RISK-ADJUSTED RETURN: An Historical and Forecasted Banking Sector Analysis through the RAROC Model

1 Introduction

Financial institutions face an increasingly competitive scenario where resources – in this case, especially the issue of 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, banks need as much information as possible to support their decision making, and the RAROC model emerges as an important tool for assisting executives of financial institutions in this process.

RAROC stands for Risk Adjusted Return on Capital and in this paper will represents the financial return that a given credit portfolio offers in relation to the amount of capital required by the regulator. In this view, risk is weighted against the expected and unexpected risk incurred. 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 (BASTOS, 2000; CAROLLO, 2008; CASTRO JUNIOR, 2011). 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).

Initially, RAROC was only used in aggregate form – comprising a financial indicator from a set of indicators already adopted in the market – and the literature extensively encompass this model for comparison between banks only and restricted to past periods (CASTRO JUNIOR, 2011; LIMA et al., 2014; KLAASSEN; VAN EEGHEN, 2015; ASSIS, 2017; DING; FENG; LIANG, 2018). This study innovates when this model is adapted to a level of openness by credit product and when propose to project the return for these products, allowing product comparison and active portfolio management. Furthermore, this paper fills a gap in the literature on the subject as proposing a new approach to the RAROC model.

2 Objectives

The aim of this work is to analyze the risk-adjusted return between credit portfolios of a financial institution in a historical and forecasted perspective. For this purpose, this paper is divided into two secondary objectives. The first one is creating a methodology to adapt the RAROC to a level of openness by product and no longer in the aggregate form as we generally see it. Measuring the profitability stratified within the institution's portfolio of credit operations, we may provide for managers a tool capable to analyze *ex-post*, month by month, whether the products actually added value to the institution in the period

The second is propose an approach to estimate the risk-adjusted returns in a 12-month future scenario, enabling an *ex-ante* prospective decision making by agents. For that, we propose a multivariate autoregressive econometric model to predict the most important variables of the RAROC equation. This model considers the relationships between the main RAROC variables as well as macroeconomic variables.

3 Theoretical Framework

Banks operate in a dynamic, volatile, regulated and competitive market and, therefore, running a financial institution 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 banks involves the establishment of appropriate policies for the company that enable comprehensive risk mediation, pricing and control (CROUHY; GALAI; MARK, 2000).

Because of those risks, 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 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.

In this context, a methodology that has been gaining ground in both Brazil and the rest of the world is the RAROC, 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; ENEMOTO, 2002). By analyzing the RAROC, the institution will have a clearer view of its investments, once the return, in this view, is weighted against the expected and unexpected risk incurred. The standard formula for RAROC 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 required capital.

Once those measures have been estimated, the calculation of RAROC is straightforward, as shown in equation (1). 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. However, they all maintain the same pattern of assessing profitability 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, 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.

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).

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).

4 Methodology

4.1 Dataset and Series Evaluation

The dataset was provided by a financial institution and encompasses data for its two core business products[1]: Payroll-linked and Working Capital loans, in a period between 2011M01 and 2019M06. Additionally, the dataset contains 13 macroeconomic variables, also reported monthly (from 2011M01 to 2024M06[2]) provided by two sources: Banco Central do Brasil (BACEN) and Instituto Brasileiro de Geografia e Estatística (IBGE). Figure 6 and Table 1 (Appendix) show all the graphs and provide details as well as the descriptive statistics for all the variables.

First, we tested the variables regarding some important assumptions. Two tests were used for stationarity: Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP). These tests were computed in level and for consecutive differences (maximum two) until the null hypothesis could be rejected, i.e. the series became stationary. The results for the Payroll-linked and Working Capital loans (Table 2) and for the macroeconomic series (Table 3) are in Appendix.

Nevertheless, looking to the graphs of the variables on first difference (especially for those from Payroll-linked loans), it appears that there are some breakpoints on these series and therefore the Bai-Perron test was computed. The Bai-Perron test (BAI, PERRON, 2003) 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, the stationarity tests were rune again and dummy variables were created. The results are in Table 4 (Appendix).

For seasonality we used a test proposed by Webel and Ollech (2017) which consists in combining results for two different seasonality tests: QS-test and kwman-test (KW). Both tests are 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 were treated by the Census X-13 method.

The last test on the series was about outliers. The Census X-13 method used to treat seasonality provided treatment for outliers as well, however, for the bank-specific

[1] The actual values have been multiplied by an unreported constant in order to maintain confidentiality.

