



## ANALYSIS OF CREDIT RATINGS DETERMINANTS: EVIDENCES IN BRAZILIAN AND AMERICAN STATES

 **Nathalia Santos de Oliveira<sup>1</sup>**

 **Fabiano Guasti Lima<sup>2</sup>**

 **Carlos Alberto Grespan Bonacim<sup>3</sup>**

 **Rafael Confetti Gatsios<sup>4+</sup>**

 **Alexandre Assaf Neto<sup>5</sup>**

<sup>1,2,3,4</sup> School of Economics, Business Administration and Accounting at Ribeirão Preto University of São Paulo, Brazil.

<sup>1</sup> Email: [natioli98@hotmail.com](mailto:natioli98@hotmail.com) Tel: (55)(16)3315-4969

<sup>2</sup> Email: [fgl@usp.br](mailto:fgl@usp.br) Tel: (55)(16)3315-4969

<sup>3</sup> Email: [carlosbonacim@yahoo.com.br](mailto:carlosbonacim@yahoo.com.br) Tel: (55)(16)3315-4969

<sup>4</sup> Email: [rafaelgatsios@fearp.usp.br](mailto:rafaelgatsios@fearp.usp.br) Tel: (55)(16)3315-4969

<sup>5</sup> Assaf Institute, Business Administration and Accounting at Ribeirão Preto University of São Paulo, Brazil.

<sup>5</sup> Email: [alexandreassafneto@gmail.com](mailto:alexandreassafneto@gmail.com) Tel: (11)5080-7506



(+ Corresponding author)

### ABSTRACT

#### Article History

Received: 10 March 2020

Revised: 13 April 2020

Accepted: 15 May 2020

Published: 1 June 2020

#### Keywords

Credit risk

Credit rating

Rating agency

Operational risk

Liquidity risk

Ordered logit.

#### JEL Classification:

G24; B23.

This piece of work, due to its relevance, aims to analyze the methodology used in the determining of ratings, not only expanding the number of variables tested and broadening the discussion on rating determinants, but also using variables which solely measure the market, liquidity credit and operational risks. Thus, the risks mentioned were compared to the ratings set for each Brazilian state from 2013 to 2017 (post-adoption of the MCASP accounting standard for financial statements) and for each American state from 2006 to 2016 (the most recently published financial datum). In face of that, this work is different from the others because it seeks to broaden the researches and the methods used in public listed companies or in financial companies, in public finances of Brazilian and American states, a subject which is little approached in researches. The ordered logit model was used since the credit rating is considered latent variables, besides following an ordinal version. The study was carried out with 50 American states, 26 Brazilian states and 648 ratings altogether. The model proposed in this work proved to be efficient, being able to successfully estimate 64.10% of the sample of the Brazilian states and 68.50% of the sample of the American states. The results reached are specially relevant for stakeholders, who are able to analyze or manage their possible investments regarding risk and return.

**Contribution/Originality:** This study contributes in the existing literature to answer which drivers explain the ratings of the Brazilian and American states. This paper is different from the others because it broadens the researches regarding credit ratings determinants since the method used by rating agencies is not transparent with regard to the rating definition process.

## 1. INTRODUCTION

The financial market is an environment composed by several agents (individual and legal entities) who are constantly transferring financial resources to one another. These transfers, on the other hand, help the development of the national business, allowing, therefore, the resource borrower to anticipate his/her consumption, improving the resource flow. The transfers of financial resources are usually related to an interest rate which corresponds to

the borrower's expected return. Several studies highlight that this return has a correlation with the risk presented by Markowitz (1952).

Countless researches and analyses were carried out in order to study the risks involved in investments and credit financing to certain agents. It was through these studies that the ratings came up. Ratings are scores awarded to investments (per security) or even to the credit institutions themselves.

The ratings represent the credit risk involved in each operation, in which the credit risk is the chance the company or country do not honor its commitments contracted in the operation, causing default. The ratings are commonly used by stakeholders<sup>1</sup> to analyze their possible investments or the management of these. Due to the prominence and complexity of these analyses, they are usually set by the so-called credit rating agencies (CRAs) which, for decades, have been gaining space in the financial market. Despite being target of accounting scandals which took place in 2000 and during the subprime crisis (2007-2008), they are still being used and studied a lot. Nowadays, the ratings are classified by three great agencies, which are Fitch, Moody's and Standard & Poor's.

