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Strategic direction re-evaluation of bank ratings in Brazil

Valdir Domeneghetti
University of São Paulo

Fabiano Guasti Lima
University of Sao Paulo

Abstract

This study aims to complement, by means of a re-evaluation, previous studies on determinants of publicly traded bank ratings, operating in Brazil, from 2006 to 2017 (2nd. quarter). Within the suitable statistical practices, the ordered Logit model with unbalanced panel data was chosen to be used. The results indicated convergence with literature in large part of the variables. New qualitative variables were inserted in the re-evaluation as this research differential: Basel index, capital source, public or private nature, in which just the global capital index was significant at 1%. Conflicting signals and significances between the models with and without dummies were found in credit losses on revenue of financial intermediation and voluntary fit. For the others, results were revalidated in literature. A detail which is also observed is the alignment of bank credit rating to the Country, by the agencies, due to the resurgence of the financial economic crisis, a factor which can entail greater difficulties for banks to fit in the schedule in progress of Basel III, whose fully implementation forecast is in 2019.

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Contact: Valdir Domeneghetti - domeneghetti@usp.br, Fabiano Guasti Lima - fgl@usp.br.
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1 . INTRODUCTION

This work follows the structure of the paper by Lima, Silveira & Fonseca (2018). The automation process of the international financial system is constant and does not allow setbacks; its future certainly holds difficult situations of comprehension and measurement, an example of which is the blockchain database (confidence protocol), which provides a "certain validity" to cryptocurrency. Bitcoin is the most well-known cryptocurrency, which is not under government control in any country and is traded at the margins of the formal financial system; because of its value expression in today's market, a trading platform for this virtual currency is being structured by the CME Group, which is controlled by the Chicago Mercantile Exchange (the largest mercantile exchange).

Another major factor in the market is the automated negotiations by algorithms which can be processed at a high frequency (high-frequency trading—simultaneous offers which are not always accomplished or are constantly re-evaluated with small gains in each transaction, in significant volume) whose performance, reach, or even risk exposure, have not yet been measured (Almeida, 2016).

The complexity of financial products, the increasing interrelationships between firms in several countries and the lack of barriers between the markets have brought more volatility to businesses and investors. Whether they are institutions, sole proprietorships or small-sized entities, more risks must be taken, either because of a need to perpetuate gains or for seeking greater spreads.

The increasingly advanced software, the higher definition computer screens, the capacity of information processing to present data in colored graphs, and the available complex numerical arrangements lead the public and market operators to forget that such equipment only answers the questions; it does not ask them (Bernstein, 1997).

This greater volatility and complexity of financial products had its greatest consequence, the "subprime" world financial crisis from 2008 on, which culminated in the North American bank failures, the reduction of international liquidity and a greater need for "compliance alongside the market agents". Global financial institutions began to have greater control over their financial operations, with a notably broad focus on the credit risk rating of several financial tools used in the market, regulated by the Basel III agreement; this has not brought more tranquility to investors, since there are uncertainties regarding the effectiveness of rating agencies in measuring the risk level of firms in the wake of the breakdown that took place with investment and securities banks which had been typified as low risk (Bissoondoyal-Bheenick & Treepongkaruna, 2011; Hassan & Barrell, 2013 & Salvador, Pastor & Guevara, 2014).

When reviewing the 8% capital index based on risk that has been fixed since 1993, in the studies for the Bank for International Settlements (BIS) by the Basel Committee on Banking Supervision (BCBS), the use of agency ratings for the banks and securities was not found to produce the necessary effects and became the focus of critical analysis (Altman & Saunders, 2001).

Currently, the implementation of the Basel III agreement, whose participants must accomplish three specific components to improve 2013 levels by 2019, is in progress. The three components are: core capital (shares and retained profits—from 4.5% to 9.5%), additional capital (core capital + additional capital = Level I—from 5.5% to 11.0%) and Level II (Level I + Level II = Regulatory Capital — from 11.0% to 13.0%), requiring adjustments from the banks with the consequent margin reduction for the leverage of asset operations (Bacen, 2013).