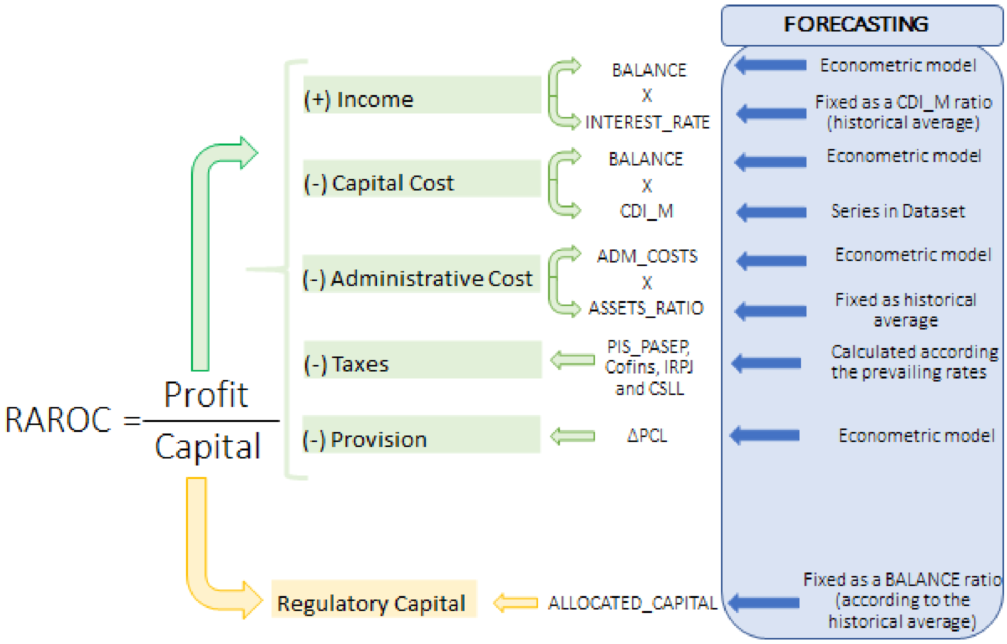
[2] From 2011M01 to 2019M06 the variables contain realized values and from 2019M07 to 2024M06 contain a prediction period provided by the financial institution since the bank maintain a contract with a financial consulting firm, which provides several macroeconomic variables with 5 years forecasting.

data, we also test those series for the presence of outliers in order to reinforce the robustness of the econometric model (specially for the endogenous variables). Therefore, we used Boxplot graphs and dummy variables were created to consider the presence of outliers. After this point, all variables used and tested are considered in stationary form and considering the treatments about seasonality and outliers.

4.2 RAROC methodologies

In this work, we applied mathematical and econometrics procedures using the software Eviews version 10 and R version 3.6.1 in order to produce inferences and projections based on the selected sample. Therefore, two different perspectives for the RAROC model were created: Historical and Forecasted. The RAROC models proposed follow a simple equation and Figure 1 summarizes a diagram of the construction of each variable and the forecasting approach.

Figure 1 – RAROC model proposed



Source: authors

Next sections provide more details regarding each model.

4.2.1 Historical Approach

Here we propose simple mathematical procedures to calculate the RAROC variables for each product in the historical period (102 months) based on the data available from the database. The Income from financial intermediation corresponds to the interest charged by banks on loans made and it can be calculated by multiplying the loan interest rate by the balance of operations (KONG; LI; YE, 2017). As can be seen from Equation (2), it increases as the Balance or Interest Rate increases.

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

On the other hand, the Capital Cost corresponds to the interest paid by banks to those who deposit money with the institution, and it denotes the capital used by banks in order to make loans, known as “funding”. According to the Central Bank's Bank Economics Report (BACEN, 2018), the funding cost is strongly linked to the CDI

(Brazilian Interbank Deposit) rate[3] and it may be adopted as the average funding cost of financial institutions. Therefore, following Equation 3, the Capital Costs' formula is defined as the product of Balance and CDI rate.

$$Capital\_Cost_t = BALANCE_t * CDI\_M_t \tag{3}$$

Administrative Costs represent all the expenses arising from the organizational structure of the institution such as wages, data processing, communications, rent, among others, which support the company's activities (BRUGNERA; GIENTORSKI, 1998). 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:

$$Administrative\_Cost_t = ADM\_COST_t \; * ASSETS\_RATIO_t \tag{4}$$

For Provision Costs, the database provides only the balance of Provision for Credit Loss (PCL) and 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 5.

$$Provision\_Cost_t = PCL_t - \; PCL_{t-1} \tag{5}$$

Lastly, taxes are calculated According to the Brazilian Internal Revenue Service (RFB) and follow two different rules according to the tax base: profit or revenue. Financial institutions in Brazil are subject to four taxes: 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) 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 6 and 7) in order to calculate the taxes due.

$$Profit\_Tax_t = (Income_t - Capital\_Cost_t) * (PIS\_PASEP \; + Cofins) \tag{6}$$

$$Revenue\_Tax_t = (Income_t - Capital\_Cost_t - Profit\_Tax_t - Administrative\_Cost_t - Provision\_Cost_t) * (IRPJ \; + CSLL) \tag{7}$$

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.