When setting the ratings by the rating agencies, several factors are taken into account, such as, market, operational, liquidity and credit risks and other qualitative methods. The understanding of these risks is essential for the development of a mechanism which can help risk management, evidencing which factors may influence the rating movement, whether positively or negatively. Moreover, with the growth of the risk management studies, the companies are investing more and more in human resources and in tools which can minimize the risks involved in investment and financing decisions, consequently increasing its return.

In the public sphere, the state indebtedness began during the military rule, and in order to restrain public deficit, the Fiscal Responsibility Law (FRL) was created. Macedo and Corbari (2009) state, in their work, that management of debt and funds sources became more effective and the debt rollover was rarely used by municipalities. Since the indebtedness factors are present in a company's or agency's accounts, they present a higher credit risk, therefore, according to the hypothesis of this paper, they would present a lower rating. The ratings usually help investors regarding the safety level of investing in a company, or, in the case of countries, of investing in debt securities. Since, according to the FRL in Brazil, the states and cities cannot issue debt securities, its core function is to present conditions of investment in the territory analyzed, for instance, the risk level the setting of company is exposed to.

The overall objective of this paper is to answer which are drivers that better explain the state rates. The present work was carried out due to the importance in analyzing the methodology used to determine the ratings, expanding the number of variables tested and broadening the discussion on rating determinants. Moreover, it makes use of variables which solely measure the market, liquidity, credit and operational risks of Brazilian and American states.

Due to the MCASP<sup>2</sup> change, the period to be considered for the Brazilian states will be from 2013 to 2017 (the most recent datum published by the National Treasury); for the American states, the database will be comprised from 2006 to 2016 (the most recent financial datum published).

In face of that, this work is different from the others because it seeks to broaden the content and the methods used in public listed companies or in financial companies, in public finances of Brazilian and American states, a subject which is little approached in researches.

Due to the relevance of this theme, the issue regarding it and the objectives presented, the guiding hypothesis of the research is the following:

---

<sup>1</sup> "A person such as an employee, client or citizen involved with an organization, society, etc. and, therefore, who has responsibilities regarding it and is interested in its success" ((Cambridge University Press, 1995) translated by us).

<sup>2</sup> MCASP - *Manual de Contabilidade Aplicada ao Setor Público* - Guide of Accounting Applied to the Public Sector.

H1: The risk indicators identified in the public information of accounting statements are able to justify the rating given to the states by the rating agencies.

## 2. BIBLIOGRAPHIC REVIEW

### 2.1. Risk

According to Gitman (1976) risk is related to the uncertainties of returns. As time goes by, companies and investors have been paying more and more attention to the risk, therefore, risk analysis has been widely used, becoming essential for investment, financing management and decision-making analysis. The risk analysis process involves several factors, such as gathering information, calculations and analyses. And, thus, tools and techniques which are able to measure the risks involved are often necessary.

The risks are usually classified into categories, “even though it is possible to segregate the types of individual risks, in practice, the risks appear in a combined way in many occasions, that is, more than a risk type can be present in just one enterprise” (Lima, 2018).

In the financial scope, the risks can be classified in five types: operational, liquidity, legal, of market and of credit (Jorion, 2007). Next, a brief definition of each type of risk, according to Jorion (2007) will be presented.

Due to the highlight and complexity of these analyses, the risks are commonly analyzed and published by credit rating agencies (CRAs), which, for decades, have been gaining space in the financial market. Despite having been target of accounting scandals, they are still have been widely used and studied.

Currently, the ratings are classified by three large agencies: Fitch, Moody's and Standard & Poor's.

On a simplified basis, regarding the credit rating levels issued by the three largest rating agencies of the world, Standard & Poor's and Fitch use scales A, B, C, D, in which the highest rating is AAA and the worst is D. On the other hand, according to Moody's rating, the best rating is Aaa and the worst is C.

### 2.2. Empirical Literature Review

The rating system created in 1924 by John Knowles Fitch, is based on the company's ability to pay its debts, that is, assessing its credit risk. In the course of time, Moody's and S&P started to analyze and classify the companies with ratings. It was only in 1966, that studies began to come out in order to attempt to forecast the variables used by companies. Horrigan published a paper in 1966 trying to forecast the long-term rating. The studied was based on short-term indicators, such as liquidity and working capital, and long-term indicators, such as solvency and working capital for investments, as well as profit margin and ROI (Return on Investment). After performing the multivariate analysis, he was approximately 54% and 57% successful in forecasting Moody's and Standard & Poor's ratings respectively.