Therefore, this work aims to develop a robust reevaluation model by rating the strategic direction of banks which operate in Brazil to typify and measure the important variables tied to the risk ratings of publicly traded banks from 2006-2017 (2nd quarter). This study has relevance due to the gap of existing works on the theme, discouraged by the growing use of sophisticated, automatized and diversified trading tools, which hamper the forming of a database for critical analysis and comparison in empirical studies.

Studying minimally explored fields and segments is necessary; the set of indices for this work aims to improve the relationship between the credit risk of the banks operating in Brazil and the assignment of rating agencies which contributes to the investors and market as a whole, due to the relevance of the financial system in the country's context.

2 . LITERATURE REVIEW

The databases utilized indicated rare studies on the analysis of the strategic direction of bank ratings which are updated, demonstrating that the factors approached in the introduction (growing use of sophisticated automatized and diversified trading tools) can contribute to inhibiting researchers in reviewing the theme, even by forming unstable and difficult time comparison databases. In the research, the variables were analyzed with the ordered logit model, which is usually used in nonparametric samples.

When using the ordered logit model, Karminsky & Khromova (2016) considered 3,256 banks (base sample from 1996-2011) and determined that the agencies that assign credit ratings are influenced by economic and trading cycles. The alignment of bank ratings which took place in Brazil in 2006-2017 (2^{nd} quarter) corroborates with the sovereign risk of the country at a speculative level. In the study, the financial variables with a greater significance on ratings, leverage, capital cost, financial performance, nonpayment, liquidity/solvency, core business extra income and relevance, along with economic cycles such as price index, foreign trade and Gross Domestic Product (GDP), maximized the model efficiency.

Using the model with panel data, D'Apice, Ferri & Lacitignola (2016) analyzed whether the economic-financial variables were correlated to the agency ratings, considering a 241-bank sample comprised of 39 countries. It was determined that after the 2008 subprime crisis, there was an inflection by rating agencies to focus on bank efficiency.

Multiple linear regression models, ordered logit, support vector machines (SVM) and logical analysis of data (LAD) were used by Hammer, Kogan & Lejeune (2012), to analyze the data of 800 banks, spread over approximately 70 countries in one year (2001). The logical analysis of data and the ordered logit had greater accuracy, respectively.

Hassan & Barrell (2013), through the ordered logit model in a sample of U.S. and England banks (206) during the period from 1994-2009, noticed that efficiency, size and performance depicted 74% to 78% of the banks' credit ratings. They also suggested rating flaws in the prevention and review of the Basel III precepts.

Analyzing the data of banks in Australia (20) and England (49)—from 2006-2009—Bissoondoyal-Bheenick & Treepongkaruna (2009), through an ordered probit model, denoted that compliance in capital adequacy, good assets, liquidity and proper operational performance explained most of the ratings.

By using the stepwise least squares (SLS) model for separating the binary variables included in the ordered probit model, Gogas, Papadimitriou & Agrapetidou (2014), considered the rating of 92 U.S. banks from 2008-2011 and indicated that the size, performance and good assets are efficient estimators, drawing an analogy with the timing loss of the rating agencies in foreseeing the 2008 problems (subprime crisis).

Focusing on Spain, Salvador et al. (2014) used a 44-bank sample from 2000-2009, and through an ordered probit model, they determined that the 2008 crisis sped up the downgrade of small- and medium-sized banks, possibly due to the drop in performance.

This study focuses on the ratings of banks operating in Brazil, with the definition of several explanatory variables in works of this theoretical framework and in the literature analysis indices of balance sheets (Assaf Neto, 2002). The ordered logit model, when applied, best maximized the reach of the strategic rating direction of the banks in the sample.

3 . METHODOLOGY

3.1. Sample

The study focuses on publicly traded banks with stocks in the B3 (new name due to the merger of BM&FBOVESPA and CETIP), with a foreign long-term credit rating (Long Term Bank Deposits—Foreign) stipulated by Moody's during the 2006-2017 (2nd quarter) period. Alternatively, for the banks which have not had their credit ratings stipulated by Moody's, the Fitch rating was used.