4.2.2 Forecasted Approach

For the forecasting RAROC, an econometric model is created to predict the most important variables of the RAROC equation, and the remainder variables are calculated by simple mathematical procedures. This methodology is mostly based on Levieuge (2015) and follows multivariate autoregressive models, such as Vector Auto-Regressive (VAR) and Vector Error Correction Model (VECM). 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. The follow dynamic model is proposed:

[3] 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.

$$X_t = \Psi_0 + \sum_{i=1}^{p} \Psi_i W_{t-i} + \Theta D_t + E_t \tag{8}$$

where X is a vector that includes the endogenous variables from bank-specific data (BALANCE, PCL and ADM_COSTS). W contains lagged endogenous variables and additionally includes exogenous variables from the macroeconomic data. D contains dummies created to suit the assumptions issues. Finally, E is the vector of the residuals.

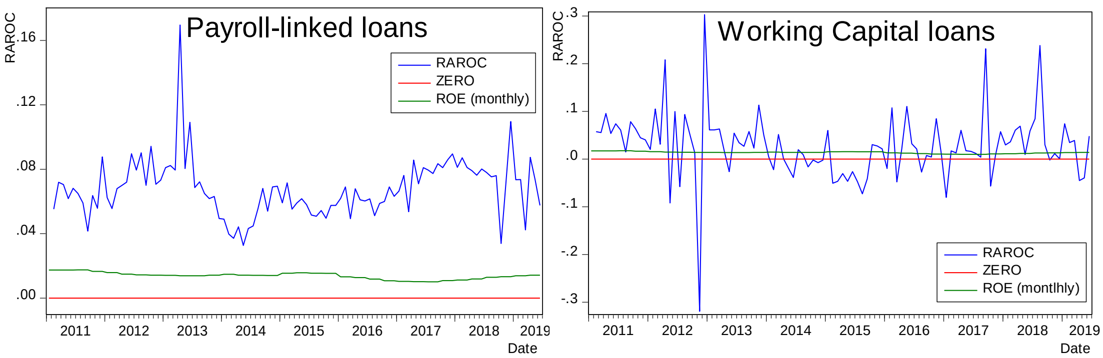
The vectors X and W were selected according to theoretical relevance and analyzing statics such as t-statistic and Information Criterions, resulting in distinct models for each product. The macroeconomic data were also tested in lags (until 12), once the effects of the macroeconomic variables could occur with a delay. After choosing the most relevant variables, a range of statistic tests were used to assess the validity of the model. These tests include cointegration and causality, and also a number of tests related to the residuals, such as normality, autocorrelation and heteroskedasticity. Finally, to check the robustness of the model, the inverse roots of the autoregressive characteristic polynomial, coefficients of determination, and some graph analysis of the fitted versus the actual values are used.

5 Empirical Results and Discussion

5.1 Historical RAROC

The historical RAROC investigated the products' profitability between 2011M01 to 2019M06 , 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 as well as relate those returns with the product's variables or even macroeconomic events. For this purpose, it was observed if the return was positive (it added value in that month) or negative (it destroyed value). In addition, following Chlopek (2013), the return was compared to the ROE median of the four main banks operating in Brazil[4] which is used as a benchmark to examine whether the product generated value above the market median. Figure 2 shows the results for both products.

Figure 2 – Regulatory RAROC



Source: authors

Payroll-linked loans returned 8.13% on average with positive and greater average market values throughout the entire period. The return has reached double digits in 6 periods and the highlight was in 2013M04 when it pays back 18.20%, driven mainly by a large reversal of provision. On the other hand, 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 (see Figure 11 in Appendix). In

[4] Although RAROC and ROE are different indices, ROE is the most publicized index. It was collected at Economática (2019) website (Figure 6 in Appendix).

addition, during this period the NPL increased sharply from R$ 157 million at the end of 2013 to over R$ 200 million in the first half of 2014, having 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. Once more, an important factor was the control of NPL in this period, which steadily reduced from the second half of 2014 to the historic low of 137 million in 2016M07. 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.

