2.8948	
	3	4.4782	6.4468		3	2.0011	2.8808	
	4	3.4179	5.8769		4	1.8036	3.1011	
	5	2.8092	6.1644		5	1.4849	3.2584	
ΔPCL	1	5.0618	5.0618		1	6.9102	6.9102	
	2	3.3921	4.0311		2	6.1912	7.3574	
	3	2.8914	4.1624		3	4.8576	6.9929	
	4	2.1962	3.7762		4	3.7451	6.4395	
	5	1.7332	3.8032		5	2.9994	6.5819	
ΔINTEREST RATE	1 *	72.1360	72.1360	**2012M05, 2014M03, 2016M12**	1 *	33.1036	33.1036	**2012M05, 2013M11, 2016M12**
	2 *	120.9657	143.7515		2 *	62.9989	74.8657	
	3 *	**181.1517**	**260.7856**		**3 ***	**103.1969**	148.5620	
	4 *	137.9197	237.1446		4 *	87.7057	150.8046	
	5 *	109.5213	240.3306		5 *	72.0161	**158.0302**	
ΔALLOCATED CAPITAL	1	4.2565	4.2565		**1 ***	**11.1072**	**11.1072**	**2013M01**
	2	4.3758	5.2000		2	6.3783	7.5798	
	3	3.8791	5.5843		3 *	5.9736	8.5995	
	4	3.2696	5.6219		4	4.5434	7.8121	
	5	2.8072	6.1600		5	3.2188	7.0631	
ΔADM COSTS	1	0.4682	0.4682		1	1.5815	1.5815	
	2	0.6706	0.7969		2	1.1461	1.3620	
	3	0.8269	1.1904		3	1.0103	1.4545	
	4	0.7676	1.3199		4	0.9333	1.6048	
	5	0.5222	1.1458		5	0.7589	1.6654	

* Significant at the 0.05 level.

Source: elaborated by the author

As seen above, for the Payroll-linked loans the Bai-Perron test confirms that the ΔBALANCE variable has one breakpoint (in 2016M12) and the ΔINTEREST_RATE variable has three breakpoints (in 2012M05, 2014M03 and 2016M12). Based on the breakpoint tests for these two variables, the stationarity tests were taken again considering these breakpoints. Now, the tests confirm that these two variables are actually I(1) with breakpoints and no I(2). The statistics of the stationarity tests with breakpoints are in Appendix C, Table 28 and Table 29. Besides from considering the stationarity tests again, the result of breakpoint tests was used to create dummies for the variables with breakpoint.

For the Working Capital loans, on the other hand, the Bai-Perron test was computed to create dummies as all the variables are I(1) (except for the WRITE_OFF that is stationary on level). Therefore, according to the tests, the variable ΔBALANCE has one breakpoint (in 2015M05), ΔINTEREST_RATE has three breakpoints (in 2012M05, 2013M11 and 2016M12) and ΔALLOCATED_CAPITAL has one breakpoint (in 2013M01). Dummy variables were created at those points in order to be tested in the econometric models.

The same procedure for stationarity test was taken for all the 21 macroeconomics variables. The results are in Appendix C, Table 30. After these procedures, Table 12 summarizes the stationarity tests for all the series:

Table 12 – Summary of stationarity tests for all variables

Series	Order	Series	Order
CDI_M	I(1)		
COMMITTED	I(1)		
CREDIT	I(2)	BALANCE Product 1	I(1) with break
CREDIT_C	I(2)	NPL Product 1	I(1)
CREDIT_H	I(2)	PCL Product 1	I(1)
CREDIT_R$	I(2)	INTEREST_RATE Product 1	I(1) with break
CREDIT_R$_C	I(2)	ALLOCATED_CAPITAL Product 1	I(1)
CREDIT_R$_H	I(2)	WRITE_OFF Product 1	I(0)
EXCHANGE	I(1)	ADM_COSTS Product 1	I(1)
GDP	I(2)		
HOUSEHOLDS_DEBT	I(1)		
IBC_BR	I(2)		
IBOVESPA	I(1)	BALANCE Product 2	I(1)
INCC	I(1)	NPL Product 2	I(1)
IPCA	I(0)	PCL Product 2	I(1)
IPI	I(2)	INTEREST_RATE Product 2	I(1)
NPL_C	I(1)	ALLOCATED_CAPITAL Product 2	I(1)
NPL_H	I(1)	WRITE_OFF Product 2	I(0)
SELIC_M	I(1)	ADM_COSTS Product 2	I(1)
SELIC_T	I(1)		
UNEPLOYMENT	I(1)		

Source: elaborated by the author

After this point, all these variables are used and tested in stationary form, which means, the variables I(0) are used/tested in level, I(1) variables in first difference and I(2) variables in second difference.

Another important test computed is about seasonality. The results from the tests for the macroeconomics variables are in Table 13.

Table 13 – Seasonality tests for macroeconomic variables

SERIES	QS_TEST	KW_TEST	SEASONALITY
D_CDI_M	0.00000	0.00000	TRUE
D_COMMITTED	1.00000	0.75725	FALSE
D2_CREDIT	0.00000	0.00000	TRUE
D2_CREDIT_C	0.00000	0.00000	TRUE
D2_CREDIT_H	0.00000	0.00000	TRUE
D2_CREDIT_R$	0.00000	0.00000	TRUE
D2_CREDIT_R$_C	0.00000	0.00000	TRUE
D2_CREDIT_R$_H	0.00000	0.00000	TRUE
D_EXCHANGE	1.00000	0.11336	FALSE
D2_GDP	0.00000	0.00000	TRUE
D_HOUSEHOLDS_DEBT	0.03551	0.02090	FALSE
D2_IBC_BR	0.00000	0.00000	TRUE
D_IBOVESPA	0.15371	0.11956	FALSE
D_INCC	0.00000	0.00000	TRUE
IPCA	1.00000	0.00002	TRUE
D2_IPI	0.00000	0.00000	TRUE
D_NPL_C	0.00004	0.00029	TRUE
D_NPL_H	0.00001	0.04097	TRUE
D_SELIC_M	0.00000	0.00000	TRUE
D_SELIC_T	1.00000	0.27116	FALSE
D_UNEPLOYMENT	1.00000	0.53810	FALSE

Source: elaborated by the author

The macroeconomic series with seasonality were treated by Census X-13 method[16]. The same seasonality tests were run for the Payroll-linked and Working Capital loans. The results are in Table 14.

Table 14 – Seasonality tests for Payroll-linked and Working Capital

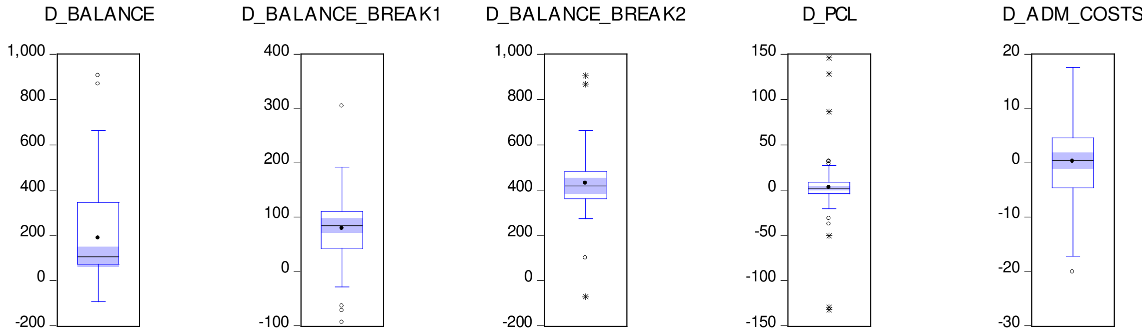
SERIES	Payroll-linked			Working Capital		
	QS_TEST	KW_TEST	SEASONALITY	QS_TEST	KW_TEST	SEASONALITY
D_BALANCE	0.49857874	0.03847934	FALSE	0.4055464	0.0389749	FALSE
D_NPL	0.00003026	0.00023889	TRUE	1.0000000	0.4091202	FALSE
D_PCL	0.83726131	0.07505484	FALSE	1.0000000	0.9302188	FALSE
D_INTEREST_RATE	1.00000000	0.38094663	FALSE	0.0370305	0.0019177	FALSE
D_ALLOCATED_CAPITAL	1.00000000	0.93672987	FALSE	0.0121490	0.0080285	TRUE
WRITE_OFF	0.00030202	0.04870195	TRUE	1.0000000	0.5279843	FALSE
D_ADM_COSTS	1.00000000	0.04161341	FALSE	0.0448337	0.1035919	FALSE

Source: elaborated by the author

[16] The Census X-13 method used to treat seasonality provided treatment for outliers as well.

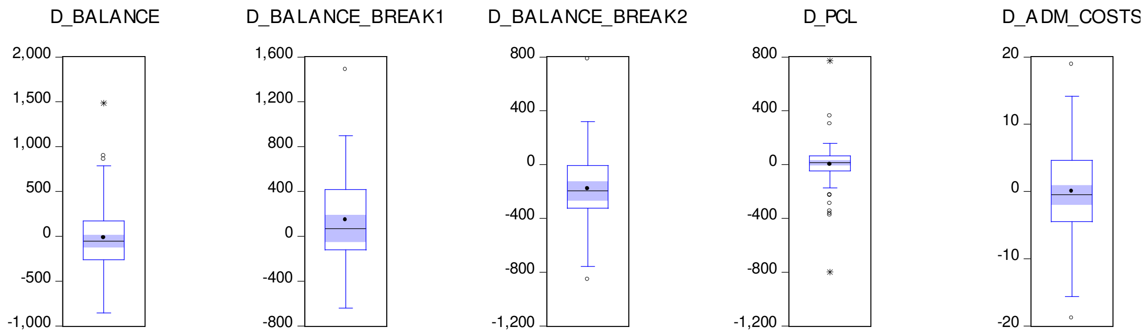
However, for the bank-specific data, we also test those series for the presence of outliers. The reason for this is to reinforce the robustness of the econometric model to be used, since these variables are endogenous in the model and, for that reason, a more careful analysis is required. Therefore, for this purpose it was used the Boxplot graphs for the Payroll-linked and Working Capital endogenous series. The results are in Figure 18 and Figure 19 and dummy variables were created to consider the presence of outliers.

Figure 18 – Boxplot Payroll-linked series



Source: elaborated by the author

Figure 19 – Boxplot Working Capital series



Source: elaborated by the author

4.2.2 Value at Risk (VaR) Model

The first assumption about the series to be used in the VaR model is on stationarity. The WRITE_OFF variables for both Payroll-linked and Working Capital are proved to be stationary in level (Table 12). Once the variables are stationary, the next step is to estimate, via maximum likelihood, the parameters for the four distributions that would fit the WRITE_OFF variable. Table 15 shows these parameters.

Table 15 – Estimated parameters for the distributions

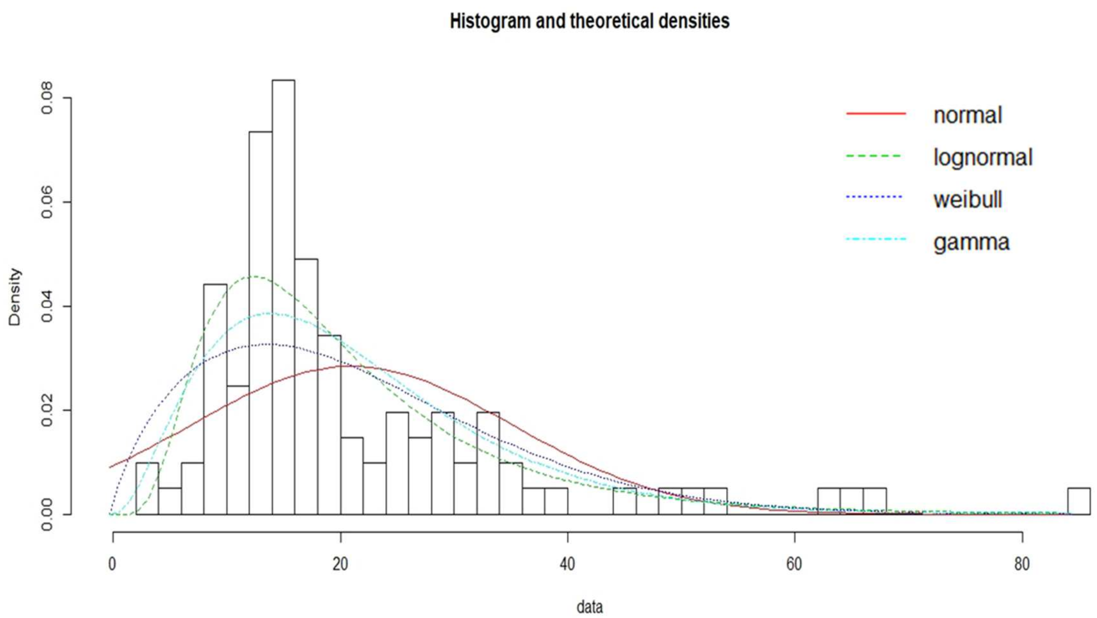
Estimated Parameters Payroll-linked							
NORMAL		LOG_NORMAL		WEIBULL		GAMMA	
mean	20.984	ln mean	2.866	shape	1.650	shape	2.968
std dev.	14.069	ln std dev.	0.593	scale	23.667	rate	0.141
Estimated Parameters Working Capital							
NORMAL		LOG_NORMAL		WEIBULL		GAMMA	
mean	60.942	ln mean	3.655	shape	1.047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

Estimated by MLE method

Source: elaborated by the author

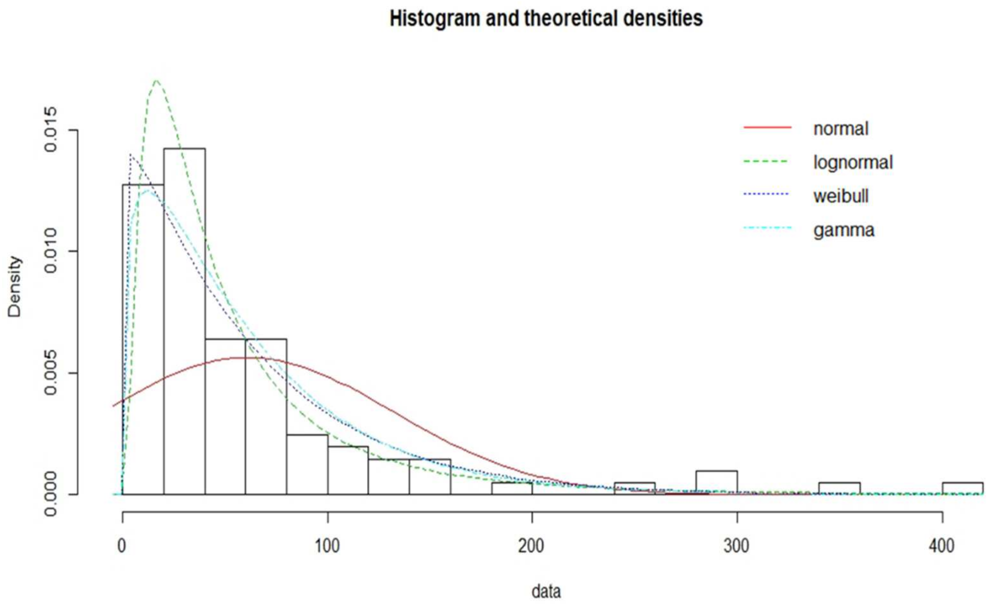
Based on the parameters from Table 15, the theoretical distribution for the data is created. In Figure 20 and Figure 21 are the histograms from the select data of each product and how the distribution curves created fits it.

Figure 20 – Histogram and Theoretical Distributions for Payroll-linked



Source: elaborated by the author

Figure 21 – Histogram and Theoretical Distributions for Working Capital



Source: elaborated by the author

Based on the graphs is possible to have an idea of which distribution best fit the data. However, to confirm if the distributions really apply to the data and to select which one fits best, the KS-test is used (Table 16).