The criterion adopted to collect bank credit rating information was the one available at the end of the business quarters (March, June, September and December of each year). The choice of long term bank deposits (foreign) was because of the greater number of ratings stipulated by both rating agencies. For the purpose of balancing in the model and the standardization of grades, the ratings were changed into a 0 to 7 scale, as demonstrated in Table I, in which 0 is the best investment level rating and 7 is the worst speculative level rating. In the study, the scales 0, 1, 6 and 7 have not appeared in the indices of the banks analyzed in the sample—2006-2007 period.

Table I.

Rating Conversion of the rating agencies in own scale

Moody´s	Fitch Rating	Conversion Scale	Typification
Aaa	AAA	0	Investment level with high quality and low risk
Aa1, Aa2 and Aa3	AA+, AA and AA-	1	
A1, A2 and A3	A+, A and A-	2	
Baa1, Baa2 and Baa3	BBB+, BBB and BBB-	3	Medium quality investment level
Ba1, Ba2 and Ba3	BB+, BB and BB-	4	Speculation category with low rating
B1, B2 and B3	B+, B and B-	5	
Caa1, Caa2 and Caa3	CCC	6	High default risk and low interest
Ca, C	DDD	7	

Source: Elaborated by the authors based on the rating agency sites—Fitch Rating and Moody's.

The sample of the banks operating in Brazil with stocks listed in B3 has 13 elements, in which 4 of them are large- and 9 are medium-sized, using the criterion of the monetary authority Bacen.

Table II indicates that at the end of each year (from 2006 to 2017), 55.1% of the banks in the sample had a speculative-level rating (rates 4 and 5 of the transformation scale); on the other hand, 44.9% of the banks were rated with investment levels (rates 2 and 3). It was also determined that in 2016 and 2017 (2nd quarter), all the banks of the sample presented speculative levels (rates 4 and 5) when there was an alignment of the bank ratings, regardless of the economic-financial situation of each one to the sovereign risk in Brazil.

The representative sample indicates that the 13 banks analyzed hold 63.45% of the total assets (R$ 4.758 of 7.498 trillion reais) and 76.38% of the fixed service sites (17,133 out of 22,431) for the 2nd quarter of 2017 (Bacen/FI Data, 2017).

Table II.

Sample banks: long-term bank deposits (foreign) credit risk—2006-2017 period

Year	Credit risk rating[a]				Risk level[b]		
	2	3	4	5	Investment	Speculative	Total
2006	2	0	0	0	2	0	2
2007	4	0	3	0	4	3	7

2008	4	1	3	0	5	3	8
2009	4	1	3	0	5	3	8
2010	4	1	4	0	5	4	9
2011	2	4	5	0	6	5	11
2012	2	4	5	0	6	5	11
2013	2	5	5	0	7	5	12
2014	0	7	5	0	7	5	12
2015	0	6	5	1	6	6	12
2016	0	0	9	4	0	13	13
2017	0	0	10	3	0	13	13
Total	24	29	57	8	53	65	118
%	20.3	24.6	48.3	6.8	44.9	55.1	100.0

[a] Analysis based on the first quarter of each year.
[b] While levels 2 and 3 represent the investment level classifications, levels 4 and 5 indicate the speculative level.
Source: Elaborated by the authors based on the rating agency sites - Fitch Rating and Moody's.

3.2. Model and Estimation Method

The strategic directions of bank ratings have the individual credit risk rank called $rat\_num\_lp_{it}$, as a dependent variable of the model in which *i* is the banks and *t* is the information quarter. As explanatory variables, the economic-financial indices and the binary variables available in the Economatica System[1] and in the FI data of Bacen (Table III) were chosen. The explanatory variables consider the relevant factors, and they are as follows: adequacy/quality of asset, solvency and liquidity (Hammer et al., 2012 and Karminsky & Khromova, 2016).

From the literature, several variables collected and allocated in the model seek to capture the effects provoked by the dependent variable. The first index, which also represents a differential in this work from the literature is the Basel index (*Ind_Basileia*), which measures the relationship between the FI reference equity and the assets value weighted by the risk (*risk weighted assets—RWA*). It is also known as the solvency index, since the financial intermediation activity of the banks involves risks usually supported by capital. The greater the index, the greater the own capital or equity surplus for carrying out greater credit risk operations. The aim of bringing this index to the model is to verify whether this index reflects the FI rating, since the objective of the index is to make the banks have enough capital to stand loss risks in their activities and reveals whether the FI is in accordance with the external and internal laws and regulations; i.e. bank compliance.