Several studies on the influence of economic-financial indicators in determining bankruptcy forecast were carried out. For instance, Altman (1968) published a paper analyzing the hypothesis of economic and financial indicators forecasting the insolvency of manufacturing companies, based on five indicators, reaching 80% of success. Besides such paper, other researches were carried out in the international sphere which became reference, such as Beaver (1966) and Ohlson (1980). In Brazil, there were Altman, Baidya, and Dias (1979) and Brito and Neto (2008).

Altman and Katz (1976) applied the same analysis method used by Altman in 1968, but the objective was to forecast debt security rating of electric utilities, correctly classifying more than 80% of the securities of the sample.

Regarding the models used, Ederington (1985) presents a study of the sensitivity of the results in relation to the analysis model used, concluding that the ordered logit is the most appropriate technique to be used.

Supported by the hypothesis that rating agencies were being more careful in their analyses, Blume, Lim, and MacKinlay (1998) applied a probit model, with accounting and market risk variables for companies with high investment level from 1978 to 1995. For market risk, the beta coefficient and the standard error of the CAPM (*Capital Asset Pricing Model*) were considered. Finally, evidences that the credit agencies have become stricter were

found. Afterwards, [Jorion, Shi, and Zhang \(2009\)](#) contested the results obtained by [Blume et al. \(1998\)](#): they used the same model and variables, however, they did not obtain evidences that the credit agencies had become stricter.

Also in the American literature, [Belkaoui \(1980\)](#) contributed with the models presented with the addition of the issued security characteristic, besides emphasizing the use of explanatory variables, with economic justifications, i.e., the company operation market. His model can explain 62.8% of the ratings of the experimental group and 65.9% of the control group. [Minardi, Sanvicente, and Artes \(2006\)](#) used an ordered logistic model with 627 American companies of the industry sector. After using a stepwise analysis, the following variables were selected: size: In(active); financial leverage: Gross debt/ total assets; ability to pay: EBIT/net financial debt; operational performance: ROA and EBIT/Net income; and stability: volatility. The model was able to classify 58.14% of the ratings correctly and only 3.26% of the ratings were considered extreme.

Regarding the recent national literature, seven papers which have also significantly contributed to the theme can be highlighted. Different from the papers mentioned, [Sales \(2006\)](#) uses just banking institutions for the sample. After using the logit model to estimate the ratings of 44 banks, he obtained 93% of correct forecast. [Lima, Fonseca, Silveira, and Neto \(2018\)](#) have also analyzed Brazilian financial institutions and used the same method. The sample comprised the period from 2006 to 2015 and the variables used were net margin, leverage, capital structure, default potential, GAP, loan/deposits index, risk-weighted assets and size. The level of correct forecast was 84.68%.

[Damasceno, Artes, and Minardi \(2008\)](#) followed the work of [Blume et al. \(1998\)](#) in order to test whether the credit rating agencies were being stricter in the analyses of Brazilian companies. Brazilian companies were rated, from 2000 to 2005, through the ordered probit model and the results led to the rejection of the hypothesis. The model was able to forecast 64.1% of the sample ratings, that is, 35.9% of error, in which 24.2% of them present a deviation of only a rating level.

[Brito, Neto, and Corrar \(2009\)](#) looked over whether default occasions of publicly-held companies in Brazil are forecasted by a risk rating system based on a total of 25 accounting indexes. Different from other papers, the conglomerate analysis was used to classify the companies into eight risk classes, being of them seven for creditworthy companies and one for companies in default. The sample comprises non-financial publicly-held companies from 1994 to 2006 and, as a result, they reveal that the model developed captures the risk before the default occurrence.

[Soares, Coutinho, and Camargos \(2012\)](#) developed a research like the previous ones, however, as variable for the model, they included a dummy<sup>3</sup> variable of corporate governance, with the hypothesis that it would present positive correlation to rating quality. The sample comprised 72 non-financial Brazilian companies in 2009. The model highlighted the following variables as significant: corporate governance, assets size and interest coverage rate, consequently corroborating the hypotheses mentioned in previous papers. Nevertheless, the corporate governance variable presented negative coefficient (-1.40), different from what was expected. Finally, the model could correctly estimate 59.7% of the ratings. [Fernandino, Takamatsu, and Lamounier \(2014\)](#) carried out a similar research, the sample comprised 56 companies. The model applied was Binomial Logit and the more significant variables were company size and return on assets, reaching the ability to correctly forecast 81%.