Table 16 – KS-tests

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: elaborated by the author

Based on the p-value for Payroll-linked loans only the Lognormal distributions is accepted. Therefore, that is the distribution used for Payroll-linked VaR (based on the parameters in Table 15). On the other hand, for Working Capital loans, there are three distributions accepted based on the p-value: Lognormal, Weibull and Gamma. Therefore, using the D-stat the Lognormal is selected.

Once the distribution is fitted, the Monte Carlo VaR can be compute. The results are in Table 17:

Table 17 – VaR results

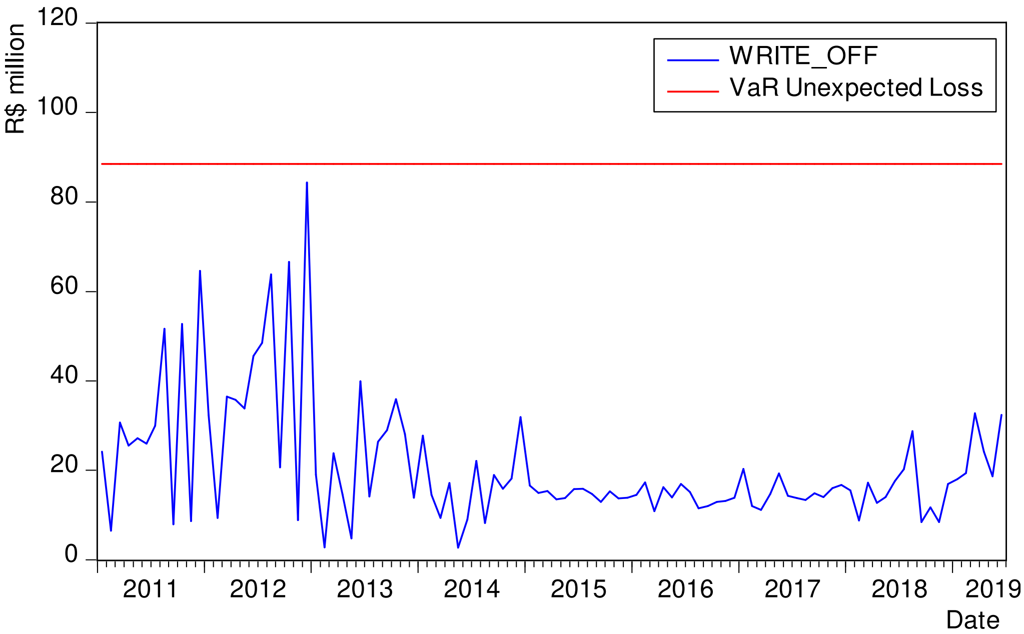
Product	monthly		one year	
	$VaR_{99.9\%}$	Unexpected Loss	$VaR_{99.9\%}$	Economic Capital
Payroll-linked	109.41	88.47	379.01	306.47
Working Capital	680.08	620.25	2,355.88	2,148.62

R$ million

Source: elaborated by the author

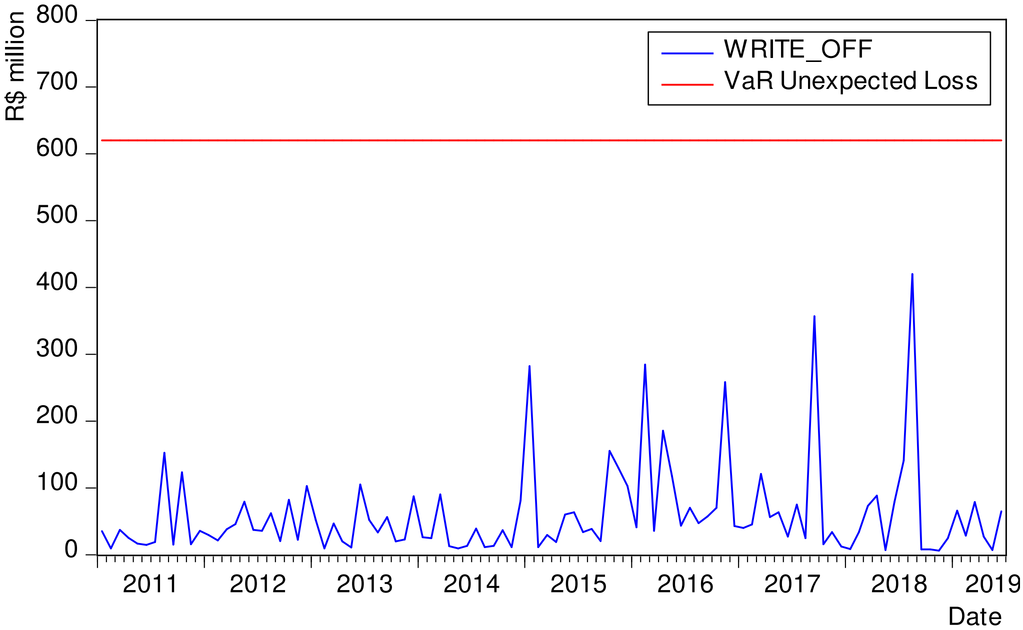
Once the VaR measures the maximum loss of a portfolio (in a 99.9% level) an important analysis consists in looking if in the period of the data, the calculated unexpected loss (VaR – mean) covers all the losses for the period (WRITE_OFF). Figure 22 and Figure 23 show it.

Figure 22 – Unexpected Loss vs Write-off for Payroll-linked loans



Source: elaborated by the author

Figure 23 – Unexpected Loss vs Write-off for Working Capital loans



Source: elaborated by the author

Based on these graphs it is possible to see that the Unexpected Loss estimated in the VaR model is sufficient to cover the losses on the historical period for both products, which means that the value is appropriate. Therefore, based on the tests and results, it is possible to confirm that the VaR model calculated is appropriate for the data and the Economic Capital calculated is accurate.

4.2.3 Vector Autoregressive (VAR/VEC) Model

Once the variables BALANCE, PCL and ADM_COSTS are not stationary in level (Table 12), running a VAR straight is rejected. Therefore, we must test for cointegration and the Johansen test is used. In Table 18 the results for the Johansen test for Payroll-linked and Working Capital loans are presented. For both products the results are not conclusively about cointegration (at 5% confidence level), because depending on the trend the variables may or may not have cointegration. At a more strict level (1%) in both products, the test shows that the variables are not cointegrated. Therefore, it is assumed that is not possible to confirm that the variables are cointegrated.

Since the variables are not cointegrated, we decided to take the first difference, transforming the variables in stationary variables, and to run a VAR model. This procedure is not supposed to be a problem, once the VAR model proposed here covers just a one-year holding period and the VAR model is proved to suit very well a short run projecting, as shown in Levieuge (2015).

Table 18 – Johansen cointegration Tests

Johansen Cointegration Test Payroll-linked					
Data Trend:	None No Intercept No Trend	None Intercept No Trend	Linear Intercept No Trend	Linear Intercept Trend	Quadratic Intercept Trend
Trace	0	0	0	1	1
Max-Eig	0	1	1	0	0
Selected (0,05 level*) Number of Cointegrating Relations by Model					
Trace	0	0	0	0	0
Max-Eig	0	0	0	0	0
Selected (0,01 level*) Number of Cointegrating Relations by Model					
Johansen Cointegration Test Working Capital					
Data Trend:	None No Intercept No Trend	None Intercept No Trend	Linear Intercept No Trend	Linear Intercept Trend	Quadratic Intercept Trend
Trace	0	0	1	0	0
Max-Eig	1	0	1	0	0
Selected (0,05 level*) Number of Cointegrating Relations by Model					
Trace	0	0	0	0	0
Max-Eig	0	0	0	0	0
Selected (0,01 level*) Number of Cointegrating Relations by Model					

*Critical values based on MacKinnon-Haug-Michelis (1999)

Source: elaborated by the author

Once defined that the model is a VAR, the next step is to choose the lag for the endogenous variables as well as to choose the exogenous variables. The variables used in the model are already treated for breakpoints, seasonality and outliers. Moreover, the dummy variables created in section 4.2.2 are also tested. Both macroeconomics and dummy variables were chosen according mostly by theoretical relevance and with the t-statistic of these variable on the model, maintain the ones that were more relevant. The stepwise[17] procedure was used to select the variables (and which lag) best fit the model.

After choosing the exogenous variables and dummies, the Information Criterions were used in order to decide the optimal number of lags for the endogenous

[17] Stepwise is an automatic procedure for fitting regression models based in specific criterions. For this work the forward selection was used, which consists starting a model with no variables and testing the addition of each predictive variable using the p-value of 0.05 as a fit criterion.

variables. Table 19 shows the criterions for both products. For Payroll-linked loans, the number of lags chosen was 4, and for Working Capital loans 6 was the number of lags chosen.

Table 19 – Information criterions

VAR Lag Order Selection Criteria Payroll-linked						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1,102.92	NA	30,182,954	25.729	26.903	26.202
1	-1,089.29	22.045	27,376,611	25.625	27.051	26.199
2	-1,061.91	42.468	18,276,561	25.211	26.889*	25.888
3	-1,049.02	19.118	16,958,359	25.124	27.053	25.902
4	-1,032.79	22.966*	14,659,241*	24.961*	27.143	25.840*
5	-1,026.96	7.865	16,080,582	25.033	27.466	26.013
6	-1,017.66	11.912	16,408,957	25.026	27.710	26.108
7	-1,013.45	5.110	18,894,554	25.134	28.070	26.317
8	-1,005.46	9.152	20,138,309	25.156	28.344	26.441
VAR Lag Order Selection Criteria Working Capital						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1,313.13	NA	6.89E+09	31.127	33.139*	31.938
1	-1,300.99	16.926	6.54E+09	31.056	33.321	31.969
2	-1,291.16	13.029	6.57E+09	31.037	33.554	32.052
3	-1,280.81	13.029	6.56E+09	31.007	33.775	32.123
4	-1,263.16	21.012	5.60E+09	30.813	33.833	32.030
5	-1,252.27	12.243	5.61E+09	30.770	34.042	32.089
6	-1,226.22	27.509*	4.03e+09*	30.386*	33.910	31.807*
7	-1,219.61	6.534	4.53E+09	30.441	34.216	31.962
8	-1,209.18	9.610	4.73E+09	30.409	34.435	32.032

* indicates lag order selected by the criterion (0.05 level)

Source: elaborated by the author

After that, the Granger Causality test was run to confirm the ordering of the variables at the model. Table 26 in Appendix C shows the Granger Causality tests for Payroll-linked and Working Capital loans. Based on the table it is defined that the first variable for Payroll-linked loans will be BALANCE, because it Granger cause the other two variables in almost all the lags tested (in a 10% confidence level). It is also defined that ADM_COSTS will be the last variable in the model because it is Granger caused by the other two variables and only causes BALANCE and PCL in a few lags. Therefore, the order for the VAR model for Payroll-linked are: BALANCE, PCL and ADM_COSTS.

For the Working Capital loans, on the other hand, it is defined that the first variable will be PCL, because it is the only variable that Granger cause the other two variables, even whether in a few lags. The second variable will be BALANCE, because it is Granger caused by PCL and Granger cause ADM_COSTS. Finally, the ADM_COSTS will be the third. Therefore, the order for the VAR model for Working Capital are: PCL, BALANCE and ADM_COSTS.

After all the definitions about the model, such as the order of the variables, the optimal number of lags for the endogenous variables and which are the dummy and exogenous variables, the VAR models for Payroll-linked and Working Capital loans are computed. The results for these models are in Appendix C, Table 31 and Table 32, where may be found the coefficients estimated for all variables as well as the standard errors and the coefficient of determination for each model.

Once the model is chosen, it is important to run some tests on the residuals and check the robustness of the model. The first assumptions for the residuals is that they follow a normal distribution. For this purpose, the Jarque-Bera test was used, with three different methods for orthogonalization: Cholesky, Residual Correlation and Residual Covariance. The results for the tests are in Table 20 for Payroll-linked and Working Capital loans.

Table 20 – Residual Normality Tests

VAR Residual Normality Tests								
	Payroll-linked				**Working Capital**			
Orthogonalization: Cholesky (Lutkepohl)								
Component	Skewness	Kurtosis	Jarque-Bera	Prob.	Skewness	Kurtosis	Jarque-Bera	Prob.
1	-0.11973	2.85415	0.29151	0.8644	0.10912	3.20333	0.32992	0.8479
2	-0.19264	2.66596	0.96426	0.6175	-0.10361	2.51187	1.04282	0.5937
3	0.16806	3.16967	0.52571	0.7689	-0.01568	3.46910	0.81968	0.6638
Joint				0.9387				0.9012
Orthogonalization: Residual Correlation (Doornik-Hansen)								
Component	Skewness	Kurtosis	Jarque-Bera	Prob.	Skewness	Kurtosis	Jarque-Bera	Prob.
1	-0.12270	2.86738	0.28936	0.8653	0.10219	3.35256	1.79348	0.4079
2	-0.19683	2.77226	0.68145	0.7113	-0.03576	2.58789	0.20735	0.9015
3	0.12229	3.16737	0.99640	0.6076	-0.06024	3.21113	1.09123	0.5795
Joint				0.9227				0.7972
Orthogonalization: Residual Covariance (Urzua)								
Component	Skewness	Kurtosis	Jarque-Bera	Prob.	Skewness	Kurtosis	Jarque-Bera	Prob.
1	-0.11954	2.85571	0.25310	0.8811	0.10683	3.51188	1.64811	0.4386
2	-0.19856	2.71321	0.83776	0.6578	-0.01833	2.61755	0.44241	0.8016
3	0.13335	3.16292	0.51309	0.7737	-0.02204	3.43838	1.12572	0.5696
Joint				0.9398				0.7291

Null Hypothesis: Residuals are multivariate normal

Source: elaborated by the author

Based on Jarque-Bera test is possible to confirm that all the variables for both models presents residuals normally distributed. Another assumption on the residuals is about Autocorrelation. In order to confirm that the residuals do not present autocorrelation, the LM test was used and the results can be seen in Table 21 and Table 22, for Payroll-linked and Working Capital loans, respectively.

Table 21 – Residual Serial Correlation Tests for Payroll-linked

VAR Residual Serial Correlation LM Tests				
Lag	LRE* stat	Prob.	Rao F-stat	Prob.
1	16.7712	0.0524	1.9279	0.0525
2	6.9051	0.6470	0.7668	0.6472
3	10.0987	0.3426	1.1340	0.3428
4	9.9370	0.3556	1.1153	0.3558
Null hypothesis: No serial correlation at lag h				
Lag	LRE* stat	Prob.	Rao F-stat	Prob.
1	16.7712	0.0524	1.9279	0.0525
2	21.6375	0.2485	1.2223	0.2495
3	30.1391	0.3079	1.1319	0.3110
4	37.0924	0.4184	1.0363	0.4252
Null hypothesis: No serial correlation at lags 1 to h				

*Edgeworth expansion corrected likelihood ratio statistic.

Source: elaborated by the author

Table 22 – Residual Serial Correlation Tests for Working Capital

VAR Residual Serial Correlation LM Tests				
Lag	LRE* stat	Prob.	Rao F-stat	Prob.
1	10.8124	0.2888	1.2231	0.2892
2	13.3469	0.1475	1.5283	0.1479
3	15.6977	0.0735	1.8180	0.0737
4	4.3412	0.8876	0.4761	0.8877
5	11.9729	0.2148	1.3619	0.2152
6	7.1602	0.6204	0.7959	0.6208
Null hypothesis: No serial correlation at lag h				
Lag	LRE* stat	Prob.	Rao F-stat	Prob.
1	10.8124	0.2888	1.2231	0.2892
2	23.8593	0.1597	1.3691	0.1614
3	37.0696	0.0938	1.4420	0.0972
4	41.2039	0.2534	1.1729	0.2656
5	48.1511	0.3466	1.0802	0.3716
6	67.2971	0.1056	1.3134	0.1316
Null hypothesis: No serial correlation at lags 1 to h				

*Edgeworth expansion corrected likelihood ratio statistic.

Source: elaborated by the author

The LM test confirms that the residuals do not present autocorrelation for a 5% level of confidence for both products. Finally, homoscedasticity is the last assumption about the residuals and for this purpose the White test was performed. The results for both Payroll-linked and Working Capital are in Table 23.