In this study, the performance factor was measured by the FI net margin (*marg_liq*), as in Karminsky & Khromova (2016), Gogas et al. (2014), Caporale, Matousek & Stewart (2012) and Hammer et al. (2012). The net margin is calculated by the net profit ratio generated by the revenue of financial intermediation in each period *t*.

The FI's assets quality adequacy was measured by the leverage, obtained by the ratio between Total Assets (AT) and Net Equity (PL). An increase in this index raises the bank risk since a lower PL in face of the AT indicates a lower capability for the institution to absorb losses in difficult periods (Salvador et al., 2014 and Hammer et al., 2012). The second variable consists of the default potential (*inadimpl*), obtained by the ratio between the PDD

[1] Economatica is considered a reference in the development of Investment Analysis solutions. Since its founding in 1986, the company has maintained a 100% focus on collecting and managing highly reliable databases, as well as continuously developing high-performance analytical tools.

(Provision of Doubtful Debtors) and the financial volume of credit operations, since the high values in this variable jeopardize the FI solvency.

For the solvency and liquidity factors, indices which evaluate the capability of the bank honoring their short-term obligations was raised. In this research, loss jeopardy regarding revenues for financial intermediation (*pdd_rec_fin*) was used, since the high values of this index reveal revenue jeopardy in covering loss; the loans/deposits index (*empr_dep*) was used, which was obtained by dividing the credit operations by the total of the deposits raised; the significant values of this measure indicate a greater volume of credits released because of the values raised, reducing the bank's liquidity potential. In addition, the participation of the credit operation volume in relation to total assets (*part_empr*) was considered. For direct liquidity evaluation, the immediate liquidity (*liqimediata*) obtained by dividing the availabilities of liquidity financial investments by the cash deposit was adopted; the voluntary fit (*encaixevol*) is a fairer liquidity measure, since it only considers the availabilities and cash deposits, the risk exposed assets variable (*at_expos_risco*) represented by the sum of securities and marketable securities (TVM), the derivative tools and credit operations, and the commercial lease in relation to total assets.

To compose the analysis, qualitative variables were also sought, and they are as follows: the origin of bank capital (*origem_cap*), a dummy variable in which 1 represents banks with national capital and 0 (Zero) for foreign capital. This variable captures whether the capital origin has an influence on the ratings or if the banks are public or private (*Privado_Público*), in which 1 is used for private banks and 0 for the public banks, and size (*bco_grande*), considering 1 for the large banks and 0 (Zero) for the medium-sized banks.

Intercept binary variables were also considered for each year, to test the hypothesis that the rating agencies have been strict on their long-term analysis, as identified by Blume, Lim & Mackinlay (1998) and Jorion, Shi & Zhang (2009). Twelve dummies were created for the years from 2006-2017, in which the constant captures the year 2006.

Table III briefly shows each one of the variables, their abbreviations, formulas used, the relationship expected to the dependent variable $rat\_num\_lp_{it}$, and which factor is captured by each independent variable (*var_ind*) of the model developed herein.

Table III.

Description of the independent variables adopted

Variable	Abbreviations	Formula	Expected Relation ship[a]	Factor captured
1. Basel Index	*Ind_Basileia*	$\frac{\text{Reference Equity Risk}}{\text{Weighted Assets}}$	−	Compliance
2. Net Margin	*marg_liq*	$\frac{\text{Net Profit}}{\text{Revenue of Financial Intermediation}}$	−	Performance
3. Leverage	*leverage*	$\frac{\text{Total Assets}}{\text{Net Equity}}$	+	Adequacy/ Assets quality
4. Default Potential	*inadimpl*	$\frac{\text{PDD}}{\text{Credit Operations}}$	+	
5. Provision of Doubtful Debtors	*pdd_rec_fin*	$\frac{\text{PDD}}{\text{Revenue of Financial Intermediation}}$	+	Solvency and Liquidity
6. Loans/Deposits Index	*empr_dep*	$\frac{\text{Credit Operations}}{\text{Deposits}}$	+	
7. Loan Participation	*part_empr*	$\frac{\text{Credit Operations}}{\text{Total Assets}}$	−	