[Silveira, Lima, and Fonseca \(2017\)](#) analyzed 45 non-financial Brazilian companies, from 2010 to 2015, after the IFRS (International Financial Reporting Standards) adoption. In that paper, variables which measure solely the risks of market, liquidity, credit and operation were used, without any distinction of risk factors. the model applied was the ordered Logit model and the results showed that the variables of company size, indebtedness, yield and capital cost impacted significantly, corroborating the papers mentioned before.

In the public sector, the financial analyses are scarcer compared to the private one, specially because the consolidation and regularization of public American information started belatedly. [Brown \(1993\)](#) performed a study

---

<sup>3</sup> The dummy variable is often used in the research field to transform categorical data into binary data ([Thomas & Wonnacott, 1972](#)).

with basis provided by the Government Finance Officers Association (GFOA), with 700 American counties and making use of an analysis through the population size, it was fractionated in 4 groups. The basis for his research was the pre-GASB 34-12 of 1989. The use of the 10-point test aims to assess the municipal financial condition with regard to national comparisons, based on the population size. The 10 indicators used can be summarized in: revenues (indicators 1-3), expenditures (4), operating position (5-7) and debt structure (8-10). The test provides a broad and comparable view of the government operations, being simple and accessible.

Michel (1977) has also carried out a study with American counties in order to create a statistical model which could forecast the classification of the ratings of municipal and corporate traits, applying methodology similar to the corporate one in municipal data. The methodology applied by Michel consisted in bond ratings of the 50 largest American cities, except New York and Washington D.C., for a 10-year period (1962-1971). Nevertheless, the study was not efficient.

Norcross and Gonzalez (2018) assessed the capacity of American states to honor their short and long-term commitments, from 2006-2016 financial statements. The analysis is carried out according to five dimensions which, when combined, produce a general solvency classification. These five dimensions are: solvency of cash, budget, long-term, at service level and trust fund. Through this study it was possible to conclude that some states display consistent performance, presenting continuous structural deficits, underfunded pensions and other liabilities of post-employment benefits. It was also observed that some states have strong dependence of tax revenues of oil, requiring volatility in the short-term solvency and high oscillations in the levels of cash and revenue. Finally, it was possible to observe some implications regarding the great tax reforms in several American states which, in general, revealed neutral or positive results. Also in the American sphere, there were several other papers which contributed significantly with the models developed, moreover, the majority of them used countless indicators to examine the position and financial condition of public entities, such as Petersen (1977); Zehms (1991); Bowman (1997).

When we approach the theme in Brazil, there is an even greater lack of financial analyses in public accounting, specially due to the recent regularization of accounting standards and the implementation of the MCASP. On May 4th, 2000, the National Congress legislated the *Lei Complementar n° 101 LRF (Lei de Responsabilidade Fiscal - Fiscal Responsibility Law)* which, according to Zuccolotto, Ribeiro, and Abrantes (2008):

FRL embodies some rules to the budgetary-nature procedures through the reinforcement of four pillars: planning, control, transparency and responsibility. Thus, it creates a planning system which aims to control public deficit.

Due to this theme importance, Zuccolotto et al. (2008) sought to analyze some characteristics of public finance behavior in capital cities of the Brazilian states, using as parameter, the precept and limits set by the FRL. The sample covered the period from 1998 to 2006 and it proposed indicators which measured the structure of the revenues, costs, per capita, liquidity, budgetary and indebtedness. Regarding the results reached, an increase in the dependence of the counties on the intragovernmental transfer was verified, that is, insufficient tax collection.

### 3. METHODOLOGY

#### 3.1. Study Sample

The study sample comprises financial information, GDP and ratings of 26 Brazilian states during the 2013-2017 period (post-adoption of the MCASP). Regarding the 50 American states, the period of data collection is from 2006 to 2016.

Due to the non-disclosure of ratings of the capitals and the lack of financial information, the capitals of both countries were excluded from the sample. In order to enlarge the database, rating information of Moody's, Standard & Poor's and Fitch were considered, setting a priority among them, as described before.