Table 23 – Residual Heteroskedasticity Tests

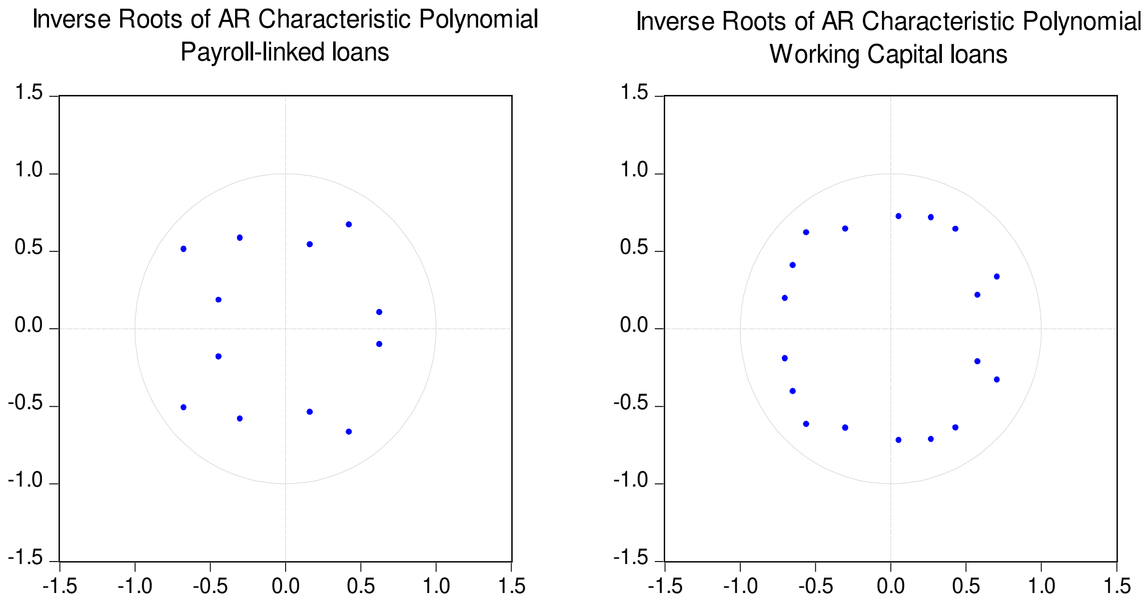
VAR Residual White Heteroskedasticity Tests					
Payroll-linked			**Working Capital**		
Component	Chi-sq	Prob.	Component	Chi-sq	Prob.
res1*res1	48.475	0.335	res1*res1	68.135	0.670
res2*res2	42.383	0.583	res2*res2	63.258	0.809
res3*res3	51.419	0.237	res3*res3	71.941	0.546
res2*res1	36.525	0.812	res2*res1	77.698	0.362
res3*res1	51.975	0.221	res3*res1	76.081	0.411
res3*res2	39.758	0.693	res3*res2	65.925	0.737
Joint	268.764	0.510	Joint	422.829	0.758

Null hypothesis: the variances for the errors are equal (homoscedasticity)

Source: elaborated by the author

White test confirms that the residuals are homoscedastic for both products. Finally, some robustness checks were performed. First, in order to check if the models are stable, it was checked the inverse roots of the characteristic polynomials (Figure 24). Once all the values are inside the unit circle it is affirmed that the models are stable.

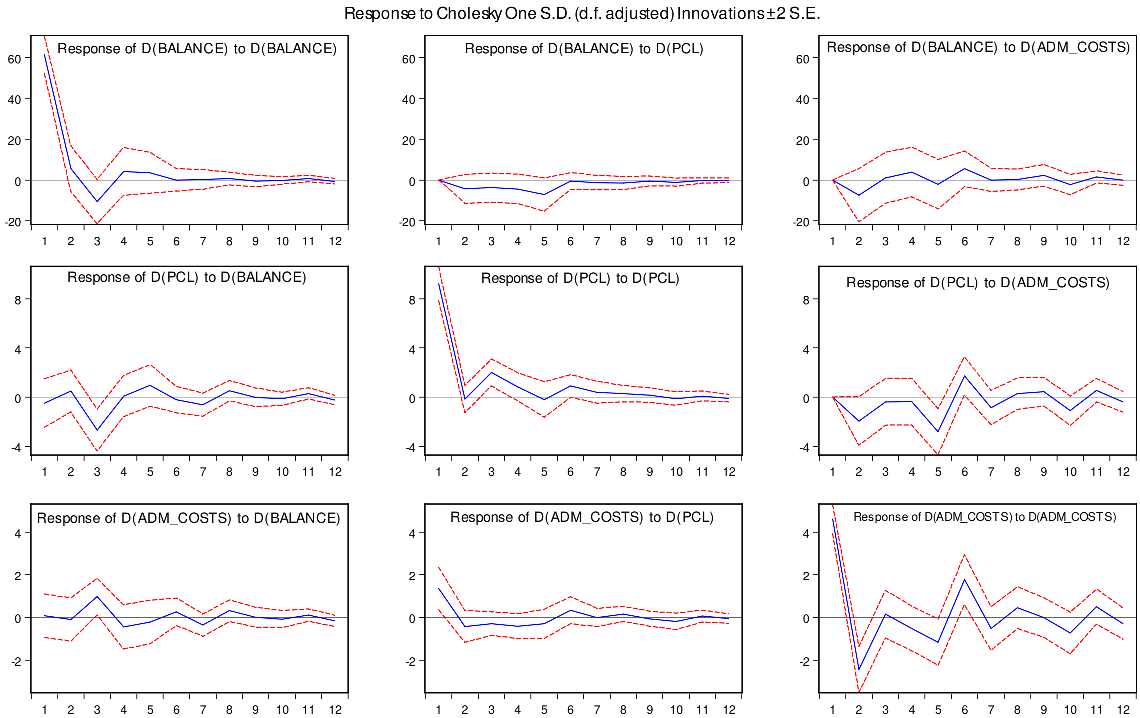
Figure 24 – Inverse Roots of the Characteristic Polynomials



Source: elaborated by the author

After that, it is possible to analyze the Impulse Response functions. Figure 25 shows the results for Payroll-linked loans. It is noticed that the main impacts found occurred in the impulses of the autoregressive terms, especially in relation to the Administrative Costs where the impulse responses spread throughout the analyzed period. For Balance and Provision, the effect is positive and large in the first period, but decreases rapidly and is almost nil after the sixth period. Regarding the other variables, the effects are smaller. However, the effect of the Provision on the Balance stands out, when a shock in the provision decreases the Balance for 5 consecutive periods and also effects in the opposite direction, i.e. impulses in the Balance over the Provision, when effect alternates between positive and negative for 8 periods until it disappears.

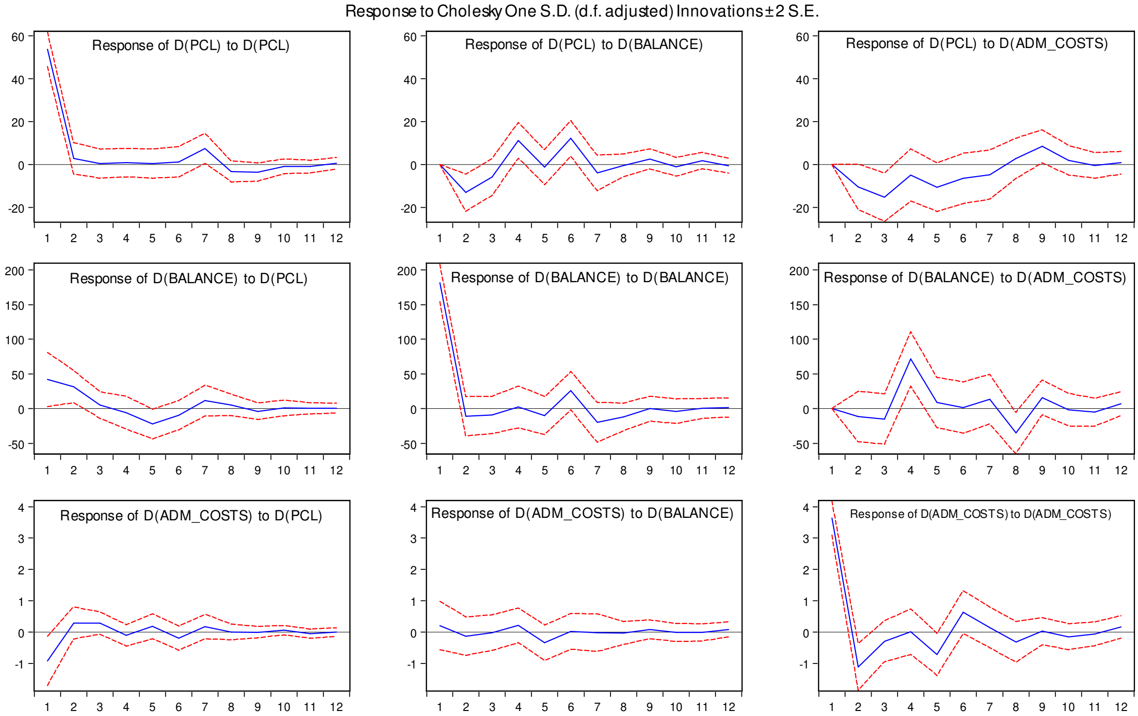
Figure 25 – Impulse Response Function for Payroll-linked



Source: elaborated by the author

Figure 26 shows the results for Working Capital loans. As in Payroll-linked, the main effects are in the autoregressive terms and especially in the first period, although there are also significant effects for the Provision in the seventh period, for the Balance in the sixth period and alternating effects for Administrative Costs up to the ninth period. For the other variables, it is noteworthy that shocks in Administrative Costs have a response in both Balance and Provision. Finally, it is also highlighted that the Provision and the Balance present responses to the impulse in both directions.

Figure 26 – Impulse Response Function for Working Capital



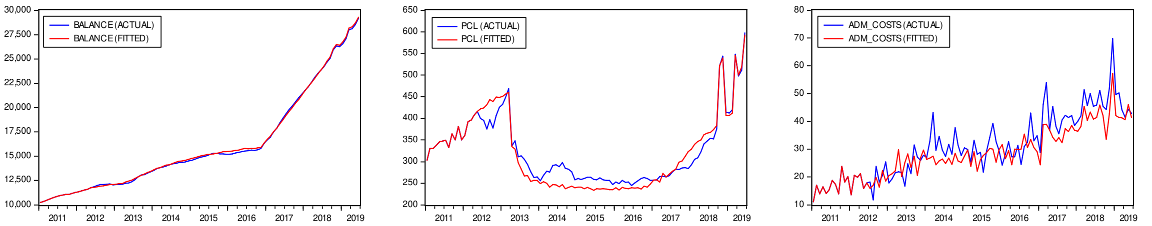
Source: elaborated by the author

Another important analysis is about the Variance Decomposition. Table 27 in Appendix C shows the results for Payroll-linked and Working Capital loans. Regarding Payroll-linked, it is clear that the Balance has almost all its variance explained by itself, reaching the end of the 12th period with the total error being explained by 94% by itself, 3% by Provision and 3% by Administrative Costs. For Working Capital, the breakdown of the variance of the Balance is more strongly influenced by the other variables, since at the end of the period analyzed the Provision is responsible for 8% of the variance and Administrative Costs for 16%.

For the Provision and Administrative Costs variables, both Payroll-linked and Working Capital products have very similar variance decomposition. For the Provision, the variable itself is responsible for 77% and 72% of the variance breakdown in the 12th month for Payroll-linked and Working Capital, respectively. For Administrative Costs, the variance was almost entirely explained by the variable itself, reaching 89% and 92% at the end of the period analyzed for Payroll-linked and Working Capital, respectively.

Finally, the last robustness check is about the Coefficient of Determination (R^2) and the graphs of the fitted values versus the actual values. These analyses allows to check if the model proposed is accurate and, therefore, a good model for predictions. Figure 27 shows the R^2 and the fitted vs actual values for Payroll-linked loans while Figure 28 shows it for Working Capital loans.

Figure 27 – Graphs of Fitted vs Actuals values for Payroll-linked loans

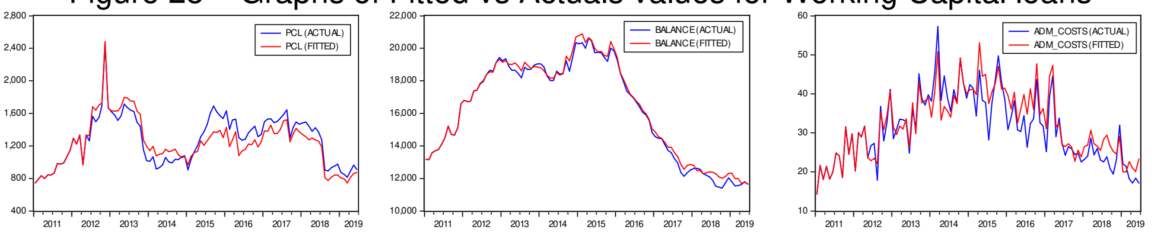


R-squared: 93,74% Adj. R-squared: 91,26% R-squared: 94,17% Adj. R-squared: 91,86% R-squared: 62,29% Adj. R-squared: 47,33%

Source: elaborated by the author

The adjusted R^2 index is high for the variables BALANCE and PCL (91% for both) and moderate (47%) for the ADM_COSTS variable. Moreover, analyzing the graphs of fitted versus actual values for these three variables it is possible to check that the model correctly captures the trends for the series.

Figure 28 – Graphs of Fitted vs Actuals values for Working Capital loans



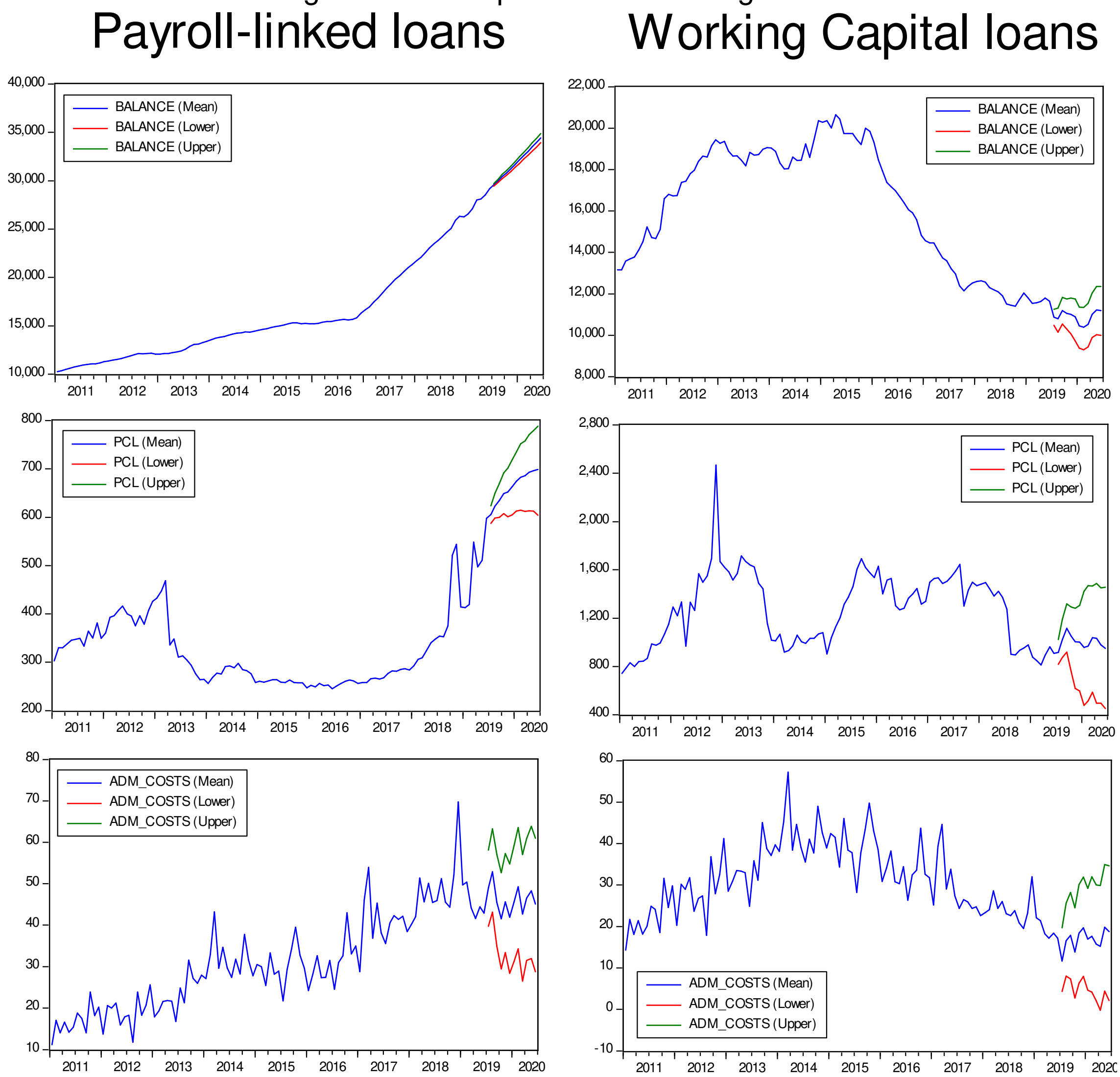
R-squared: 94,53% Adj. R-squared: 89,75% R-squared: 85,71% Adj. R-squared: 73,25% R-squared: 84,26% Adj. R-squared: 70,53%

Source: elaborated by the author

The adjusted R^2 index is high for the three variables: PCL (89%), BALANCE (73%) and ADM_COSTS (70%). Additionally, analyzing the Graphs of fitted versus actual values for these three variables it is possible to see that the model correctly captures the trends for the series.