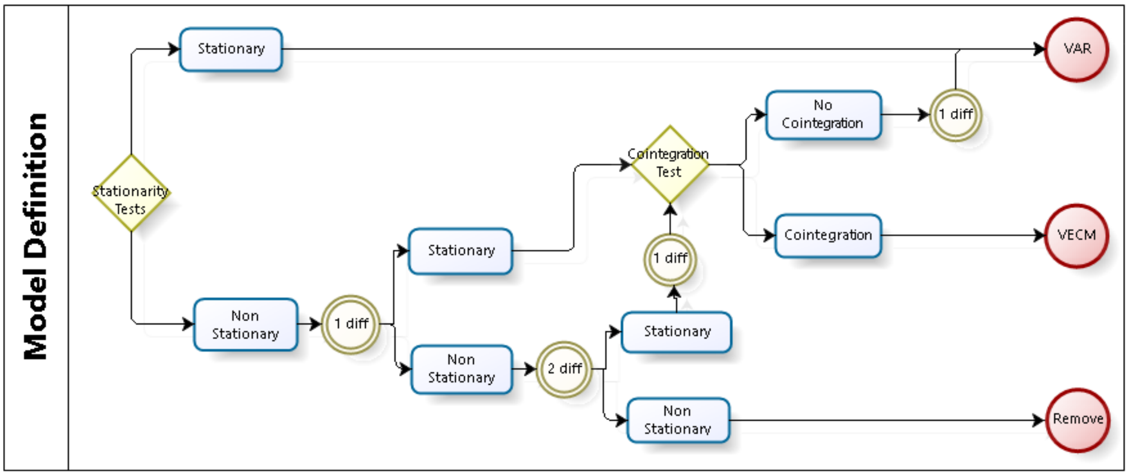
Working Capital loans presented 4.03% return on average, but a result that fluctuated greatly during the period with several months of negative returns. We highlight a strong negative period in 2012M11 when the return reached -30.38% mainly affected by the provision expenses that increased 45.60% this month. In addition, the product return was negative in another 19 months and was below ROE by 27 times. The negative return was influenced by the balance that decreased significantly, affecting revenues and by the inflated NPL that affected the provision, especially from 2015 to 2017 when the Brazilian economy shrunk resulting in a sharp reduction in credit volume, a large increase in unemployment rates, and a high income commitment by the end of 2016. However, it is also important to highlight that the product had a positive return in several months, including return over 20% in 4 points. At these periods, there was an excessive level of written off balance that influenced the provision and therefore the income. In addition, there was also a sharp reduction in NPL, probably due to a more active management action to collect arrears. Hence, we see that it is required an active management in order to take appropriate measures to mitigate periods of sharp decrease. 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.

In conclusion, although the Working Capital 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 the importance of 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 the next section) as this way managers can act in advance, anticipating actions to avoid possible scenarios where the return projection is negative, for example.

5.2 Forecasted RAROC

For the autoregressive multivariate model proposed to forecast the RAROC, the first tests considered were about stationarity and cointegration in order to select between a Vector Autoregressive (VAR) or a Vector Error Correction Model (VECM). 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 3 summarizes this procedure.

Figure 3 – VAR/VEC Model Definition



Source: Feld and Schuster (2020)

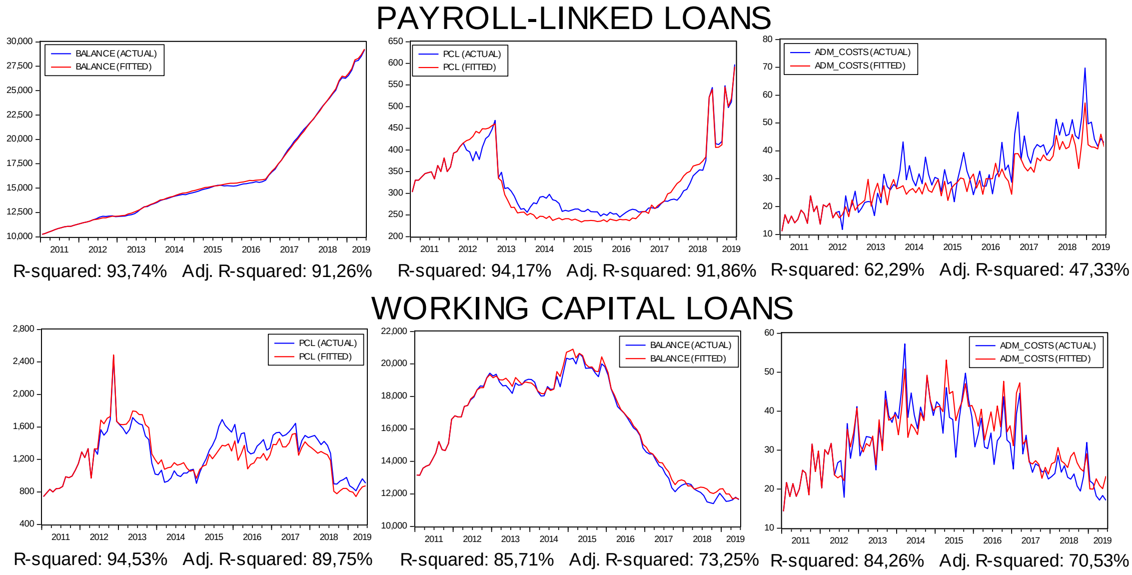
Once the variables BALANCE, PCL and ADM_COSTS are not stationary in level (Table 2), running a VAR straight is rejected. Therefore, we must test for cointegration and the Johansen test is used. The results for both products reveal that the tests are not conclusive about cointegration (at 5% confidence level), because, depending on the trend, the variables may or may not have cointegration. At a stricter level (1%) in both products, the test shows that the variables may not be considered cointegrated and, therefore, 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 this model is proved to suit very well a short run projecting, as shown in Levieuge (2015).