The gathering of municipal information was discarded since it did not have enough financial nor rating information. The levels of ratings used in this paper were rated according to Table 1, following a 0 to 7 scale, in which 0 is the best rating and 7, the worst one.

Table-1. Credit rating classification.

Moody's	Standard & poor's / fitch	Credit risk	Meaning
Aaa	AAA	0	Investment Level with high quality and low risk
Aa1	AA+	1	
Aa2	AA		
Aa3	AA-		
A1	A+	2	
A2	A		
A3	A-		
Baa1	BBB+	3	Mean quality Investment Level
Baa2	BBB		
Baa3	BBB-		
Ba1	BB+	4	Speculation category with low classification
Ba2	BB		
Ba3	BB-		
B1	B+	5	
B2	B		
B3	B-		
Caa1	CCC+	6	High default risk and low interest
Ca	CC		
C	C		
C	D		

Source: for the rating levels, Standard & Poor's, Moody's and Fitch.

### 3.2. Variables

In the development of the model, 4 indicators will be tested, according to Table 2. The indicators were based on the papers evinced in the chapter of empirical literature review of this paper. In order to analyze the rating determinants of the states, the credit risk level of the states, PBL  $it$ , was considered as dependent variable, in which  $i$  represents the states and  $t$  is a dummy of the year of the information.

Table-2. Description of the independent variables adopted.

Risk type	Variable	Initials	Formula	Expected relationship
Operational risk	State independence level of transfers from other government spheres	IND	$\frac{\text{Budgetary Rev.} - \text{Intra Gov.l Fiscal Transf.}}{\text{Budgetary Expenditures}}$	+
Liquidity risk	State size	SIZE	$\ln(\text{GDP})$	-
	Indicates the short-term liquidity	LIQ	$\frac{\text{Current Assets} - \text{Current Liabilities}}{\text{Total Assest}}$	-
Credit risk	Ability to pay costly debts	PAY	$\frac{\text{Non} - \text{Current Loans LP} + \text{Current Loans}}{\text{Receita Corrente}}$	+

The indicators used in this research, shown above, are able to identify the different risk types and their correlation with credit ratings. For liquidity risks, two indicators will be considered. The first one is represented by state size (SIZE), which is calculated by Napier's logarithm of GDP (Gross Domestic Product) and its expected relation is negative, that is, it is expected that the largest the state size, the greater its ability to honor the

commitments assumed. The second indicator to be considered represents the liquidity risk is the (LIQ), which will seek to indicate the state liquidity at short term, and it is a representativeness of the balance sheet.

Regarding the credit risk, it is represented by the ability to pay costly debts (PAY), which is an adaptation of private reality to the public. In the numerator, only the costly liability will be considered, assigning to the public agent the priority of payment to the private sector which, in turn, is determined by the bankruptcy law; therefore, it was considered that the public agent has greater payment commitment in agreements with banking institutions, since the payments to suppliers are often delayed and renegotiated. With regard to the denominator, the current net revenue was considered as proxy for the ability to pay, since public accounting does not have generating profits as its main activity. A positive relation is expected, that is, the lower the loans and/or the greater the current revenue, the lower the rating will be, consequently the better the scores.

Finally, the operational risk is represented by each state dependence level of transfers from other government spheres (IND). The numerator represents the amount received by the state, of transfers from other spheres, in programs or onlending because some states are dependent, having their ongoing costs funded by transfers from the Union. Regarding the denominator, the budgetary costs would be a notation of how much of funds has been planned, that is, the cost expectation each state has. Since this state presents high dependence, a positive relation is expected, that is, the higher the level, the greater the rating, since a greater rating means worse scores.

### 3.3. Statistical Technique

The model used in this paper is similar to that applied by [Silveira et al. \(2017\)](#). According to [Brito and Neto \(2008\)](#) the logistic regression, or logit analysis, is a model suitable for the situation in which the dependent variable is categorical and binary, for instance, “yes” or “no”, “solvent” or “not solvent” and “female” or “male”. [Greene \(2003\)](#) describes the ordered logit model as a model with latent variables. The credit ratings, besides being considered a latent variable, follow an ordinal version, therefore, their use enables the use of ordered logit model for the  $RAT_{it}$  variable, in which it is the dependent variable of the model that represents the credit risk level of the sample. In face of that, the objective of ordered logit is to generate a mathematical function whose answer allows to set the probability of an observation to belong to a previously determined group, due to the behavior of a set of independent variables. The use of ordered logit is highlighted, to detriment of the multinomial logistic model, since its use of the regression allows the results to be interpreted in percentage terms, having a logic relationship with regard to the theme approached, credit risk. Another advantage offered by the logit model is the flexibility of the presumptions in relation to other techniques, highlighting, thus, as a more robust technique regarding the presumptions are not met. The according [Silveira et al. \(2017\)](#). The logistic regression model takes on the following relation: (1)