Lastly, Figure 29 shows the forecasting for the variables of Payroll-linked and Working Capital loans.

Figure 29 – Graphs of Forecasting series



Source: elaborated by the author

4.3 RAROC RESULTS

This section presents the main results found for the RAROC models and it is divided into three subsections: Regulatory RAROC, Economic RAROC and Forecasted RAROC.

The RAROC model represents the financial return that a given credit portfolio offers relative to the amount of equity that is necessary to face this credit portfolio, risk-based. In other words, it represents the opportunity cost of capital funded by a shareholder. Therefore, the three perspectives suggested for the RAROC model here provide distinct alternatives that might assist managers in the decision-making process.

4.3.1 Regulatory RAROC

The Regulatory RAROC aims to analyze the history of risk-adjusted product profitability. In this model, an approach was taken from 2011M01 to 2019M06 based on the regulatory models imposed by the appropriate regulatory bodies. Thus, with this model it is possible for managers to analyze *ex-post*, month by month, if the product added value to the institution in the period based on regulatory terms. In order to make this analysis, two evaluations were made about the historical return. In the first one, it is observed only if the return was positive or negative. In the second, following Chlopek (2013), the return is compared to the ROE median of the four main banks operating in Brazil[18]. Although RAROC and ROE are different indices, ROE is the most used index by the market in the analysis of this sector and, consequently, it is the most publicized index. Therefore, it is used as a benchmark.

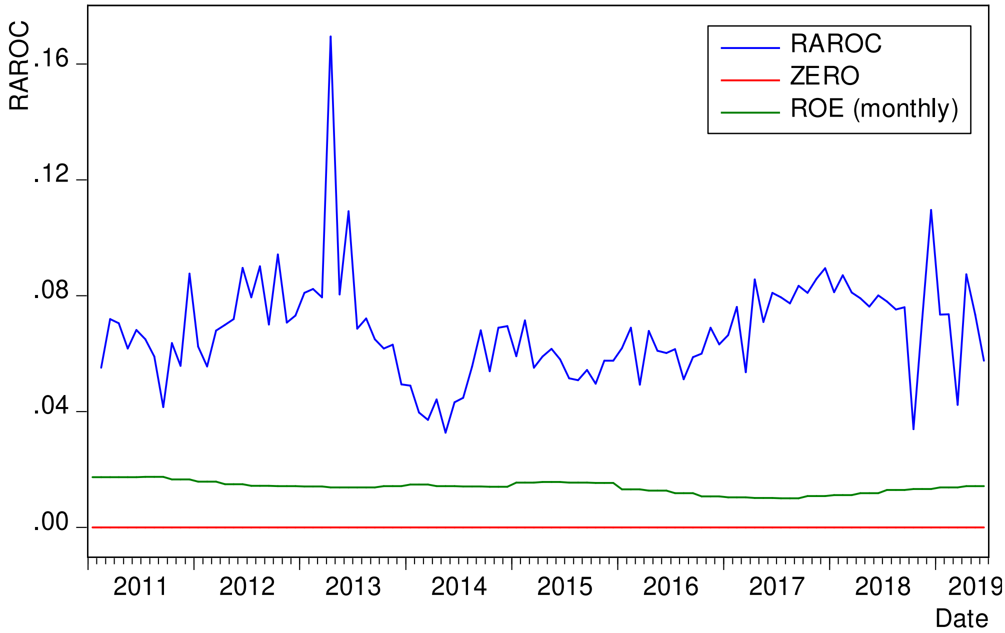
In the first analysis, the interpretation is quite intuitive. In case of positive returns, it means that the product in question added value to the institution that month. Otherwise, the product destroyed value in that period. In the second analysis, as ROE measures how much these four banks returned on average over the period, by analyzing the regulatory RAROC using this indicator, it is possible to examine whether the product generated value above the market median. It may occur that the product has generated a positive value in some month but this return is less than the market return. The expected goal is that the RAROC of the product is higher than the ROE, which indicates that the product in question not only generated value for the institution, but also added a value higher than the market median, which indicates that this product drives up the return of the bank as a whole. If the return is positive but lower than ROE, it means that the product generated value but less than the market average.

Looking at the payroll-linked loans in Figure 30 it can be seen that this product had a positive return throughout the entire period. It is also possible to notice that the product had returns superior then ROE throughout the period and, therefore, added value to the institution above the average market return value. Thus, managers may

[18] ROE stands for Return on Equity and represents the net income divided by the equity. It is widely used on financial market to analyze performance. The median of the four main banks operating in Brazil was collected at Economatica (2019) website. The data provided on the web site is quarterly and represents the annual ROE. Therefore, the ROE was transformed to monthly in order to compare with the Regulatory RAROC calculated. Figure 36 in Appendix C shows the data.

analyze this product as a good investment because it brings a good risk-adjusted return and pays above-average allocated capital. Therefore, it is possible to suggest that the bank in question, based on this regulatory RAROC view, should continue to invest capital in this product, as the returns are satisfactory.

Figure 30 – Regulatory RAROC from Payroll-linked loans



Source: elaborated by the author

During the period analyzed, payroll-linked loans returned 8.13% on average. The highlight in 2013M04 was when it returned 18.20% driven mainly by a large reversal of provision in that month. Also noteworthy are the 2012M10, 2013M06, 2017M04, 2017M12, 2018M02 and 2018M12 points as additional high return points, with the return reaching double digits in these months.

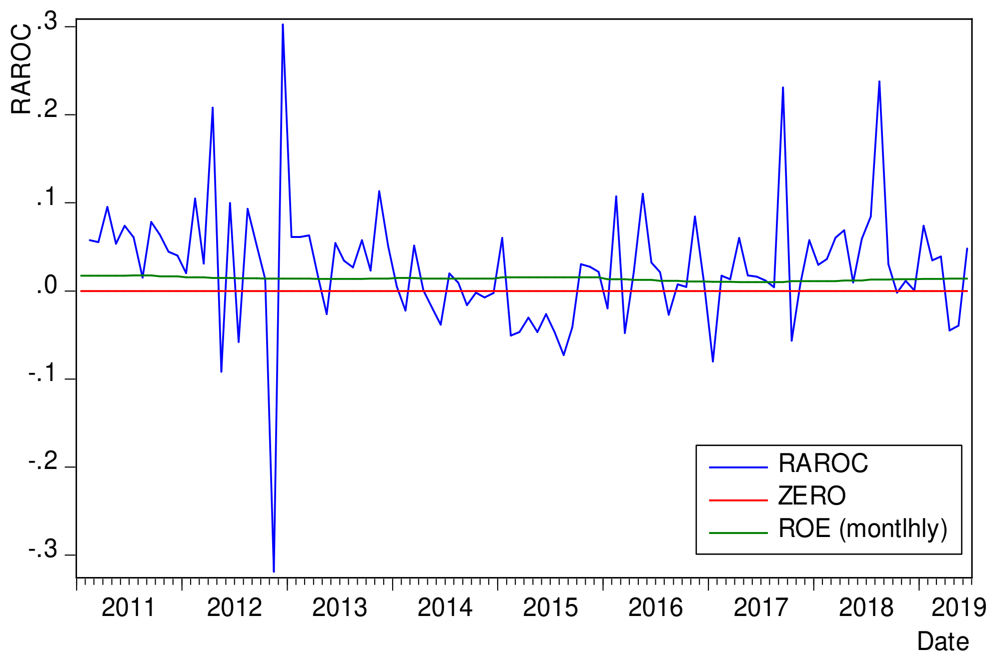
It is also noted that the return decreased between 2013M07 and 2014M05, which is the beginning of a strong recession in the Brazilian economy, where credit volume levels decreased considerably as can be seen in the macroeconomic variables (see Figure 35 in Appendix C). In addition, during this period product delinquency (represented by the variable NPL) increased sharply from R$ 157 million at the end of 2013 to over R$ 200 million in the first half of 2014. The increase in delinquency has a strong impact on provision levels and therefore the profitability of the product.

However, it is important to note that even during 2014 the return increased again and the rest of the historical series was reasonably constant and high. Again an important factor was the control of delinquencies in this period, which steadily reduced from the second half of 2014 to the historic low of 137 million in 2016M07 (see Figure 13). Finally, in the last months of analysis there were three strong negative peaks downward in 2018M10, 2019M03 and 2019M06. In all three occasions, they were motivated by high provision flows. In particular, the period from 2018M10 stands out when there was an increase of 38.90% in the provision volume.

In conclusion, it is possible to affirm that Payroll-linked loans presented a good return in the analyzed period. It is important to highlight that, in addition of presenting positive returns throughout the history, it can be concluded that it was at a constant level even in periods of economic crisis, which reinforces the importance of having this type of product in the portfolio.

On the other hand, when analyzing Working Capital in Figure 31, it is clear that this product presented a result that fluctuated greatly during the period under analysis. The product presented several periods of return below zero, which means that in these periods the capital allocated to this product did not remunerate the invested capital, on the contrary, it destroyed the institution's value. However, it is important to note that the product also showed positive results at many points when it had very significant returns.

Figure 31 – Regulatory RAROC from Working Capital loans



Source: elaborated by the author

The average return on Working Capital loans over the reporting period was 4.03%. We highlight a strong negative period in 2012M11 when the return reached -30.38% mainly affected by the provision expenses that increased 45.60% this month. In addition, the product return was negative in another 19 months and was still below ROE by 27 times in the period analyzed. This means that on several occasions the product offered below average market return and often still a negative return, destroying value of the institution. The negative return was caused by the balance that decreased significantly affecting revenues and, above all, by the very high delinquency that affected the provision.

The product had an average delinquency rate of 3.70% over the entire period, and this rate was very high especially from 2015 to 2017, a period in which the Brazilian economy shrunk resulting in a sharp reduction in credit volume and a large increase in unemployment rates. In addition to a very high income commitment by the end of 2016 (see Figure 35 in Appendix C with the macroeconomic variables). The Working Capital delinquency rate averaged 5.30% in this period, reaching 8.38% in 2016M09, 7.54% in 2017M06, 7.92% in 2017M07 and 7.44% 2017M08.

However, it is also important to highlight that the product had a positive return in several months. Including return over 20% in 4 points. In 2012M12 the return was 31.43%. This point followed the negative peak of -30.38% and the explanation is very similar. As in 2012M11 there was a considerable increase in provision as previously stated, the following month a large number of overdue operations were written off at a loss. This procedure ends up “clearing the portfolio” as it is known in the banking sector and, consequently, when clearing overdue transactions the provision level drops a lot, which explains this very high return in 2012M12. Another high return point was in 2012M04 when it reached 21.81% influenced by a 27.34% drop in provision. In 2017M09 and 2018M08, the returns were 24.48% and 25.14% respectively. In these occasions again there was a very high level of written off balance that influenced the income. The write off was 356.85 million in 2017M09 and 419.84 million in 2018M08, while the historical average of product write offs is 60.94 million.

In addition, the product returned 2-digit RAROC in another 6 months throughout the series, which helped pull the average return up. It is important to note that in the higher months of RAROC, in addition to the high reversal of PCL, there was also a sharp reduction in delinquency (NPL) in the period, probably due to a more active management action to collect arrears. Another important factor for RAROC's positive return was the stabilization of the product balance, which interrupted the downward cycle in 2018M08 by reinforcing the product's revenues. In addition, it is noted that the return on output remained at negative levels for almost the entire period between 2014 and 2015. However, after this period the return began to improve. Although much more modest, it was in line with the macroeconomic credit volume which has risen sharply since 2017 (see Figure 35 in Appendix C).

Therefore, it can be concluded that Working Capital loans had a moderate RAROC, showing good returns at certain times, but negative returns over many periods. Active management and close attention are required from managers, especially in order to analyze the reasons that led the product to present such negative returns and to take appropriate measures to ensure that this does not occur, i.e. to mitigate periods of strong falls when the indicator shows negative returns, as it will be destroying the institution's capital. If it is not possible to mitigate these negative returns, an alternative would be to add more resources to more profitable products, such as the Payroll-linked loans or other products that may be analyzed.

Although the return is lower than Payroll-linked, it is important to mention that it does not necessarily means that the bank should stop offering this product and invest all capital in Payroll-linked, for example. This is because it is very important to diversify investments and a commercial bank usually stands in various products avoiding concentration risk.

The need for more active portfolio management as seen is one reason why it is important to have a prospective analysis (that will be seen in section 4.3.3) as this way managers can act in advance, anticipating actions to avoid possible scenarios where the return projection is negative, for example.

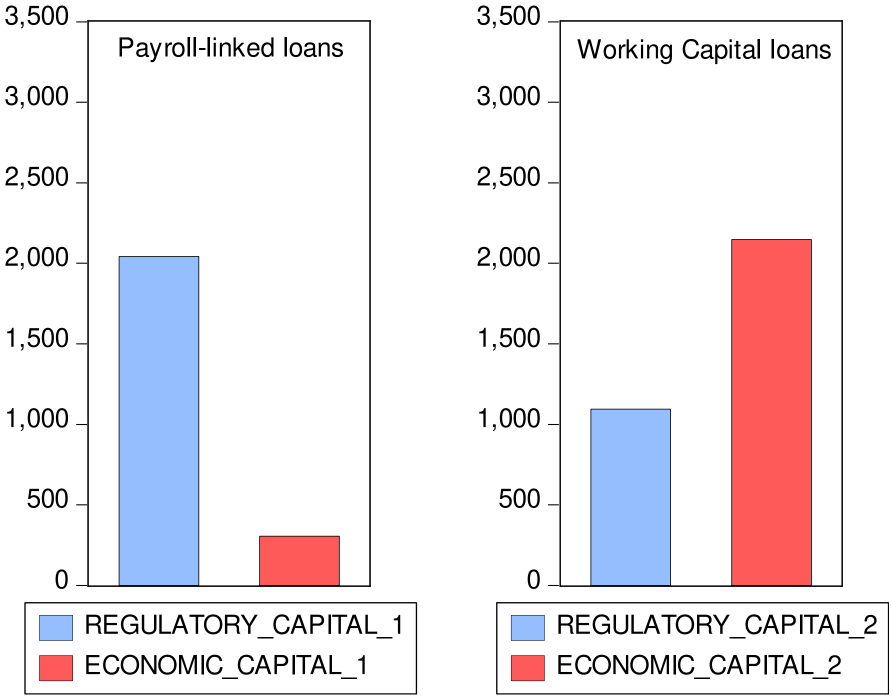
4.3.2 Economic RAROC

For Economic RAROC, the goal was to calculate the capital needed to face the unexpected losses from each product. This calculation suggests a methodology to be used as an internal model that considers the historical series of product losses to calculate the actual capital needed to cover these unexpected losses. Therefore, unlike regulatory RAROC which is standardized and equal for all institutions, the Economic

RAROC model has a customized approach to the institution, reflecting more accurately the risk of each product as well as idiosyncratic aspects of the bank/product.