To choose the exogenous (and which lag) and the deterministic variables, the stepwise procedure was used maintaining the most relevant variables accordingly to the theoretical relevance and t-statistic. After, the Information Criterions (Likelihood Ratio, Final Prediction Error, Akaike Information Criterion, Schwarz Information Criterion and Hannan-Quinn Information Criterion) were used to decide the optimal number of lags for the endogenous variables (4 for Payroll-linked and 6 for Working Capital). Finally, the Granger Causality test was used to ordering the endogenous variables in the model (Payroll-linked: BALANCE, PCL and ADM_COSTS; Working Capital: PCL, BALANCE and ADM_COSTS).

After that, the VAR models for Payroll-linked and Working Capital loans were computed (Table 5 and Table 6 in Appendix) and the assumptions from the residuals were tested. For normality, the Jarque-Bera test was used (with three different methods for orthogonalization: Cholesky, Residual Correlation and Residual Covariance) and the results confirm that all the variables for both models present residuals normally distributed. For serial correlation, the Breusch-Godfrey test (LM) stated that the residuals do not present autocorrelation for a 5% level of confidence for both products. Finally, the White test was performed for heteroskedasticity and the results show that the residuals are homoscedastic for both products.

About the robustness of the model, the inverse roots of the characteristic polynomial shows that all the values are inside the unit circle and it is affirmed that the models are stable. For Payroll-linked loans the adjusted R^2 index is high for BALANCE and PCL (91% for both) and moderate (47%) for ADM_COSTS. For Working Capital loans, 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 (Figure 4) it is possible to check that the model correctly captures the trends for the all the series.

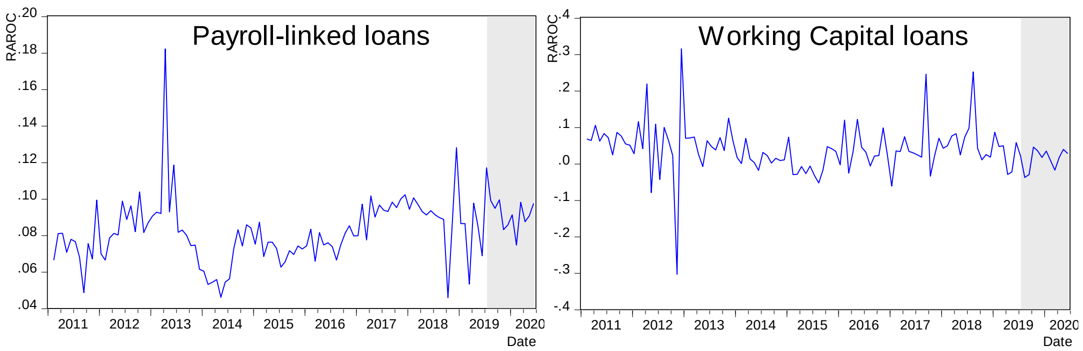
Figure 4 – Graphs of Fitted vs Actuals Values



Source: authors

Finally, the three main variables of each product (BALANCE, PCL and ADM_COSTS) were projected. 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 an *ex-ante* 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. Figure 5, in the shaded area, shows the projected results for RAROC regarding the Payroll-linked and Working Capital loans.

Figure 5 – RAROC forecasting for Payroll-linked loans



Source: authors

The projected results for Payroll-linked presented the average return of 9.31%, thus a positive return and above the average 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.

Therefore, this forecasting RAROC view may be an important tool in order to support executives 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 shown in the econometric models.

6 Conclusion

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, two different perspectives for this model were created: Historical and Forecasted RAROC. Methodologically, we propose a scheme to calculate the RAROC variables stratified by product along the historical period and a Vector Autoregressive (VAR) model for forecasting the RAROC. This way, the results allow to compare different credit products in a risk-based return.

The Historical RAROC provides for managers a tool capable to analyze *ex-post*, month by month, whether the products actually added value to the institution in the period as well as relate those returns with the product's variables or even macroeconomic events. The Forecasted RAROC enables an *ex-ante* prospective decision making considering the risk-adjusted returns in a 12-month future scenario, considering 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. The overall tests reveal that the models created had a good performance and therefore satisfactory results.

These models were applied to a financial institution credit portfolio and the results reveal that Payroll-linked loans presented a superior RAROC in both perspectives, with positives and greater average market values throughout the entire period. Therefore, this product adds value to the institution – even in periods of economic crisis – and managers may consider this product as a good investment of capital. Working Capital loans, on the other hand, presented a result that fluctuated greatly during the period with several months of negative returns, 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, otherwise this product does not present itself as a good capital investment . Although the return is lower than Payroll-linked loans, it is important remembering that diversify investments avoids a high concentration risk.