$$p = \frac{1}{1 + e^{-g(RAT_{it})}} \quad (1)$$

In which  $e$  is the base of natural logarithms (approximately 2.718) and  $p$  is the probability of the event taking place and  $(1 - p)$  is the probability of the event not taking place.  $g(x)$  is the key equation to estimate credit rating: (2)

$$g(RAT_{it}) = \beta_0 + \beta_1 VI_1 + [...] + \beta_n VI_n + \varepsilon \quad (2)$$

In which,  $\varepsilon$  consists in the error term with normal distribution with zero average and  $\sigma^2$  variance,  $g(RAT_{it})$  is the dependent variable, credit rating, represented by a numerical scale,  $\beta_n$  is the estimated coefficients and  $VI_n$  is the independent variables.

Thus, the  $RAT_{it}$  variable is estimated from the  $RAT_{it}^*$  variable through the following rule: (3)

$$RAT_{it} = \{0 \text{ if } RAT_{it}^* < \tau_0 \text{ 1 if } \tau_0 \leq RAT_{it}^* < \tau_1 \text{ 2 if } \tau_1 \leq RAT_{it}^* < \tau_2 \text{ 3 if } \tau_2 \leq RAT_{it}^* < \tau_3 \text{ 4 if } \tau_3 \leq RAT_{it}^* < \tau_4 \text{ 5 se } \tau_4 \leq RAT_{it}^* < \tau_5 \text{ 6 se } \tau_5 \leq RAT_{it}^* < \tau_6 \text{ 7 se } RAT_{it}^* \geq \tau_6 \} \quad (3)$$

In which  $\tau_0$  to  $\tau_6$  are the cut-off limits within the levels of  $\mu_{\theta-1}$  and  $\mu_{\theta}$ .

#### 4. RESULT ANALYSIS

The final sample used in the model comprises 50 American states and 26 Brazilian states. The 648 ratings used in this paper database, as well as its distribution, are presented in Table 3, in which the data per scale, year and country is evinced. It is possible to notice that all the American states, in the period (2006 to 2018) analyzed have rating equal to or lower than 3.

Table-3. Sample of the rating score per year and country.

Year	BR						Overall BR	US				Overall US
	1	2	3	4	5	7		0	1	2	3	
2006								9	39	2		50
2007								9	39	2		50
2008								11	37	2		50
2009								11	37	2		50
2010								11	37	2		50
2011	2						2	13	35	2		50
2012	3						3	13	35	2		50
2013	5		2				7	15	33	2		50
2014	5		2				7	15	32	3		50
2015	3	2		1			6	16	31	3		50
2016	3	1		1	1	1	7	14	33	2	1	50
2017	4			1	1	1	7	14	33	2	1	50
2018	5	1		1	1	1	9					
Overall	30	4	4	4	3	3	48	151	421	26	2	600

Table-4. Brazilian indicators per year.

Year	Credit risk	Liquity risk	Operacional risk	Rating	BR Total
2010	0	0	0		0
2011	0	0	0	2	2
2012	0	0	0	3	3
2013	8	8	27	7	50
2014	27	27	27	7	88
2015	27	27	27	6	87
2016	27	27	27	7	88
2017	27	27	27	7	88
2018	27	27	27	9	90
Overall total	143	143	162	48	496

Table-5. American indicators per year.

Year	Credit risk	Liquity risk	Operacional risk	Rating	BR Total
2006	0	50	0	50	151
2007	0	50	0	50	151
2008	0	50	0	50	151
2009	0	50	0	50	151
2010	0	50	0	50	151
2011	0	50	0	50	151
2012	0	50	0	50	151
2013	50	50	50	50	251
2014	50	50	50	50	251
2015	50	50	50	50	251
2016	50	50	50	50	251
2017	0	0	50	50	151
2018	0	0	0		51
Overall total	200	550	250	600	2263

Table 4 and Table 5 demonstrates the distribution of the sample of the independent and dependent variables. The model applied to Brazil and United States ignores the SIZE indicator, since it presented low correlation with the dependent variable, nevertheless, in the model in the United States, the indicator presented relevant correlation. In the Brazilian base, it was possible to collect data from 2013 to 2018, on the other hand, for the United States, the sample was larger, from 2006 to 2018.