The calculation was made based on 2019M06. In this period the Economic Capital calculated for both products was R$ 2.46 billion. In comparison, Regulatory Capital was R$ 3.14 billion in this same period. Therefore, Economic Capital was lower by R$ 680.88 million, or 27.73%. Additionally, in Figure 32 it is possible to compare the Economic and Regulatory Capital for each one of the products.

Figure 32 – Regulatory versus Economic Capital



Source: elaborated by the author

Note that for Payroll-linked loans, Economic Capital was substantially lower than Regulatory Capital. While Regulatory Capital was R$ 2.04 billion, Economic Capital was R$ 306.47 million. Therefore, a difference of R$ 1.74 billion or almost 7 times smaller. For Working Capital, on the other hand, the Economic Capital was much higher than the Regulatory. Economic Capital was R$ 2.15 billion while Regulatory Capital was R$ 1.09 billion. Thus, Economic Capital was R$ 1.05 billion above the Regulatory.

This disparity between the two products is due to their own characteristics, which are taken into account in the internal model. Product 1 is pay-rolled, i.e. the discount is made directly to the customers' payroll and then automatically passed on to the bank. This fact makes the default rate much lower than other products, such as Working Capital, for example. For comparison purposes, the average Payroll-linked delinquency rate was 1.15% while the Working Capital rate was 3.63% in the period. Higher delinquency, consequently, will lead to higher losses, affecting significantly the model designed to calculate Economic Capital.

As stated earlier, the model created seeks to calculate the capital needed to meet unexpected losses. Therefore, if the history of losses presents higher values and, therefore, more distant from the average or, even if the history presents very large oscillations, it is expected that the model calculate a larger Economic Capital value for this product. This was the case of Working Capital, where the average loss was R$ 60.94 million with a standard deviation of R$ 71.15 million. In comparison, Payroll had an average loss of R$ 20.99 million with standard deviation of R$ 14.14 million (see Table 7).

In addition to a higher average and standard deviation, Working Capital also shows in Figure 14 that there were many peaks with very high losses during the period. We highlight the points in 2015M01 (R$ 282 million), 2016M02 (R$ 285 million), 2016M11 (R$ 258 million), 2017M09 (R$ 357 million) and 2018M08 (R$ 420 million). These high peaks contribute to the variation of losses being larger and, consequently, the greater the risk involved generating a larger calculation also for the economic required capital.

Payroll-linked, on the other hand, present smaller loss values as can be seen in Figure 13. Looking at the chart shows that the losses are smaller and even more behaved around the mean, especially when analyzing the period from 2015. Thus, the Economic Capital needed to face these losses became much smaller, which was to be expected.

Consequently, the internal model, when calculated based on the reality of the risks for each product, is able to predict that, in the sum of the two products, the Economic Capital required to meet these losses is much smaller than that required by the regulator, which is quite conservative. Thus, using the internal model will yield a much higher return on allocated capital as shown in Table 24. As can be seen from the table, although Working Capital RAROC decreased from 5.72% to 2.91% the Payroll-linked loan RAROC would go from 6.87% to 45.75%. Therefore, the sum of the two products would yield a much higher return when considering the internal model.

Table 24 – Regulatory versus Economic RAROC

Product	Date	Regulatory RAROC	Economic RAROC
Payroll-linked loans	2019M06	6.87%	45.75%
Working Capital loans	2019M06	5.72%	2.91%

Source: elaborated by the author

According to Allen, Boudoukh and Saunders (2004), internal models are more sophisticated than standardized ones and thus more sensitive to the risks of each portfolio. Also according to the authors, the Regulatory Capital tends to be higher than economically necessary, corroborating what was observed in this work.

Therefore, the major advantage of using the internal model would be a better allocation of capital, allowing banks to reduce their capital charges and increase their potential profitability. Given that resources – in this case the capital – are scarce, by better allocating capital, managers will be optimizing their decision making and the result will be a higher return on allocated capital compared to the Regulatory, becoming the banks more competitive. In addition, it could use this capital offer more loans, increasing its customer base and bringing even more returns.

Furthermore, the result found in this paper may be used for managers to encourage the use of internal models in Brazil. Since Basel II banks have been stimulated to develop internal models, however to this day all banks operating in Brazil officially use the Standardized Approach (SA).

4.3.3 Forecasting RAROC

Lastly, the forecasted RAROC model is presented, where the goal is to estimate what the risk-adjusted returns would be in a possible future scenario, enabling an *ex-ante* prospective decision making by agents. In this stage, using an econometric model, the three main variables of each product were projected.

The econometric models used in the projection are multivariate autoregressive models. Thus, they take into account the relationships between the variables of each product among themselves contemporary and in their lags. In addition, they also take into account other variables such as the created dummies and the relationships with macroeconomic variables (exogenous in the model).

The interrelationship between the variables was important to capture the effects that one of the variables might have on others. The relationship with the macroeconomic variables was very important because it allows the analysis of the connection among the model variables and the real economy variables. This relationship brings greater dynamism to the model and allows incorporating the projections of the economy – which consequently affect the bank's portfolios – into the model, adjusting the projections for each product in line with the available macroeconomic projections.

The result of the forecasting models is in Table 25 for the variables: BALANCE, PCL and ADM_COSTS.

Table 25 – Forecasting results

Date	Payroll-linked loans			Working Capital loans		
	Balance	PCL	Adm Costs	Balance	PCL	Adm Costs
2019M07	29,568.51	605.90	49.01	10,879.97	915.97	11.63
2019M08	29,975.76	623.14	52.88	10,793.86	1,022.69	16.57
2019M09	30,430.39	634.69	45.48	11,183.02	1,115.19	17.91
2019M10	30,802.55	648.81	41.52	11,048.93	1,052.33	13.86
2019M11	31,235.26	652.26	45.62	11,016.85	1,003.80	18.42
2019M12	31,690.95	662.96	41.96	10,888.10	1,002.19	19.64
2020M01	32,138.36	674.28	45.60	10,449.17	958.16	16.92
2020M02	32,596.61	683.07	49.26	10,389.67	969.54	17.64
2020M03	33,032.82	685.85	42.66	10,537.43	1,037.47	15.75
2020M04	33,507.14	693.23	46.53	11,019.32	1,034.84	15.20
2020M05	33,957.44	696.45	48.24	11,217.91	977.51	19.86
2020M06	34,422.98	698.70	45.10	11,202.63	950.44	18.75

Source: elaborated by the author

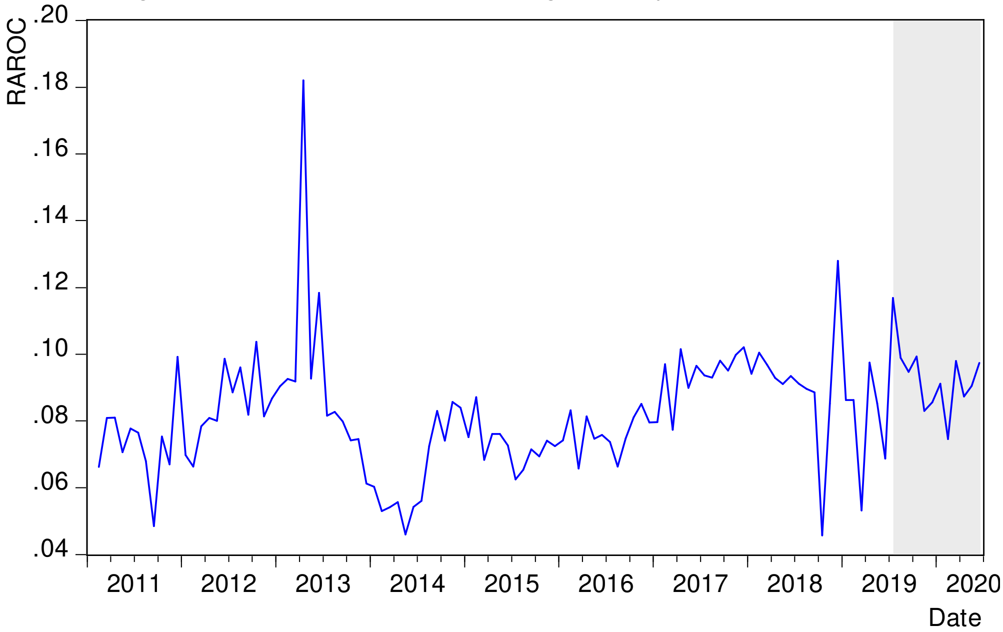
For Payroll-linked loans, the BALANCE grows almost steadily. During the period, the average growth rate was 1.38%, indicating that the projections show a scenario of stability, which was already seen, mainly from 2017. The Provisions balance (PCL) also showed growth in all projected periods, although with a larger variation, as some months should grow by 2.85% (2019M08) while others as in 2020M06 it should grow only 0.32%. Finally, the ADM_COST is the variable that most fluctuated during the projection, since out of the 12 projected months, 5 are negative. In the first month of the series (2019M07) the projected value was R$ 49 million, while the projections are that at the end of the period (in 2020M06) the value will reach R$ 45 million, therefore a decrease of R$ 4 million.

For Working Capital loans, it is clear that there were generally more fluctuations in projections compared to Payroll-linked, since all three variables presented projections alternating between positive and negative values during the 12 months of the projection. In the BALANCE variable, there is a sharp drop in the first month of projection when the variable should reach R$ 10.88 billion, a decrease of R$ 768 million or 6.60%, compared to the last figure realized in 2019M06 when it reached R$ 11.65 billion. In the remaining projection months, the balance should fluctuate significantly, but with a slight recovery trend, which means that the projected balance at the end of the period is close to the last balance realized in 2019M06, indicating a stagnation trend in the portfolio volume in 12 months and hence in income.

In the provision (PCL), the expected effect is similar. Although it is expected to fluctuate, the provision in the last projection month (R$ 950 million) is close to the last data in 2019M06 when it reached R$ 910 million. Furthermore, it is noteworthy for the months 2019M08 and 2019M09, when there is a projected increase of 11.65% and 9.04%, respectively, could seriously damage the profitability of the product return. Finally, ADM_COST is the variable with the largest variation, as occurred for Payroll-linked, however with even greater fluctuations. As an example, there are the periods 2019M08, 2019M11 and 2020M05 when the projection is for an increase of 42.57%, 32.93% and 30.62%, respectively. Thus, the projection is that the variable reaches R$ 18.75 million at the end of the forecasting. Although an important variable in the model, it is important to highlight that they have limited effects on profitability due to their low representativeness compared to the others.

Figure 33, in the shaded area, shows the projected results for RAROC regarding the Payroll-linked loan product. Based on these three projected variables, it was possible to calculate the estimated RAROC for both products in a 12-month future scenario. This perspective gives managers a prospective view on the return that the product may generate in the future. Recalling that the models take into consideration not only the effects of the variables among themselves, but also their relationship with relevant macroeconomic variables, aligning the projection of product returns with the economic scenarios. Observing the projected RAROC, it can be seen that the average return over the 12 months was 9.31%, thus a positive return and above the average return on the market. In addition, it is important to highlight that in all projection months the return was positive, with the lowest value recorded at 7.46% in 2020M02. It is noticed that there was a strong increase in the first month of the projection (2019M07), when it reaches 11.69%. However, over the next 7 months a downward trend is shown when it reaches the low point, as previously mentioned. However, it then returns a growth trajectory ending the projection at 9.74%. Thus, it can be stated that, if the projections are confirmed, this product will continue to remunerate the invested capital properly and, therefore, should continue to receive resources and occupy a relevant part of the bank's total portfolio.

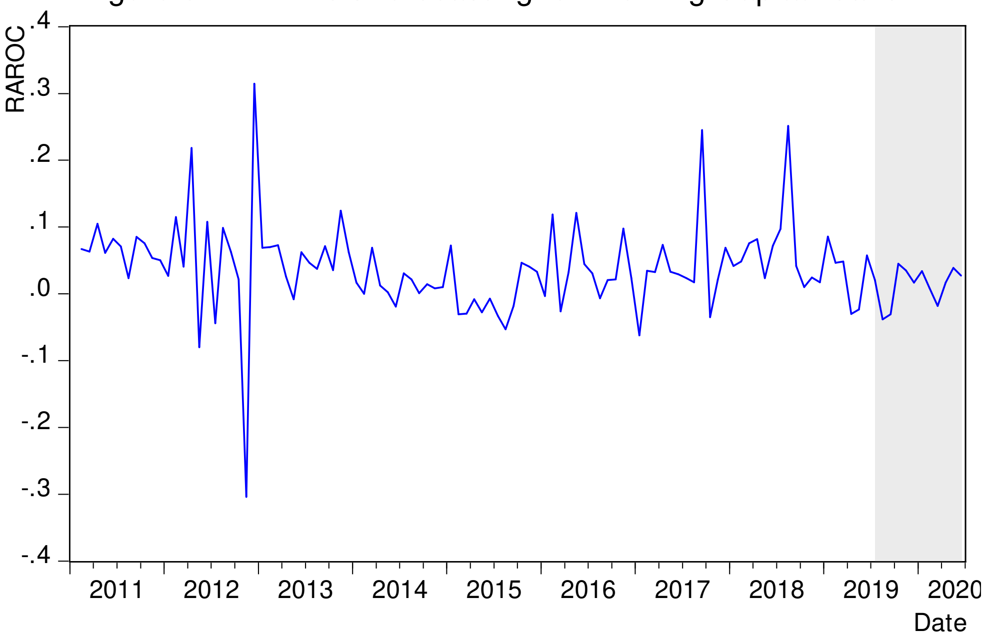
Figure 33 – RAROC forecasting for Payroll-linked loans



Source: elaborated by the author

Figure 34 shows the projected results for RAROC relative to the Working Capital product.

Figure 34 – RAROC forecasting for Working Capital loans



Source: elaborated by the author

In Working Capital, the average RAROC for the 12 months projected is 1.29%, thus much lower compared to Payroll-linked loans. In addition, the average RAROC is still below the market average ROE (in the most recent data available for the second quarter of 2019 the average monthly ROE was 1.42%). Furthermore, it is noteworthy that there are projected negative returns in three periods: in 2019M08 when it should reach -3.81%, in 2019M09 reaching -3.03% and in 2020M03 when it reaches -1.83%. On the other hand, it is also important to highlight that in the other 9 months the return was positive, and in 8 of them, besides being positive, it was higher than the market ROE. Thus, it can be concluded that, although there is greater volatility, Working Capital loans have a considerable potential for return. However, for this potential to be achieved, it is up to the managers to take the necessary measures to mitigate the risks and ensure a positive return, since without active management, that is, without measures that change the current projected scenario, the product does not present itself as a good capital investment.

Therefore, this forecasting RAROC view may be an important tool in order to support managers in their need for more active portfolio management. It is important to have a projected vision so managers might act in advance, anticipating actions to avoid possible scenarios where the return projection is negative, for example. In addition, it is also important take into account the relationship between the products and macroeconomic variables as seen in the econometric models.

5 CONCLUDING REMARKS

The aim of this work was to analyze the risk-adjusted return for the banking sector through the RAROC model. In order to achieve that purpose, three different perspectives for this model were created: Regulatory (and historical) RAROC, Economic RAROC and Forecasted RAROC. The database used was provided by a financial institution and contains data for the two core business products of the bank: Payroll-linked and Working Capital loans. This data covered a period between 2011M01 to 2019M06. In addition, macroeconomic variables were used in the econometric models.