For simplification purposes, the methodology proposed at this paper as well as the conclusions were deduced from a sample that only contains 2 products. That is the main limitation of this work, once different products may lead to different analysis and results. However, the results presented here can be considered satisfactory and may contribute to a strategic management focused on risks. Therefore, it is possible to expand the model suggested here to other products and other institutions. Additionally, 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

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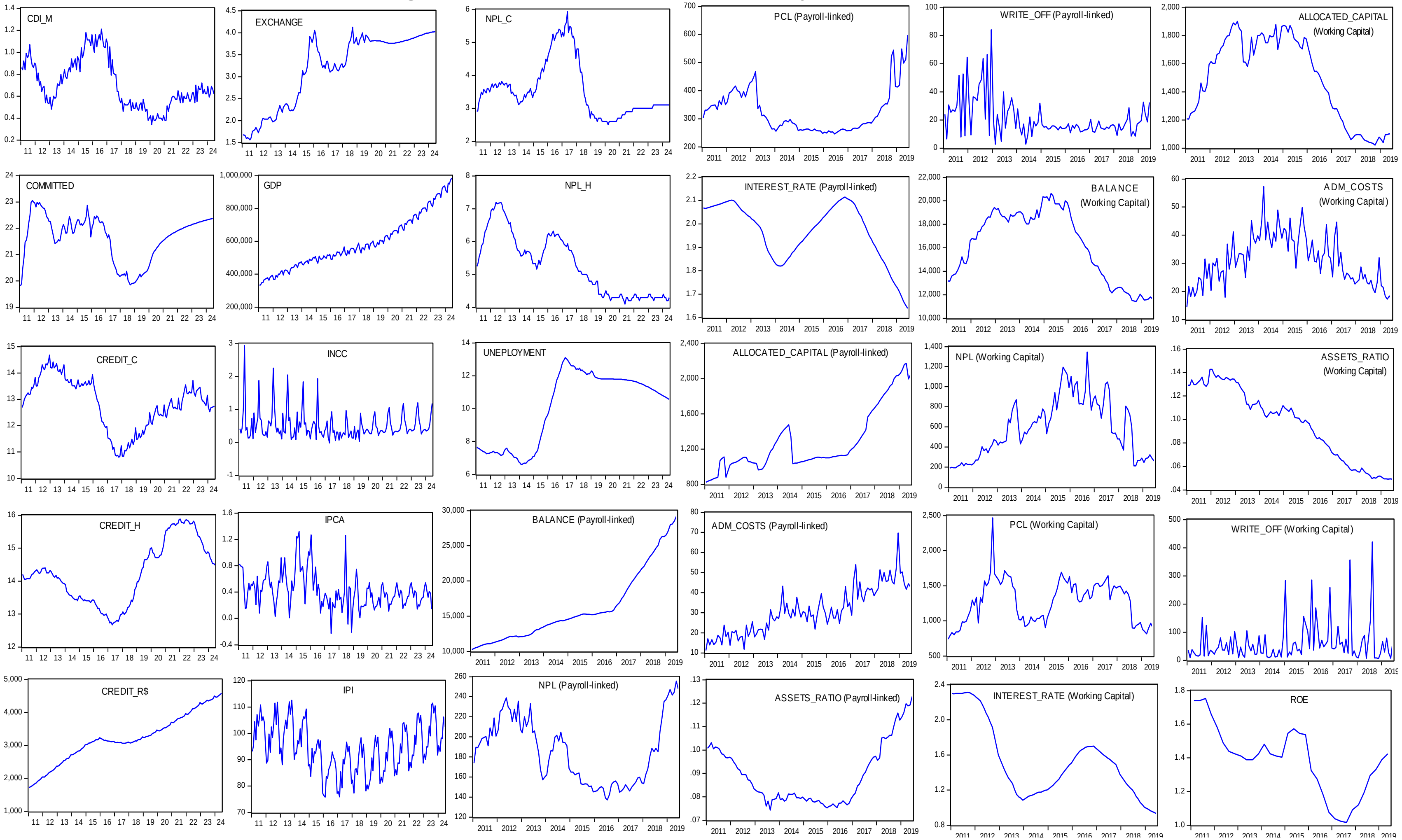
APPENDIX – EXTRA SERIES AND MODELS EVALUATION