Table 6 presents a descriptive analysis of the sample, and it is possible to notice that the credit risk indicator (PAY) in the United States is, on average, 60% lower than in Brazil. However, regarding the liquidity risk (LIQ) and operational risk (IND) indicators, Brazil presents better results.

Table-6. Descriptive statistics of the model variables for the whole sample and stratified per country.

BR/US	SIZE	PAY	LIQ	IND	RAT
BR	189	143	143	162	48
US	767	200	550	250	600
BR	25.18	57%	15%	13%	2.13
US	26.26	24%	21%	46%	0.80
BR	1.25	42%	15%	7%	1.79
US	1.24	16%	15%	11%	0.52
BR	28.34	211%	57%	32%	7.00
US	29.09	84%	86%	70%	3.00
BR	22.62	6%	-35%	2%	1.00
US	23.91	0%	-8%	12%	0.00

The descriptive statistics per rating level are shown in Table 7. As expected, on average, the greater the rating level, the greater the risk relation of the indicators. Regarding the classification of the levels used, Chart 1 was followed, in which the investment level with high quality and low risk is represented by level 1 (Rating from 0 to 2), mean-quality investment level, level 2 (Rating 3), speculation category with low classification, level 3 (rating 4 to 6) and finally, level 4 (rating 7).

The models specified by the Equation 1 were estimated by using the ordered logit, according to Silveira et al. (2017) being the results presented in Table 8.

The columns regarding the BR and US models, represent respectively the results obtained from the estimates performed for the sample of both countries. The results presented corroborate the signs expected for each indicator. Thus, the operational risk (IND) was expected to be negative and it had negative result in the Brazil Model.

**Table-7.** Descriptive statistics of the dependent variables of the model per rating level.

BR	SIZE	PAY	LIQ	IND
Level 1				
Count	24	26	26	29
Average	26.76	75%	9%	9%
Standard Deviation	1.07	0.45	0.08	0.06
Level 2				
Count	4	3	3	4
Average	26.11	67%	9%	9%
Standard Deviation	0.96	0.56	0.10	0.02
Level 3				
Count	3	7	7	7
Average	26.76	98%	-6%	7%
Standard Deviation	0.42	0.53	0.15	0.03
Level 4				
Count	1	3	3	3
Average	27.19	198%	-2%	4%
Standard Deviation	-	0.11	0.02	0.01
Level 1				
Count	598	199	549	248
Average	25.95	24%	21%	46%
Standard Deviation	1.03	0.16	0.15	0.11
Level 2				
Count	2	1	1	2
Average	27.43	41%	6%	36%
Standard Deviation	0.02	-	-	0.19

**Table-8.** Results of the ordered logit model for the Brazilian and American States.

Variables	BR Model Coef.	Std. Err.	P>z	Us Model Coef.	Std. Err.	P>z
IND	24.24	11.70	0.04	3.79	1.83	0.04
PAY	3.23	1.48	0.03	6.71	1.28	0.00
LIQ	-11.37	4.11	0.01	0.77	0.74	0.30
SIZE				-0.55	0.15	0.00
N	39			200		
R <sup>2</sup>	22.30%			9.21%		
Wald test	42.11			34.98		

Regarding the credit risk (PAY), liquidity risk (LIQ) and (SIZE), there was a relation as expected. In the Brazil model, a increase of the determination coefficient ( $R^2$ ) was evinced when the independent variable of GDP (SIZE) was taken off, explaining 64.10% of the results and 7.69% was classified a level above or a level below the ratings scale summing up 71.79%. On the other hand, in the model applied in the United States, all the variables presented a correlation, displaying an explanatory power of 67.50% and 30.50% was classified a level above or a level below the ratings scale summing up 98.00%. This model was successful in 25 out of the total of 35 samples of the Brazilian states, reaching 64.10% of the success rate. The distribution of the forecasts will be demonstrated in Table 9. In Table 10, on the other hand, it is possible to observe the distribution of the forecasts for the American model, in which it was able to forecast 68.50% of the sample, that is, 135 out of the total of 200 samples.