The RAROC model represents the risk-adjusted return on capital and its main objective was to measure banks' portfolio risk and to assess the amount of equity needed to face depositor exposures (ENOMOTO, 2002). Several applications of the RAROC model in financial institutions are found in the literature and the model can be used both *ex-ante* and *ex-post* as assisting managers in defining which portfolios bring risk-adjusted returns and facilitating the comparison and analysis of the performance of these portfolios in a view that prioritizes risk-adjusted invested capital, for example (CASTRO JUNIOR, 2011). This work innovates to propose a new approach to profitability analysis for credit operations of a financial institution through the RAROC methodology, allowing to measure profitability stratified within the institution's portfolio and to project its values for a relevant future period.

Methodologically, a Value at Risk (VaR) model with Monte Carlo Simulations was used for the Economic RAROC and a Vector Autoregressive (VAR) model was used for the Forecasting RAROC while for the Regulatory RAROC a historical approach was performed. The overall tests reveal that the models created had a good performance and therefore satisfactory results.

The Regulatory RAROC analyzed the history of risk-adjusted product profitability between 2011M01 to 2019M06 based on the regulatory models, providing for managers a tool capable to analyze *ex-post*, month by month, whether the products actually added value to the institution in the period. Payroll-linked loans returned 8.13% on average with positive and greater average market values throughout the entire period. Therefore, this product added value to the institution – even in periods of economic crisis – and managers may consider this product as a good investment and the bank should keep allocating capital in this product. Working Capital presented 4.03% return on average, but a result that fluctuated greatly during the period with several months of negative returns – when the capital allocated to this product destroyed the institution's value – but it also showed positive results at many points when it had very significant returns. Therefore, it is required an active management in order to take appropriate measures to mitigate periods of sharp decrease. Although the return is lower than the return of Payroll-linked loans, it is very important to diversify investments avoiding a high concentration risk.

For Economic RAROC, the main goal was to calculate the capital needed to face the unexpected losses of each product via a Value at Risk (VaR) model that used the historical series losses. In this perspective, idiosyncratic aspects of the bank/product are considered, resulting in a more customized and accurately approach. The Economic Capital calculated for both products was R$ 2.46 billion, lower then Regulatory Capital by R$ 680.88 million or 27.73% (corroborating Allen, Boudoukh and Saunders, 2004). However, for Payroll-linked loans, the Economic Capital was substantially lower than the Regulatory Capital while in Working Capital was the opposite. This disparity is due to the products' characteristics, once Payroll-linked presented losses much lower and close to the mean in comparison to the Working Capital. Thus, using the internal model will yield a much higher return on allocated capital. Although Working Capital RAROC decreased from 5.72% to 2.91% the Payroll-linked loan RAROC would go from 6.87% to 45.75%. Therefore, the sum of the two products would yield a much higher return when considering the internal model.

Therefore, the major advantage in using the internal model would be a better allocation of capital, allowing banks to reduce their capital charges and increase its potential profitability. Given that resources are scarce, by allocating capital more efficiently, managers will be optimizing their decision-making and the result will be a much higher return on allocated capital compared to the Regulatory, becoming more competitive. In addition, the bank could use this capital to offer more loans, increasing its customer base and therefore its return. Furthermore, the result found in this paper may be used for managers to encourage the use of internal models in Brazil. Since Basel II banks have been stimulated to develop internal models, however to this day all banks operating in Brazil officially use the Standardized Approach (SA).

For Forecasting RAROC the goal was to estimate the risk-adjusted returns in a possible future scenario, enabling an *ex-ante* prospective decision making by agents.

The econometric models used in the projection take into account the relationships between the variables and other variables such as the macroeconomic ones. Particularly, the relationship with the macroeconomic variables was very important once it allowed the analysis of the connection between the products and the real economy, aligning the projection of product returns with the economic scenarios and bringing greater dynamism to the model.

Based on these econometric models it was possible to calculate the estimated RAROC for both products in a 12-month future scenario. The projected results for Payroll-linked had the average return of 9.31%, thus a positive return and above the average return on the market. Therefore, it can be stated that, if the projections are confirmed, this product will continue to remunerate the invested capital properly and hence should continue to receive resources and be a relevant part of the bank's total portfolio. The results for Working Capital presented an average of 1.29%, thus much lower compared to Payroll-linked loans and the market average return. One may be concluded that, although there is greater volatility, Working Capital loans have a significant potential for return. However, it is up to the managers to take the necessary measures to mitigate the risks so as to ensure a positive return, since without active management, that is, without measures that change the current projected scenario, the product does not present itself as a good capital investment.

The results presented here may contribute to a strategic management focused on risks. As this is a complex approach, some simplifications were necessary, such as the analysis of only 2 bank products (representing 40% of the portfolio). In addition, this work adopted a novel approach on how the RAROC model may be employed by financial institutions and the result can be considered satisfactory and useful, enabling to expand to other products and/or other institutions.

Finally, as shortly discussed previously, future work could investigate the use of the model proposed here for another interesting applications, such as to assist in the definition of the cut-off points for credit operations and pricing the most appropriate interest rate for different products. Moreover, analyzing different credit products from those studied in this paper could provide interesting results for comparison purposes.

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APPENDIX A – R SCRIPT FOR HISTORICAL RAROC

```
#########################################################################.
#          DISSERTATION RAROC
#     NAME: Wagner Eduardo Schuster
#     Model: Regulatory RAROC
#     Proposal: Calculate a historical regulatory RAROC for each product
#                 (2011M01 to 2019M06)
#########################################################################.

# setup
rm(list=ls());gc()
options(max.print = 1000, scipen = 50)
options(OutDec= ".")

# libraries
#install.packages("readxl")
library(readxl)
library(data.table)
library(xlsx)

# set directory
setwd("D:/DISSERTATION/DATABASE/")

# Import Database
BASE <- read_excel("DATABASE_BANK.xlsx", sheet = 1) # Payroll-linked loan
BASE <- read_excel("DATABASE_BANK.xlsx", sheet = 3) # Working Capital loan

BASE <- as.data.table(BASE)

# Taxes
PIS_PASEP <- 0.0065
Cofins <- 0.04
IRPJ <- 0.25
CSLL <- 0.15

TAX_1 <- PIS_PASEP + Cofins      # PIS/Pasep and Cofins (profit)
TAX_2 <- IRPJ + CSLL             # IRPJ and CSLL (revenue)


# RAROC components:

# INCOME (Balance * Interest Rate)
BASE$INCOME <- BASE$BALANCE * BASE$INTEREST_RATE/100

# CAPITAL COST (Balance * CDI)
BASE$CAPITAL_COST <- BASE$BALANCE * BASE$CDI_M/100

# ADMINISTRATIVE COST (Administrative Costs * Assets Ratio)
BASE$ADMINISTRATIVE_COST <- BASE$ADM_COSTS * BASE$ASSETS_RATIO

# PROVISION COST
BASE$PROV_COST <- BASE$PCL-shift(BASE$PCL)

# TAXES
# Tax 1 (profit)
BASE$TAX_1 <- (BASE$INCOME - BASE$CAPITAL_COST)*TAX_1
# adjust negative tax
```

```
BASE$TAX_1 <- ifelse(BASE$TAX_1<0,0,BASE$TAX_1)

# Tax 2 (revenue)
BASE$TAX_2 <- (BASE$INCOME - BASE$CAPITAL_COST - BASE$TAX_1 -
BASE$ADMINISTRATIVE_COST - BASE$PROV_COST)*TAX_2
# adjust negative tax
BASE$TAX_2 <- ifelse(BASE$TAX_2<0,0,BASE$TAX_2)

# NET PROFIT
BASE$NET_PROFIT <- (BASE$INCOME - BASE$CAPITAL_COST - BASE$TAX_1 - BASE$TAX_2 -
BASE$ADMINISTRATIVE_COST - BASE$PROV_COST)

BASE$RAROC <- BASE$NET_PROFIT / BASE$ALLOCATED_CAPITAL

# Plot
plot(BASE$RAROC, type="l")
abline(h=0, col='red')

# export
write.xlsx2(BASE, "Regulatory_RAROC.xlsx")
```

APPENDIX B – R SCRIPT FOR ECONOMIC RAROC

```
###########################################################################.
#          DISSERTATION RAROC
#     NAME: Wagner Eduardo Schuster
#     Model: Economic RAROC (Monte Carlo Simulations)
#     Proposal: Calculate an economic RAROC for each product based on
#                  a VaR by Monte Carlo Simulations
###########################################################################.

# setup
rm(list=ls());gc()
options(max.print = 1000, scipen = 50)
options(OutDec= ".")

# libraries
#install.packages("readxl")
#install.packages("fitdistrplus")
library(readxl)
library(fitdistrplus)
library(foreach)
library(doParallel)
library(xlsx)
library(writexl)

####################################################
# Function to fit the data for distribution curves   --------------------#
####################################################
FIT_DISTRIBUTION<-function(DATABASE)
{
  # Estimating the parameters of a known theoretical distribution curve (MLE method)
  FIT_NORMAL      <- tryCatch({
    fitdist(DATABASE,"norm", method = "mle")
  }, error = function (err){
  FIT_NORMAL      <- fitdist(DATABASE,"norm", method = "mle",lower = c(0, 0))
  })

  FIT_LOGNORMAL   <- fitdist(DATABASE,"lnorm",method = "mle")

  FIT_WEIBULL      <- tryCatch({
    fitdist(DATABASE,"weibull", method = "mle")
  }, error = function (err){
    FIT_WEIBULL      <- fitdist(DATABASE,"weibull", method = "mle",lower = c(0, 0))
  })

  FIT_GAMMA       <- fitdist(DATABASE,"gamma", method = "mle",lower = c(0, 0))

  # KS test to select the distribution that best fits the data
  KS_NORMAL <- ks.test(jitter(DATABASE),"pnorm",mean=FIT_NORMAL$estimate["mean"],
                  sd=FIT_NORMAL$estimate["sd"])

  KS_LOG_NORMAL <-
ks.test(jitter(DATABASE),"plnorm",meanlog=FIT_LOGNORMAL$estimate["meanlog"],
                     sdlog=FIT_LOGNORMAL$estimate["sdlog"])

  KS_WEIBULL <- ks.test(jitter(DATABASE),"pweibull",shape=FIT_WEIBULL$estimate["shape"],
                   scale=FIT_WEIBULL$estimate["scale"])
```

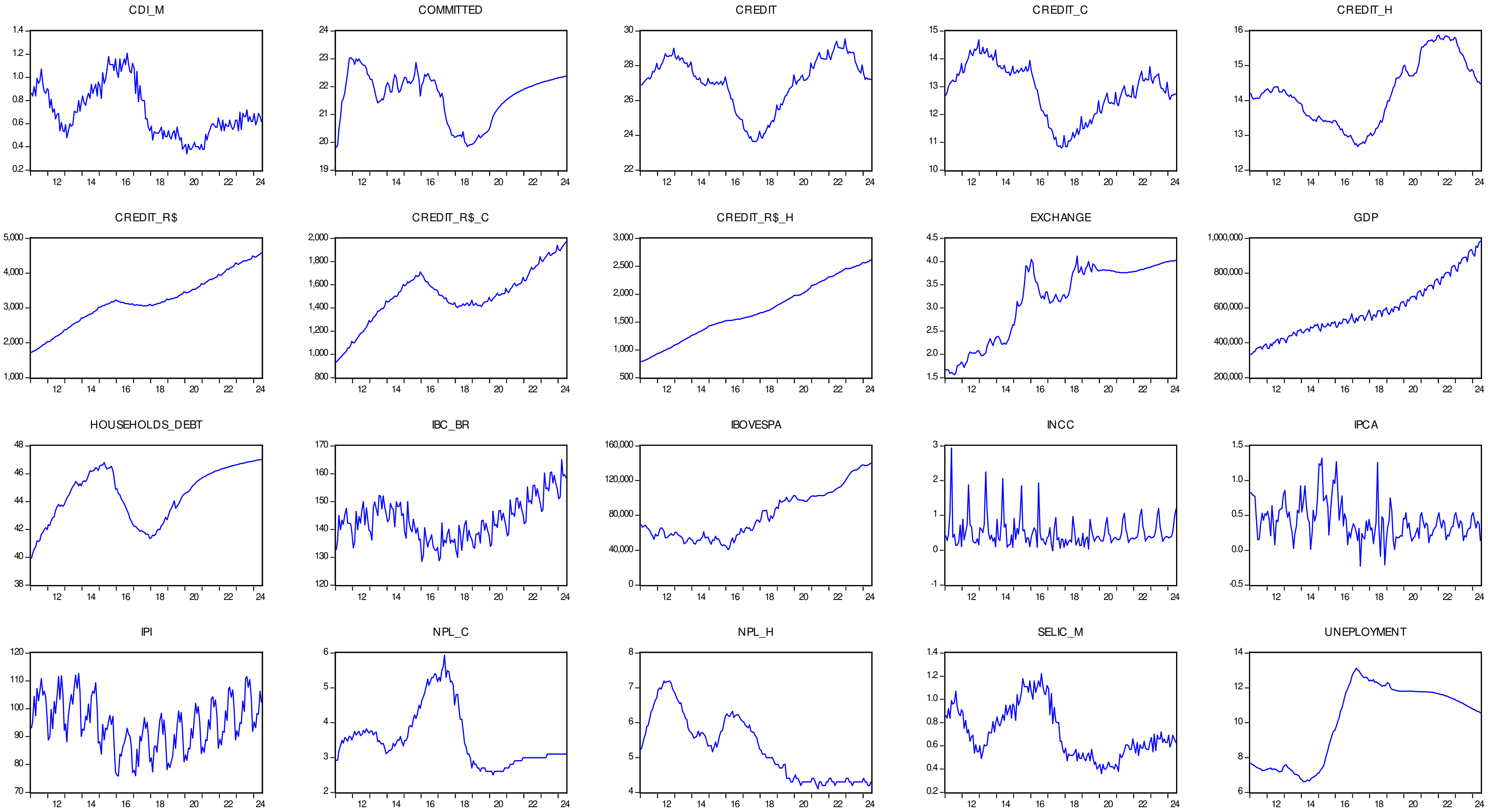
```
  KS_GAMMA <- ks.test(jitter(DATABASE),"pgamma",shape=FIT_GAMMA$estimate["shape"],
                  rate=FIT_GAMMA$estimate["rate"])

  # KS results
  KS_TESTS <- cbind(KS_NORMAL$statistic,
KS_LOG_NORMAL$statistic,KS_WEIBULL$statistic,KS_GAMMA$statistic)
  colnames(KS_TESTS) <- c("KS_NORMAL", "KS_LOG_NORMAL","KS_WEIBULL","KS_GAMMA")
  row.names(KS_TESTS) <- "D"

  # P-Values
  P_VALUES <- cbind(KS_NORMAL$p.value,
KS_LOG_NORMAL$p.value,KS_WEIBULL$p.value,KS_GAMMA$p.value)
  KS_TESTS <- rbind(KS_TESTS, P_VALUES)
  row.names(KS_TESTS)[2] <- "P_Value"

  # Selecting the best fit (min KS)
  RESULTS_KS <-c (KS_NORMAL$statistic,
                  KS_LOG_NORMAL$statistic,
                  KS_WEIBULL$statistic,
                  KS_GAMMA$statistic)
  BEST_FIT <- c("norm",
              "lnorm",
              "weibull",
              "gamma"
  )[which.min(RESULTS_KS)]

  # saving results
  if(BEST_FIT=="gamma")
  {
    RETURN_DISTRIBUTION <- FIT_GAMMA
    DISTRIBUTION_TYPE <- "gamma"
    RANDOM_FUNCTION <- "rgamma"

    # Calculating mean for Gamma (mean=shape*scale where scale= 1/rate)
    DISTRIBUTION_MEAN <- FIT_GAMMA$estimate["shape"]*
      (1/FIT_GAMMA$estimate["rate"])

  }else if(BEST_FIT=="weibull")
  {
    RETURN_DISTRIBUTION <- FIT_WEIBULL
    DISTRIBUTION_TYPE <- "weibull"
    RANDOM_FUNCTION <- "rweibull"

    # Calculating mean for Weibull (mean=scale*gammafunction(1 + 1/shape))
    DISTRIBUTION_MEAN <- FIT_WEIBULL$estimate["scale"]*
      gamma(1+1/FIT_WEIBULL$estimate["shape"])

  }else if(BEST_FIT=="lnorm")
  {
    RETURN_DISTRIBUTION<-FIT_LOGNORMAL
    DISTRIBUTION_TYPE <- "lnorm"
    RANDOM_FUNCTION <- "rlnorm"

    # Calculating mean for LogNormal (mean=exp(u + 1/2 sig^2)) u = mi (expected value); sig = sigma
(standar deviation)
    DISTRIBUTION_MEAN <- exp(FIT_LOGNORMAL$estimate["meanlog"]+
                        0.5*FIT_LOGNORMAL$estimate["sdlog"]^2)

  }else if(BEST_FIT=="norm")
```

```
 {
  RETURN_DISTRIBUTION <- FIT_NORMAL
  DISTRIBUTION_TYPE <- "norm"
  RANDOM_FUNCTION <- "rnorm"

  # Calculating mean for Normal (mean=mean)
  DISTRIBUTION_MEAN <- FIT_NORMAL$estimate["mean"]
 }

 # Setting the return parameters of the function
 RETURN <- list(RETURN_DISTRIBUTION=RETURN_DISTRIBUTION,
                DISTRIBUTION_TYPE=DISTRIBUTION_TYPE,
                DISTRIBUTION_MEAN=DISTRIBUTION_MEAN,
                RANDOM_FUNCTION=RANDOM_FUNCTION,
                KS_TESTS=KS_TESTS,
                FIT_NORMAL=FIT_NORMAL,
                FIT_LOGNORMAL=FIT_LOGNORMAL,
                FIT_WEIBULL=FIT_WEIBULL,
                FIT_GAMMA=FIT_GAMMA)
 return(structure(RETURN))
}

# set directory
setwd("D:/DISSERTATION/DATABASE/")

# Import Database
BASE <- read_excel("DATABASE_BANK_MILLION.xlsx", sheet = 1) # Payroll-linked loan
BASE <- read_excel("DATABASE_BANK_MILLION.xlsx", sheet = 3) # Working Capital loan


# Histogram
#par(mfrow=c(1,2))
hist(BASE$WRITE_OFF)

# Product 1
hist(BASE$WRITE_OFF, xlim=c(-0.3, max(BASE$WRITE_OFF)), breaks=30)

# Product 2
hist(BASE$WRITE_OFF, xlim=c(-5, max(BASE$WRITE_OFF)), breaks=15)
#par(mfrow=c(1,1))


# Fitting
FIT_BASE <- FIT_DISTRIBUTION(BASE$WRITE_OFF)

# KS-tests
FIT_BASE$KS_TESTS
write.xlsx2(FIT_BASE$KS_TESTS, "KS_tests2.xlsx")


# Graph comparing Histogram vs Distribution curves
# denscomp(list(FIT_BASE$FIT_NORMAL, FIT_BASE$FIT_LOGNORMAL,
FIT_BASE$FIT_WEIBULL, FIT_BASE$FIT_GAMMA),
#        legendtext = c("normal", "lognormal","weibull","gamma"), xlegend = "topright", breaks=15)

denscomp(list(FIT_BASE$FIT_NORMAL, FIT_BASE$FIT_LOGNORMAL, FIT_BASE$FIT_WEIBULL,
FIT_BASE$FIT_GAMMA),
      legendtext = c("normal", "lognormal","weibull","gamma"), xlegend = "topright")
```

```
# Save results:

# Random Function
RANDOM_FUNCTION <- FIT_BASE$RANDOM_FUNCTION
# Distribution curve
DISTRIBUTION_TYPE <- FIT_BASE$DISTRIBUTION_TYPE
# Parameters
PARAMETERS <- FIT_BASE$RETURN_DISTRIBUTION$estimate


#######################################################
#   MONTE CARLO SIMULATIONS ---------------------------------------------#
#######################################################

# Setting number of scenarios and repetitions
NUMBER_SCENARIOS <- 100
NUMBER_REPETITIONS <- 10000
VECTOR_SIMULATIONS <- NUMBER_REPETITIONS*NUMBER_SCENARIOS
PERIOD <- 12

####################################################
# LOOP SIMULATIONS -----------------------------------------------------#
####################################################

# monte carlo function
MONTE_CARLO <- function(NUMBER_REPETITIONS)
{
  # create random numbers according to the amount of desired scenarios and distribution curve
parameters
  RANDOM <- do.call(RANDOM_FUNCTION, c(n=NUMBER_SCENARIOS, as.list(PARAMETERS)))

  return(RANDOM)
}

# Vector for Simulations
VECTOR_SIMULATIONS <- foreach(1:NUMBER_REPETITIONS, .combine='c') %do%
MONTE_CARLO(NUMBER_REPETITIONS)

# calculating expected loss, unexpected loss and economic capital
VaR <- quantile(VECTOR_SIMULATIONS,0.999)
EXPECTED_LOSS <- FIT_BASE$DISTRIBUTION_MEAN
UNEXPECTED_LOSS <- VaR - EXPECTED_LOSS
ECONOMIC_CAPITAL <- UNEXPECTED_LOSS * sqrt(PERIOD)
```