Figure 6 – Macroeconomic and Bank-specific series



Source: authors

Table 1 – Details and Descriptive Statistics of the Variables

Variable	Details	Product	Mean	Std Dev.	Min	Max	N
BALANCE	Sum of the balance for each product at the reference date. R$ million.	Payroll-linked	16.130,20	5.012,45	10.249,20	29.190,30	
		Working Capital	16.232,15	2.982,35	11.400,10	20.641,90	
NPL	Sum of the Nonperforming Loans (NPL) balance (credit operations in default for more than 90 days). R$ million.	Payroll-linked	185,56	32,27	137,10	255,60	
		Working Capital	589,07	291,64	189,50	1.346,20	
PCL	Sum of the Provision for Credit Losses (PCL) balance, calculated by regulatory model (2.682/99). R$ million.	Payroll-linked	325,43	77,78	245,20	597,60	
		Working Capital	1.275,07	304,45	741,70	2.466,20	
INTEREST_RATE	Balance-weighted average interest rate for each product.	Payroll-linked	1,96	0,12	1,64	2,12	102
		Working Capital	1,52	0,42	0,93	2,31	
ALLOCATED CAPITAL	Sum of the Allocated Capital balance, calculated by the regulatory model. R$ million.	Payroll-linked	1.277,57	354,60	824,00	2.173,50	
		Working Capital	1.492,59	299,72	1.021,00	1.901,20	
ADM_COSTS	Sum of Administrative Costs at the reference date. R$ million.	Payroll-linked	31,06	11,56	11,10	69,80	
		Working Capital	31,04	8,80	14,30	57,30	
ASSETS_RATIO	Ratio of the balance to the total assets of the bank.	Payroll-linked	0,09	0,01	0,07	0,12	
		Working Capital	0,10	0,03	0,05	0,14	
Variable	**Details**	**Source**	**Mean**	**Std Dev.**	**Min**	**Max**	**N**
CDI_M	Brazil interbank deposit rate. Month cumulative change	BACEN (4391)	0,70	0,22	0,34	1,21	
COMMITTED	Brazil households income committed to debt.	BACEN (19881)	21,65	0,87	19,82	23,05	
CREDIT_C	Credit operations to corporates. GDP percentage.	BACEN (20626)	12,84	0,98	10,80	14,68	
CREDIT_H	Credit operations to households. GDP percentage.	BACEN (20627)	14,23	0,94	12,67	15,88	
CREDIT_R$	Financial system credit operations. R$ billion.	BACEN (20539)	3.204,48	722,84	1.718,71	4.583,14	
EXCHANGE	Exchange rate. Month average R$/US$.	BACEN (3697)	3,19	0,81	1,56	4,12	
GDP	Nominal GDP of Brazil. R$ million.	BACEN (4380)	589.124,21	162.271,24	333.330,50	984.783,47	162
INCC	Building index of Brazil. Month percentage.	BACEN/FGV (192)	0,50	0,42	-0,02	2,94	
IPCA	Consumer price index of Brazil. Month percentage.	BACEN/IBGE (433)	0,42	0,27	-0,23	1,32	
IPI	Industrial Production Index of Brazil. Index 2012=100.	IBGE (PZ27)	94,52	9,01	75,80	112,60	
NPL_C	Corporates nonperforming loans. Percentage.	BACEN (21086)	3,54	0,84	2,50	5,94	
NPL_H	Households nonperforming loans. Percentage.	BACEN (21112)	5,29	0,93	4,10	7,20	
UNEMPLOYMENT	Unemployment rate in Brazil. Labor force percentage.	IBGE/PNAD	10,12	2,19	6,62	13,11	

Note: statistics over period 2011M01 - 2019M06 for bank-specific variables and over period 2011M01 - 2024M06 for macroeconomic variables.