8. Immediate Liquidity	*liqimediata*	Availability + Net Interfinancial Investment / Cash Deposits	+	
9. Voluntary Fit	*encaixavol*	Availability / Cash Deposits	−	
10. Assets Exposed to Risks	*at_expos_risco*	TVM+ Derivatives + Credit / Total Assets	+	
11. Capital origin	*origem_cap*	*Binary Variable: 1 - National banks and 0 - Foreign banks*		
12. Nature: public or private	*PrivadoPúblico*	*Binary Variable: 1 - Private banks and 0 - Public banks*		Qualitatives
13. Size	*bco_grande*	*Binary Variable: value 1 for banks considered large and 0 for those considered medium*		

[a] In the evaluation of the expected relationship between the explanatory variables and the ratings ($rat\_num\_lp_{it}$), it must be considered that the credit risk levels vary from 0 to 7, where the higher the level, the lower the rating.

Source: Elaborated by the authors according to the results of the research.

In the relationship between $rat\_num\_lp_{it}$ and the independent explanatory variables (*var_ind*) summarized in Table III, the equation (1) was estimated by an ordered logit model, using the maximum likelihood method, according to Greene (2003). Such a model is justified by the use of an ordinal qualitative dependent variable and is built from a latent regression for the variable $rat\_num\_lp_{it}$, called $rat\_num\_lp^*_{it} rat\_num\_lp^*_{it}$.

$$rat\_num\_lp^*_{it} = \sum_{i=0}^{12} \beta_i \times var\_ind_{it} + \varepsilon_t \qquad (1)$$

where *var_ind* is a vector which represents all the independent variables for the *i*-th financial institution in the period *t* and $\varepsilon_t \varepsilon_t$ consists of the error term with normal distribution, zero average and $\sigma^2 \sigma^2$ variance.

After the $\beta\beta$ coefficients have been estimated, we come to:

$$rat\_num\_lp_{it} = prob\left(rat_{num_{lp}\,j} = i\right) = Prob\left(k_{i-1} \le \sum_{i=0}^{12} \beta_i \times var\_ind_{it} + \varepsilon_t \le k_i\right) \qquad (2)$$

where $k_{i-1} k_{i-1}$ and $k_i k_i$ are the cut points in each value range with the probabilities calculated by:

$$Prob\left(k_{i-1} \le \sum_{i=0}^{12} \beta_i \times var\_ind_{it} + \varepsilon_t \le k_i\right) = \frac{1}{1 + \exp(-k_i + \sum_{i=0}^{12} \beta_i \times var\_ind_{it})} - \frac{1}{1 + \exp(-k_{i-1} + \sum_{i=0}^{12} \beta_i \times var\_ind_{it})} \qquad (3)$$

where $k_0 k_0$ is defined as $-\infty -\infty$ and $k_k k_k$ is $+\infty +\infty$.

Two models were estimated, and in Model I, just the independent variables presented in Table III are considered without the year dummies, which have been included in the second model, Model II. Models for the categories of investment and speculative levels were not estimated due to very little variance in the observations.

In these estimates, it is assumed that the error term captures all the shocks that can affect the rating contemporaneously, for instance, the effects of the economic crisis and other market conditions.

There are no endogenous effects in the models since the rating is defined *posteriori* to the indices published in the financial statements of FI as suggested by Wooldridge (2010).

4 . RESULT ANALYSIS

The use of the robust ordered logit as an estimate of the model specified by equation (1) is in accordance with Caporale et al. (2012) and Hassan & Barrell (2013), whose results are described in Table IV.

Both generated models were estimated with the robust criterion for the correction of heteroscedasticity. Consequently, the *part_empr* variable was excluded from both models.

Table IV presents the results of Models I and II, with the estimates of the set of banks in the sample. In the second column, the effects on the coefficients after the inclusion of the year dummies (2006-2017) are demonstrated. The two result columns, without and with the incidence of the year dummies, corroborate the accuracy of the models and also moderate the coefficient alternance and their respective signals. The model, with the year dummies effect, maximizes its explanatory capability according to what is corroborated by the determination coefficients (R^2), from 59.01% to 69.36% in the results of the models, respectively.