APPENDIX C – EXTRA SERIES AND MODELS EVALUATION

Figure 35 – Macroeconomic Series



Source: elaborated by the author

Table 26 – Granger Causality Tests

Pairwise Granger Causality Tests Payroll-linked loans													
Null Hypothesis:		lags											
		1	2	3	4	5	6	7	8	9	10	11	12
PCL does not Granger	F-Statistic	1.904	5.217	7.647	6.800	4.161	3.286	2.530	2.531	1.846	1.798	1.626	1.424
Cause BALANCE	Prob.	0.171	**0.007**	**0.000**	**0.000**	**0.002**	**0.006**	**0.021**	**0.017**	**0.074**	**0.077**	0.111	0.178
BALANCE does not Granger	F-Statistic	5.093	2.999	3.947	3.449	3.177	2.406	2.212	3.252	2.521	2.096	1.926	1.732
Cause PCL	Prob.	**0.026**	**0.055**	**0.011**	**0.011**	**0.011**	**0.034**	**0.042**	**0.003**	**0.014**	**0.036**	**0.051**	**0.080**
ADM_COSTS does not	F-Statistic	0.146	1.350	1.514	3.260	1.671	1.210	1.013	1.308	1.057	0.991	0.921	0.912
Granger Cause BALANCE	Prob.	0.703	0.264	0.216	**0.015**	0.150	0.309	0.429	0.252	0.404	0.459	0.526	0.540
BALANCE does not Granger	F-Statistic	26.87	6.156	6.267	3.826	2.133	2.076	1.839	1.697	1.541	1.336	1.272	1.355
Cause ADM_COSTS	Prob.	**0.000**	**0.003**	**0.001**	**0.007**	**0.069**	**0.065**	**0.091**	0.113	0.150	0.229	0.259	0.211
ADM_COSTS does not	F-Statistic	1.072	1.814	3.505	2.877	2.641	2.428	2.044	1.911	1.505	1.377	1.383	1.235
Granger Cause PCL	Prob.	0.303	0.169	**0.019**	**0.027**	**0.029**	**0.033**	**0.059**	**0.070**	0.162	0.209	0.201	0.279
PCL does not Granger	F-Statistic	0.089	1.346	3.760	2.285	1.859	1.771	1.580	1.359	1.140	1.140	1.123	1.589
Cause ADM_COSTS	Prob.	0.766	0.265	**0.014**	**0.066**	0.110	0.115	0.153	0.228	0.346	0.346	0.358	0.117

Pairwise Granger Causality Tests Working Capital loans													
Null Hypothesis:		lags											
		1	2	3	4	5	6	7	8	9	10	11	12
PCL does not Granger	F-Statistic	4.813	3.091	1.800	1.564	1.168	0.873	0.882	0.750	1.087	0.951	0.911	0.824
Cause BALANCE	Prob.	**0.031**	**0.050**	0.153	0.191	0.331	0.518	0.524	0.647	0.383	0.493	0.535	0.625
BALANCE does not Granger	F-Statistic	1.692	1.033	0.724	0.521	0.635	1.292	1.009	1.140	1.007	0.983	0.822	1.575
Cause PCL	Prob.	0.196	0.360	0.540	0.721	0.673	0.270	0.432	0.347	0.443	0.466	0.619	0.121
ADM_COSTS does not	F-Statistic	0.771	0.958	0.837	1.061	0.912	0.629	0.619	1.054	1.365	1.287	1.142	1.575
Granger Cause BALANCE	Prob.	0.382	0.387	0.477	0.381	0.477	0.706	0.739	0.404	0.220	0.255	0.344	0.121
BALANCE does not Granger	F-Statistic	24.28	6.956	4.153	3.032	2.189	1.974	2.269	1.920	2.538	2.274	1.964	1.825
Cause ADM_COSTS	Prob.	**0.000**	**0.002**	**0.008**	**0.022**	**0.063**	**0.079**	**0.037**	**0.069**	**0.014**	**0.023**	**0.046**	**0.062**
ADM_COSTS does not	F-Statistic	0.051	0.037	0.039	0.305	0.877	1.117	1.116	0.954	0.855	0.888	0.789	0.744
Granger Cause PCL	Prob.	0.822	0.964	0.990	0.874	0.500	0.360	0.362	0.478	0.569	0.548	0.650	0.704
PCL does not Granger	F-Statistic	2.099	1.938	2.694	2.434	1.798	1.354	1.155	1.075	1.141	1.215	1.183	1.049
Cause ADM_COSTS	Prob.	0.151	0.150	**0.051**	**0.053**	0.122	0.243	0.338	0.389	0.346	0.297	0.315	0.417

Source: elaborated by the author

Table 27 – Variance Decompositions

Variance Decomposition using Cholesky Factors Payroll-linked loans

Cholesky Ordering: D(BALANCE) D(PCL) D(ADM_COSTS)

Period	Variance Decomposition of D(BALANCE):			Variance Decomposition of D(PCL):			Variance Decomposition of D(ADM_COSTS):		
	D(BALANCE)	D(PCL)	D(ADM_COSTS)	D(BALANCE)	D(PCL)	D(ADM_COSTS)	D(BALANCE)	D(PCL)	D(ADM_COSTS)
1	100	0	0	0.28	99.72	0.00	0.02	8.00	91.98
2	98.08	0.50	1.42	0.55	95.22	4.22	0.06	6.93	93.01
3	97.77	0.83	1.40	7.62	88.48	3.89	3.22	6.97	89.81
4	96.94	1.30	1.75	7.57	88.44	3.99	3.80	7.39	88.81
5	95.65	2.51	1.83	7.80	81.38	10.82	3.78	7.33	88.89
6	94.96	2.50	2.54	7.57	79.37	13.06	3.62	6.96	89.42
7	94.92	2.54	2.54	7.81	78.66	13.53	3.95	6.88	89.17
8	94.86	2.60	2.54	8.03	78.42	13.55	4.18	6.89	88.93
9	94.74	2.60	2.66	8.01	78.30	13.69	4.18	6.90	88.92
10	94.59	2.62	2.78	7.94	77.48	14.58	4.13	6.89	88.98
11	94.54	2.62	2.83	7.99	77.22	14.79	4.13	6.85	89.02
12	94.54	2.63	2.83	8.02	77.08	14.89	4.19	6.84	88.97

Variance Decomposition using Cholesky Factors Working Capital loans

Cholesky Ordering: D(PCL) D(BALANCE) D(ADM_COSTS)

Period	Variance Decomposition of D(PCL):			Variance Decomposition of D(BALANCE):			Variance Decomposition of D(ADM_COSTS):		
	D(PCL)	D(BALANCE)	D(ADM_COSTS)	D(PCL)	D(BALANCE)	D(ADM_COSTS)	D(PCL)	D(BALANCE)	D(ADM_COSTS)
1	100	0	0	5.10	94.90	0	6.02	0.31	93.67
2	91.14	5.41	3.45	7.71	91.93	0.36	6.03	0.40	93.58
3	84.05	5.98	9.97	7.70	91.32	0.98	6.47	0.40	93.13
4	80.54	9.24	10.22	6.83	79.96	13.21	6.52	0.68	92.80
5	78.06	9.00	12.94	7.90	78.93	13.18	6.46	1.37	92.17
6	74.28	12.33	13.39	7.97	79.09	12.95	6.52	1.34	92.14
7	73.94	12.42	13.64	8.15	78.69	13.17	6.68	1.34	91.99
8	73.85	12.37	13.78	7.96	76.56	15.48	6.64	1.33	92.03
9	72.55	12.25	15.20	7.94	76.11	15.95	6.64	1.38	91.99
10	72.47	12.27	15.27	7.94	76.11	15.95	6.65	1.38	91.98
11	72.41	12.33	15.26	7.94	76.07	16.00	6.66	1.38	91.96
12	72.40	12.34	15.27	7.93	75.98	16.09	6.65	1.41	91.94

Source: elaborated by the author

Table 28 – Breakpoints Unit Root Test for BALANCE (Payroll-linked)

Breakpoints Unit Root Test BALANCE (Payroll-linked)

Series	test	T-stat with intercept	T-stat with trend and intercept	T-stat with none	
SAMPLE 2011M01 - 2016M11					
ΔBALANCE Product 1	ADF	-4.8064***	-4.8534***	-2.7503***	I(1)
	PP	-4.8310***	-4.8938***	-2.4362***	
SAMPLE 2016M12 - 2019M06					
ΔBALANCE Product 1	ADF	-5.2643***	-5.1689***	-0.3316	I(1)
	PP	-8.4275***	-8.5329***	-1.4495	

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

Source: elaborated by the author

Table 29 – Breakpoints Unit Root Test for INTEREST_RATE (Payroll-linked)

Breakpoints Unit Root Test INTEREST_RATE (Payroll-linked)

Series	test	T-stat with intercept	T-stat with trend and intercept	T-stat with none	
SAMPLE 2011M01 - 2012M14					
ΔINTEREST_RATE Product 1	ADF	-3.4220**	3.1468	-1.2037	I(1)
	PP	-3.4220**	-2.5926	-1.2620	
SAMPLE 2012M05 - 2014M02					
ΔINTEREST_RATE Product 1	ADF	-1.3874	-1.1241	-0.8814	
	PP	-1.5867	-1.4116	-0.8814	
SAMPLE 2014M03 - 2016M11					
ΔINTEREST_RATE Product 1	ADF	-4.2378***	-5.6163***	-0.6113	I(1)
	PP	-4.3973***	-6.0810***	-0.5140	
SAMPLE 2016M12 - 2019M06					
ΔINTEREST_RATE Product 1	ADF	-3.2015**	-3.0234	-0.0085	I(1)
	PP	-5.0076***	-3.2916*	0.2138	

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

Source: elaborated by the author

Table 30 – Unit Root Tests for Macroeconomics Variables

Series	ADF			PP			
	P-Value with intercept	P-Value with trend and intercept	P-Value with none	P-Value with intercept	P-Value with trend and intercept	P-Value with none	
CDI_M	0.2024	0.3256	0.3689	0.3429	0.5867	0.3532	
COMMITTED	0.1370	0.5224	0.5255	0.1502	0.3288	0.8642	
CREDIT	0.0365**	0.1375	0.4581	0.6794	0.9087	0.6895	
CREDIT_C	0.0120**	0.0205**	0.4004	0.7134	0.8871	0.6570	
CREDIT_H	0.1749	0.2924	0.5415	0.7547	0.8726	0.7073	
CREDIT_R$	0.8537	0.0187**	0.8958	0.8108	0.8221	1.0000	
CREDIT_R$_C	0.4054	0.0552*	0.8243	0.5539	0.7708	0.9994	
CREDIT_R$_H	0.9248	0.1330	0.9170	0.9377	0.8810	1.0000	
EXCHANGE	0.3612	0.5486	0.9324	0.4960	0.7080	0.9496	
GDP	0.9999	0.9998	0.9831	0.9999	0.5189	1.0000	
HOUSEHOLDS_DEBT	0.4406	0.2885	0.8934	0.2678	0.6591	0.9655	
IBC_BR	0.8971	0.9661	0.9143	0.0032***	0.0025	0.9053	
IBOVESPA	0.9965	0.3887	0.9923	0.9966	0.4081	0.9923	
INCC	0.5970	0.9597	0.4299	0.0000***	0.0000***	0.0000***	
IPCA	0.0000***	0.0000***	0.0233**	0.0000***	0.0000***	0.0037***	I(0)
IPI	0.7514	0.9737	0.7842	0.0001***	0.0010***	0.7041	
NPL_C	0.1488	0.3223	0.3518	0.5298	0.6562	0.5876	
NPL_H	0.9279	0.0790*	0.3724	0.7726	0.0474**	0.4610	
SELIC_M	0.2292	0.3623	0.3857	0.3396	0.5905	0.3621	
SELIC_T	0.0261**	0.0772*	0.1664	0.4978	0.7715	0.3632	
UNEPLOYMENT	0.4138	0.8120	0.7178	0.6744	0.9710	0.8231	