Source: authors

Table 2 – Unit Root Tests for the Bank-specific Variables

		Payroll-linked loans				Working Capital loans			
Series	**test**	**T-stat with intercept**	**T-stat with trend and intercept**	**T-stat with none**		**T-stat with intercept**	**T-stat with trend and intercept**	**T-stat with none**	
BALANCE	ADF	2.2771	0.7247	1.8446		-0.15756	-2.30975	-0.40685	
	PP	5.5269	1.9316	6.4275		-0.65744	-2.24124	-0.37014	
NPL	ADF	-0.8779	-0.6530	0.6099		-2.25363	-2.00856	-0.92463	
	PP	-0.8733	-0.5029	0.6099		-2.20639	-1.91561	0.87049	
PCL	ADF	-0.4857	-0.4373	0.8124		-2.8790**	-2.80387	-0.38454	
	PP	-0.0932	0.3317	1.1935		-2.7709*	-2.63455	-0.39505	
INTEREST_RATE	ADF	-2.3922	-3.0855	-0.8922		-1.39796	-1.68243	-0.31391	
	PP	0.0177	-0.6649	-1.3299		-1.28641	-1.71944	-0.60511	
ALLOCATED_CAPITAL	ADF	-0.1683	-1.3486	1.6116		-0.64001	-2.46009	-0.33304	
	PP	-0.0421	-1.2250	1.8456		-0.72843	-2.48857	-0.33464	
ADM_COSTS	ADF	-1.9601	-7.1952***	0.9529		-2.5276	-2.6580	-0.3351	
	PP	-2.6040*	-7.2365***	-0.0695		-4.0686***	-4.0917***	-0.8220	
ΔBALANCE	ADF	-0.9766	-2.3201	-0.0499		-7.715979***	-8.537946***	-7.745607***	I(1)
	PP	-4.0723***	-6.2498***	-1.6837*		-8.069830***	-8.546601***	-8.101240***	
ΔNPL	ADF	-11.3093***	-11.4417***	-11.3168***	I(1)	-9.879693***	-6.548261***	-9.929757***	I(1)
	PP	-11.2347***	-11.4417***	-11.2408***		-11.89467***	-16.44674***	-11.93119***	
ΔPCL	ADF	-10.4618***	-8.6653***	-10.4319***	I(1)	-12.92625***	-13.01918***	-12.99079***	I(1)
	PP	-10.6231***	-11.0314***	-10.5431***		-12.99005***	-13.03801***	-13.05572***	
ΔINTEREST_RATE	ADF	-1.4249	-1.6033	-1.2469		-3.267099***	-3.247775*	-3.288193***	I(1)
	PP	-1.5859	-1.7648	-1.4090		-7.224913***	-7.191376***	-7.252568***	
ΔALLOCATED_CAPITAL	ADF	-8.1396***	-8.1640***	-7.8781***	I(1)	-9.692267***	-10.17256***	-9.737338***	I(1)
	PP	-8.1451***	-8.1709***	-7.8495***		-9.716129***	-10.17256***	-9.759773***	
ΔADM_COSTS	ADF	-8.5363***	-8.5005***	-8.3719***	I(1)	-8.4326***	-8.9137***	-8.4781***	I(1)
	PP	-36.6940***	-34.7296***	-23.7200***		-22.7236***	-39.8174***	-22.8442***	
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: authors

Table 3 – Unit Root Tests for Macroeconomics Variables

Series	ADF P-Value with intercept	ADF P-Value with trend and intercept	ADF P-Value with none	PP P-Value with intercept	PP P-Value with trend and intercept	PP 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_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	
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	
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	
UNEPLOYMENT	0.4138	0.8120	0.7178	0.6744	0.9710	0.8231	
Series	**ADF P-Value with intercept**	**ADF P-Value with trend and intercept**	**ADF P-Value with none**	**PP P-Value with intercept**	**PP P-Value with trend and intercept**	**PP 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_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***	
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***	
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)
ΔUNEPLOYMENT	0.0594*	0.1519	0.0058***	0.0037***	0.0123***	0.0002***	I(1)
Series	**ADF P-Value with intercept**	**ADF P-Value with trend and intercept**	**ADF P-Value with none**	**PP P-Value with intercept**	**PP P-Value with trend and intercept**	**PP P-Value with none**	
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)
ΔΔGDP	0.0000***	0.0000***	0.0000***	0.0001***	0.0001***	0.0001***	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: authors

Table 4 – Multiple breakpoints tests

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

Series	Payroll-linked Breaks	Payroll-linked Scaled F-statistic	Payroll-linked Weighted F-statistic	Payroll-linked Estimated break dates	Working Capital Breaks	Working Capital Scaled F-statistic	Working Capital Weighted F-statistic	Working Capital 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	

	1	5.4183	5.4183		1	3.6700	3.6700	
	2	4.9859	5.9251		2	2.4359	2.8948	
ΔNPL	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	
	1	5.0618	5.0618		1	6.9102	6.9102	
	2	3.3921	4.0311		2	6.1912	7.3574	
ΔPCL	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	
	1 *	72.1360	72.1360		1 *	33.1036	33.1036	
	2 *	120.9657	143.7515	**2012M05,**	2 *	62.9989	74.8657	**2012M05,**
ΔINTEREST	**3 ***	**181.1517**	**260.7856**	**2014M03 and**	**3 ***	**103.1969**	148.5620	**2013M11 and**
RATE	4 *	137.9197	237.1446	**2016M12**	4 *	87.7057	150.8046	**2016M12**
	5 *	109.5213	240.3306		5 *	72.0161	**158.0302**	
	1	4.2565	4.2565		**1 ***	**11.1072**	**11.1072**	
	2	4.3758	5.2000		2	6.3783	7.5798	
ΔALLOCATED	3	3.8791	5.5843		3 *	5.9736	8.5995	**2013M01**
CAPITAL	4	3.2696	5.6219		4	4.5434	7.8121	
	5	2.8072	6.1600		5	3.2188	7.0631	
	1	0.4682	0.4682		1	1.5815	1.5815	
	2	0.6706	0.7969		2	1.1461	1.3620	
ΔADM	3	0.8269	1.1904		3	1.0103	1.4545	
COSTS	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: authors

Table 5 – 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)

Standard errors in ( )

Source: authors

Table 6 – 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)

Standard errors in ( )

Source: authors