Table IV

Results estimated by the ordered logit model—banks which operate in Brazil—2006-2017 (2nd quarter) period

	Model I (without year dummies)		Model II (with year dummies)	
	Coef.	**p-value**	**Coef.**	**p-value**
Ind_Basileia	0.033	0.552	0.157	0.037
origem_cap	1.953	0.000	2.238	0.000
pdd_rec_fin	-10.160	0.005	-3.368	-0.415
PrivadoPublico	4.474	0.000	7.548	0.000
bco_grande	-6.026	0.000	-9.011	0.000
empr_dep	0.120	0.664	-1.395	0.000
part_empr	6.954	0.000	9.462	0.000
liqimediata	-3.857	0.000	-2.929	0.000
encaixevol	0.231	0.122	0.441	0.033
leverage	0.401	0.000	0.654	0.000
inadimpl	8.936	0.473	9.279	0.538
marg_liq	-27.112	0.000	-36.745	0.000
part_empr	omitted		omitted	
at_exp_risco	-6.106	0.000	5.582	0.013
Dummies				
2006			-12.718	0.013
2007			-10.975	0.000
2008			-12.235	0.000
2009			-12.993	0.000
2010			-10.165	0.000
2011			-9.617	0.000

2012		-9.727	0.000
2013		-9.153	0.000
2014		-9.772	0.000
2015		-9.132	0.000
2016		0	omitted
N	420		420
R^2	0.5901		0.6936
Wald Test	170.1		118
Prob>Chi2	(0.0000)		(0.0000)

Note: **Ind_basileia** (Basel index) = Supply of high liquidity assets/ Net outflows in the next 30 days; **origem_cap** (capital origin) = binary variable; **Privado_Público** (private or public nature) = binary variable; **bco_grande** (size) = binary variable; **empr_dep** (loan and deposit index) = Credit Operations/ Deposits; **part_empr** (loan participation) = Credit Operations/ Total Assets; **liqimediata** (immediate liquidity) = Availabilities + Liquidity Interfinancial Investments/Cash Deposit; **encaixevol** (voluntary fit) = Availabilities/Cash Deposit; **leverage** (leverage) = Total Assets/Net Equity; **inadimpl** (default potential) = PDD/Credit Operations; **marg_liq** (net margin) = Net Profit/ Financial Intermediation Revenue and **at_expos_risco** (risk exposed assets) = TVM + Derivatives + Credit/ Total Assets.
Source: Elaborated by the authors according to the results of the research.

The Wald test rejects the joint null hypothesis for the coefficients of the dummies which guarantees greater robustness in the estimate of Model II. Analyzing the signal and the significance of the coefficients of these dummy variables, they (albeit negative) increase the values in the year sample, which may be an indication of ratings “tightening” by the agencies due to greater credit risk exposure by the FI. In recent years, Damasceno, Artes & Minardi (2008) corroborated the results herein, characterized by impacts and crunches in the Brazilian economy with an unfavorable macroeconomic scenario and high interest rates, disfavoring the intermediation activity.

The qualitative variables, capital origin and public or private banks were significant at 1% with positive coefficients, indicating that both FI groups (medium and large) are subject to the same measuring criteria, which is a positive point in favor of the agencies. The FI size was also significant at 1%, but with a negative signal (opposite); i.e., larger banks tend to have better rating classifications. This result is similar to the studies developed for the country group (Pasiouras, Gaganis & Zopounidis, 2006; Bellotti, Matousek, & Stewart, 2011; Caporale et al., 2012 and Hassan & Barrell, 2013).

When analyzing the quantitative variables, it became apparent that, although it is not significant in Model II, the *Ind_Basileia* variable is significant at 5% in Model II, reflecting the regulatory importance imposed by the government toward the Basel III agreement compliance; it also reflects the signal, which is contrary to what is expected, since the high values of the Basel index show good solvency conditions, and they should be contributing to reducing the rating in the adopted range, with lower values for the best rating assignments.