Series	ADF			PP			
	P-Value with intercept	P-Value with trend and intercept	P-Value with none	P-Value with intercept	P-Value with trend and intercept	P-Value with none	
ΔCDI_M	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	I(1)
ΔCOMMITTED	0.0004***	0.0027***	0.0000***	0.0000***	0.0000***	0.0000***	I(1)
ΔCREDIT	0.2799	0.5947	0.0400**	0.0000***	0.0000***	0.0000***	
ΔCREDIT_C	0.3808	0.7019	0.0710*	0.0000***	0.0000***	0.0000***	
ΔCREDIT_H	0.5565	0.8748	0.1267	0.0000***	0.0000***	0.0000***	
ΔCREDIT_R$	0.5602	0.8526	0.3369	0.0000***	0.0000***	0.0000***	
ΔCREDIT_R$_C	0.5343	0.8458	0.1803	0.0000***	0.0000***	0.0000***	
ΔCREDIT_R$_H	0.1607	0.4135	0.4061	0.0000***	0.0000***	0.0001***	
ΔEXCHANGE	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	I(1)
ΔGDP	0.9537	0.8324	0.9066	0.0000***	0.0000***	0.0000***	
ΔHOUSEHOLDS_DEBT	0.0022***	0.0134**	0.0002***	0.0000***	0.0000***	0.0000***	I(1)
ΔIBC_BR	0.6383	0.7609	0.2444	0.0000***	0.0000***	0.0000***	
ΔIBOVESPA	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	I(1)
ΔINCC	0.0000***	0.0000***	0.0000***	0.0001***	0.0001***	0.0001***	I(1)
ΔIPI	0.4235	0.6345	0.0817*	0.0001***	0.0001***	0.0000***	
ΔNPL_C	0.0769*	0.2618	0.0071***	0.0000***	0.0000***	0.0000***	I(1)
ΔNPL_H	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	I(1)
ΔSELIC_M	0.0821*	0.2524	0.0077***	0.0000***	0.0000***	0.0000***	I(1)
ΔSELIC_T	0.0976*	0.2696	0.0104**	0.0000***	0.0000***	0.0000***	I(1)
ΔUNEPLOYMENT	0.0594*	0.1519	0.0058***	0.0037***	0.0123***	0.0002***	I(1)

Continue

Series	ADF			PP			
	P-Value with intercept	P-Value with trend and intercept	P-Value with none	P-Value with intercept	P-Value with trend and intercept	P-Value with none	
ΔΔCREDIT	0.0000***	0.0002***	0.0000***	0.0001***	0.0001***	0.0001***	I(2)
ΔΔCREDIT_C	0.0000***	0.0000***	0.0000***	0.0001***	0.0001***	0.0001***	I(2)
ΔΔCREDIT_H	0.0000***	0.0001***	0.0000***	0.0001***	0.0001***	0.0001***	I(2)
ΔΔCREDIT_R$	0.0001***	0.0005***	0.0000***	0.0001***	0.0001***	0.0001***	I(2)
ΔΔCREDIT_R$_C	0.0001***	0.0004***	0.0000***	0.0001***	0.0001***	0.0001***	I(2)
ΔΔCREDIT_R$_H	0.0027***	0.0154***	0.0001***	0.0001***	0.0001***	0.0000***	I(2)
ΔΔGDP	0.0000***	0.0000***	0.0000***	0.0001***	0.0001***	0.0001***	I(2)
ΔΔIBC_BR	0.0000***	0.0000***	0.0000***	0.0001***	0.0001***	0.0000***	I(2)
ΔΔIPI	0.0000***	0.0000***	0.0000***	0.0001***	0.0001***	0.0001***	I(2)

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

Source: elaborated by the author

Table 31 – Estimated VAR Payroll-linked

Vector Autoregression Estimates Payroll-linked			
	D(BALANCE)	D(PCL)	D(ADM_COSTS)
D(BALANCE(-1))	0.09084 (0.0884)	0.00915 (0.0133)	-0.000846 (0.0069)
D(BALANCE(-2))	-0.18360 (0.0821)	-0.043387 (0.0123)	0.014937 (0.0064)
D(BALANCE(-3))	0.11343 (0.0926)	0.013939 (0.0139)	0.000673 (0.0072)
D(BALANCE(-4))	-0.00895 (0.0839)	0.017848 (0.0126)	-0.001657 (0.0065)
D(PCL(-1))	-0.23946 (0.3008)	0.046201 (0.0453)	0.031916 (0.0235)
D(PCL(-2))	-0.35558 (0.3148)	0.243248 (0.0474)	-0.020881 (0.0246)
D(PCL(-3))	-0.57342 (0.3326)	0.06732 (0.0501)	-0.043274 (0.0260)
D(PCL(-4))	-0.64074 (0.3753)	-0.022034 (0.0565)	-0.003007 (0.0293)
D(ADM_COSTS(-1))	-1.6093 (1.4069)	-0.422339 (0.2118)	-0.529266 (0.1100)
D(ADM_COSTS(-2))	-0.57903 (1.5215)	-0.273099 (0.2291)	-0.236975 (0.1189)
D(ADM_COSTS(-3))	0.09845 (1.5111)	-0.176239 (0.2275)	-0.203767 (0.1181)
D(ADM_COSTS(-4))	-0.71460 (1.4088)	-0.666059 (0.2121)	-0.431728 (0.1101)
C	85.5977 (16.902)	0.885607 (2.5454)	-0.863889 (1.3217)
DUMMY_BALANCE_BREAK	372.428 (43.221)	3.658904 (6.5089)	-4.457075 (3.3799)
DUMMY_BALANCE_BREAK2_OUT_H	321.4289 (84.777)	90.4121 (12.767)	-12.18808 (6.6296)
DUMMY_BALANCE_BREAK2_OUT_L	-441.2153 (68.913)	-37.03478 (10.378)	0.473013 (5.3890)
DUMMY_PCL_OUT_H	100.5636 (57.878)	47.35813 (8.7162)	3.614288 (4.5261)
DUMMY_PCL_OUT_LL	12.03558 (62.416)	-124.5644 (9.3995)	10.48923 (4.8809)
D_UNEPLOYMENT(-1)	-181.9765 (68.250)	2.133149 (10.278)	7.758561 (5.3371)
D_CDI_M_SEA	374.9107 (134.74)	-46.30107 (20.292)	-29.03396 (10.537)
D_CDI_M_SEA(-11)	90.46652 (130.53)	-21.22293 (19.657)	-27.30849 (10.207)
D_CDI_M_SEA(-7)	302.3344 (117.48)	-9.337529 (17.693)	-26.87324 (9.1876)
D_COMMITTED(-2)	102.0898 (41.124)	-2.33118 (6.1931)	1.771247 (3.2159)
D2_CREDIT_H_SEA	-103.3423 (137.77)	-17.42354 (20.748)	20.86326 (10.774)
D2_CREDIT_H_SEA(-11)	109.5991 (152.77)	28.21458 (23.006)	-5.146792 (11.946)
D2_CREDIT_R$_SEA(-1)	0.509956 (0.7236)	0.127858 (0.1089)	0.218857 (0.0565)
R-squared	0.937433	0.941694	0.622919
Adj. R-squared	0.912605	0.918557	0.473284

Standard errors in ( )

Source: elaborated by the author

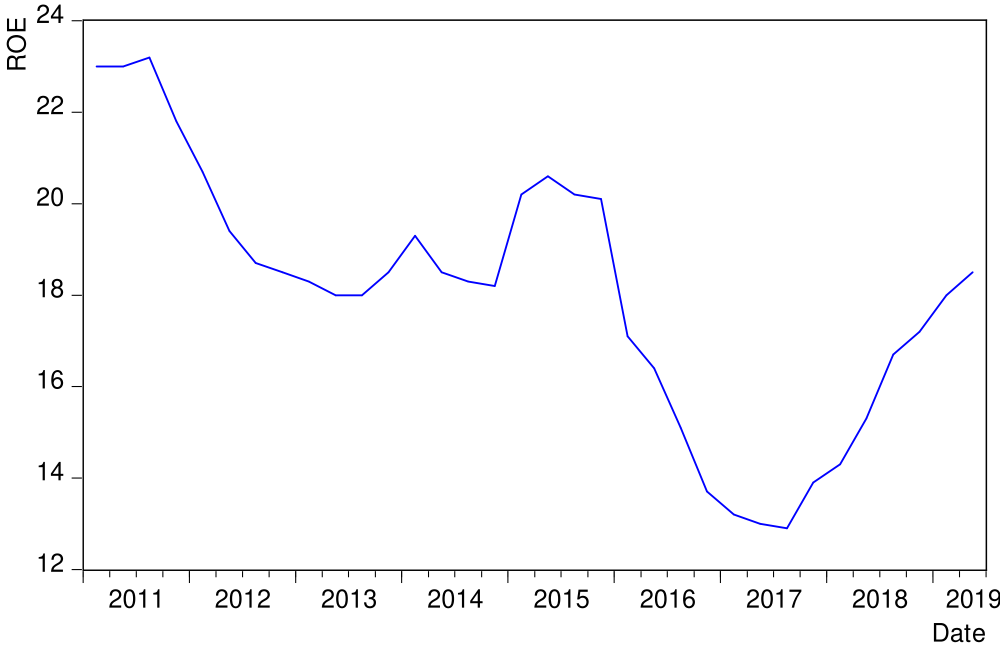
Table 32 – Estimated VAR Working Capital

Vector Autoregression Estimates Working Capital						
	D(PCL)		D(BALANCE)		D(ADM_COSTS)	
D(PCL(-1))	0.057851	(0.0565)	0.57925	(0.1960)	0.00038	(0.0039)
D(PCL(-2))	-0.006363	(0.0523)	0.060163	(0.1814)	0.004189	(0.0036)
D(PCL(-3))	-0.022001	(0.0479)	0.28123	(0.1661)	-0.001719	(0.0033)
D(PCL(-4))	-0.038275	(0.0478)	-0.298599	(0.1660)	0.000795	(0.0033)
D(PCL(-5))	-0.072342	(0.0478)	-0.296675	(0.1658)	0.000382	(0.0033)
D(PCL(-6))	0.066468	(0.0478)	0.353914	(0.1657)	0.004834	(0.0033)
D(BALANCE(-1))	-0.068941	(0.0224)	-0.056902	(0.0778)	-0.000383	(0.0015)
D(BALANCE(-2))	-0.028367	(0.0204)	-0.010651	(0.0708)	-0.00013	(0.0014)
D(BALANCE(-3))	0.057786	(0.0202)	0.004732	(0.0702)	0.001364	(0.0014)
D(BALANCE(-4))	-0.005704	(0.0189)	-0.063554	(0.0656)	-0.001293	(0.0013)
D(BALANCE(-5))	0.064226	(0.0189)	0.124971	(0.0656)	-0.000758	(0.0013)
D(BALANCE(-6))	-0.022593	(0.0189)	-0.214749	(0.0655)	-0.000276	(0.0013)
D(ADM_COSTS(-1))	-2.875069	(1.4337)	-3.130502	(4.9715)	-0.306061	(0.1003)
D(ADM_COSTS(-2))	-5.133944	(1.6621)	-3.588857	(5.7635)	-0.175435	(0.1162)
D(ADM_COSTS(-3))	-3.300618	(1.7585)	20.65773	(6.0979)	-0.063711	(0.1230)
D(ADM_COSTS(-4))	-2.92991	(1.5701)	11.3593	(5.4445)	-0.204368	(0.1098)
D(ADM_COSTS(-5))	-2.598337	(1.6064)	7.242382	(5.5704)	0.054213	(0.1120)
D(ADM_COSTS(-6))	-4.00815	(1.3539)	6.255576	(4.6949)	0.039818	(0.0947)
C	27.97856	(14.453)	14.2377	(50.117)	-0.700599	(1.0112)
DUMMY_BALANCE_BREAK	-22.23455	(19.753)	-137.2095	(68.499)	0.269163	(1.3821)
DUMMY_BALANCE_OUT_H1	-53.21851	(33.251)	685.5632	(115.30)	-1.620648	(2.3265)
DUMMY_PCL_OUT_H	250.0379	(52.052)	15.79899	(180.49)	-4.991966	(3.6419)
DUMMY_PCL_OUT_HH	493.3292	(85.512)	549.576	(296.52)	8.683327	(5.9831)
DUMMY_PCL_OUT_L	-358.3958	(25.609)	-87.77747	(88.802)	0.121333	(1.7918)
DUMMY_PCL_OUT_LL	-474.0601	(85.042)	-349.4427	(294.89)	8.242661	(5.9502)
DUMMY_ADM_OUT_H3	-62.48813	(30.486)	6.198171	(105.71)	12.5629	(2.1330)
DUMMY_ADM_OUT_L3	-17.05285	(34.492)	132.2274	(119.60)	-8.957287	(2.4133)
D_CDI_M_SEA(-6)	-56.04915	(122.43)	-1545.372	(424.57)	-2.738708	(8.5667)
D_COMMITTED(-11)	50.79954	(35.688)	627.8892	(123.75)	2.410555	(2.4970)
D_COMMITTED(-2)	-39.92716	(42.306)	280.9984	(146.70)	2.311473	(2.9600)
D_EXCHANGE(-7)	-97.31505	(67.402)	-292.3168	(233.72)	3.435413	(4.7159)
D_INCC_SEA(-5)	-4.375441	(16.694)	160.8832	(57.888)	0.003977	(1.1680)
D_INCC_SEA(-9)	16.32459	(17.446)	147.6303	(60.497)	3.482451	(1.2206)
D_NPL_C_SEA(-3)	58.80209	(55.726)	-298.9664	(193.23)	-4.344159	(3.8990)
D_UNEPLOYMENT	122.4117	(59.857)	17.05357	(207.56)	5.986155	(4.1880)
D_UNEPLOYMENT(-7)	49.6443	(68.585)	-659.3908	(237.83)	-8.325275	(4.7988)
D2_CREDIT_C_SEA(-10)	137.8816	(109.44)	1861.986	(379.49)	-0.979283	(7.6572)
D2_CREDIT_C_SEA(-11)	37.03527	(86.401)	1440.568	(299.61)	0.244781	(6.0453)
D2_CREDIT_C_SEA(-9)	38.7853	(95.354)	1295.9	(330.65)	-0.972821	(6.6717)
D2_CREDIT_R$_SEA(-1)	0.549165	(0.7323)	6.441157	(2.5395)	0.132573	(0.0512)
D2_CREDIT_R$_SEA(-8)	1.11707	(0.7866)	2.741673	(2.7278)	-0.118617	(0.0550)
D2_IPI_SEA(-9)	-6.177203	(1.7984)	-15.26743	(6.2363)	-0.184898	(0.1258)
R-squared	0.945270		0.857134		0.842600	
Adj. R-squared	0.897527		0.732507		0.705293	

Standard errors in ( )

Source: elaborated by the author

Figure 36 – ROE (median of the four main banks in Brazil)



Source: elaborated by the author based on Economatica (2019).