On the other hand, the *pdd_rec_fin* variable had significance at 1% in Model I, but it was not significant in Model II. The negative signal (opposite) is at odds with what was expected in the literature (positive), which can be explained by the fluctuation of the values of this variable during the period analyzed since the values began to fluctuate in recent years due to the worsening economic situation in Brazil.

Regarding the *empr_dep* variable, it was significant at 1% in Model II with a signal contrary to what was expected, and it was not significant in Model I. Positive values were expected, because if this index takes on higher values, they may correspond to greater volumes released in low quality credits, which would lead to a worsening rating. On the other hand, *inadimpl* was not significant in the period analyzed; this result is contrary to, for example, the literature by Karminsky & Khromova (2016), despite the signal being correct because it was a high impact index in the rating.

The other indices, *leverage* and *at_expos_risco* were significant at 1% in both models, indicating that they were positively related to the FI rating. On the other hand, *marg_liq* had a negative impact on credit risk, tending to improve the ratings when presenting high and positive values; this was expected based on the literature. The *encaixevol* has not presented significance at 1% in either model.

Presenting the efficiency of the model regarding the bank credit rating accuracy level when compared to those set by the risk rating agencies, 370 accuracies out of the 442 possible were determined, i.e., an accuracy of 83.71% (Table V).

It is highlighted that the model efficiency, with a relevant accuracy percentage, was higher than the index in the study by Öğüt, Doğanay, Ceylan & Aktaş (2012) with the exclusive Turkish bank sample which had an accuracy of 62.49%, and it aligned with the result obtained by Gogas et al. (2014) in a study of U.S. banks, which presented a similar accuracy of 83.70%.

Table V

General accuracy rate of rating forecast

Rating of Agencies	Rating Forecasted				
	2	3	4	5	Total
2	82	14	0	0	96
3	17	114	13	0	144
4	1	14	152	5	172
5	0	0	8	22	30
Total	100	142	173	27	442

Source: Elaborated by the authors according to the research results.

The forecasts are carried out through the ordered logit model in which, from the independent variables inserted in each quarter, the occurrence likelihood is calculated for each of the ratings found in the sample; i.e., the likelihood of the bank being ranked as Cat II, III, IV or V rating, according to the informative table in this paper. Thus, the forecasted rating will be considered as the one with the greatest likelihood among all the probabilities forecasted in each rating. Success is diagnosed if the rating forecast (through the greatest likelihood obtained in each of the ratings possible) is equal to the rating collected in the sample. If they are different (the forecast is lower or higher), it is seen as an error. The total of the successes refers to their sum divided by the total of the forecasted ratings.

Next, the main conclusions of the research from the literature are reviewed and the outlined objectives are presented.

5 . CONCLUSIONS

This study aimed to revalidate the rating determinants of the main Brazilian publicly held financial institutions from 2006-2017. Overall, the research revalidated that the FI ratings are mostly explained by economic-financial indices which reflect the performance and quality of the information available in the market on liquidity, compliance and their assets' solvency and bank liquidity. Additionally, the greater risk attributed to medium-sized banks compared to large-sized institutions was confirmed.

There was also evidence of rating "tightening" by the agencies due to a greater exposure to credit risk by the FI, herein evinced in recent years, characterized by impacts and crunches in the Brazilian economy with an unfavorable macroeconomic scenario and high interest rates, disfavoring the intermediation activity.

Qualitative variables, such as the measures of the Basel index and expected credit losses in the intermediation revenues, were not significant within the limits expected, as initially expected. Reasons can be explained by the transition phase in which Brazil is implementing the Basel III agreement and the aforementioned economy adversities.

This research proposes the beginning of a discussion for the revalidation of the rating determinants of Brazilian financial institutions which is essential in periods of crisis and change, not only in accounting for but also in the adjustments to the international criteria of credit risk assignment in legislations occurring in Brazil. It is also worth highlighting the complex design of structured operations in markets which are more exposed to interest fluctuations, as in Brazil. The importance of such analysis, for the banks, lies in the knowledge of the need to revalidate their risk models with variables that actually impact their rating, which directly affect their investment and loan decisions.

New research can expand the spectrum demonstrated herein with comparisons between developing country FIs, the separation of specific crisis periods with more fractionated data and differentiated statistical methods with greater qualitative variables.

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