**Table-9.** Success rate of the Brazilian ratings forecasts.

Rating	Observed	Predicted	Total
0	11	45	56
1	8	124	132
2		8	8
3		4	4
Total	19	181	200

Table-10. Success rate of the US ratings forecasts.

Observed/ Predicted	1	4	5	7	Total
1	22				22
2	3	1			4
3	3				3
4	4				4
5			2	1	3
7		1	1	1	3
Total	32	2	3	2	39

In Figure 1, we can see the model success rate along the period analyzed, 2013 to 2018, both for Brazil and the United States.

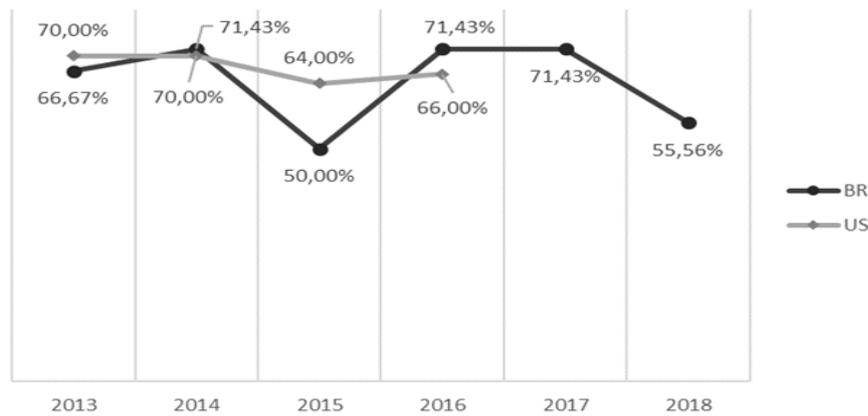


Figure-1. Success rate of the ratings forecast during the period (2013-2018).

The following variables: liquidity (LIQ), ability to pay (PAY) and operational risk showed to be statistically significant in both models, Brazilian and American. However, the variable size (SIZE) was significant only in the American model, moreover, all the variables presented the expected signs. When comparing the results, it is possible to notice that the PAY variable presents high significance in both models, which is possibly justified by the importance of the debts of a state in face of the other variables. Finally, the models were relevant, since the Brazilian and American ones explain 64.10% and 68,5%, respectively.

### 5. FINAL CONSIDERATIONS

This paper aimed to answer which drivers better explain the ratings of the Brazilian and American states. After collecting the data and the calculation of the indicators mentioned previously, it was possible to obtain a model for the Brazilian states which is able to forecast 64.10% of the ratings successfully. The American model can forecast 67.50% of the sample ratings, confirming the hypothesis that the risk variables identified in this paper are able to justify the ratings assigned by the rating agencies.

This paper is different from the others because it broadens the researches regarding credit ratings determinants since the method used by rating agencies is not transparent with regard to the rating definition process. Moreover, the explicitness of the indicators and their form of calculation are extremely important for the decision-making by stakeholders, who are able to make their investment and financing decisions become more efficient and beneficial.

At last, limitations with respect to lack of available rating data of the Brazilian states were identified, since information is little considered in public accounting. The enlargement of the sample, both time of the indicators and the number of ratings, as well as the use of other variables which can increase the predictive power of the model developed.

**Funding:** This study received no specific financial support.

**Competing Interests:** The authors declare that they have no competing interests.

**Acknowledgement:** All authors contributed equally to the conception and design of the study.

## REFERENCES

- Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, 23(4), 589-609. Available at: <https://doi.org/10.1111/j.1540-6261.1968.tb00843.x>.
- Altman, E. I., Baidya, T. K., & Dias, L. M. R. (1979). Forecasting financial problems in companies. *Business Administration Magazine*, 19(1), 17-28.
- Altman, E., & Katz, S. (1976). *Statistical bond rating classification using financial and accounting data*. (M. Schiff, & G. Sorter, Eds.). Paper presented at the Proceedings of the Conference on Topical Research in Accounting.
- Beaver, W. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research*, 4, 71-111. Available at: <https://doi.org/10.2307/2490171>.
- Belkaoui, A. (1980). Industrial bond ratings: A new look. *Financial Management*, 9(3), 44-51.
- Blume, M. E., Lim, F., & MacKinlay, A. C. (1998). The declining credit quality of US corporate debt: Myth or reality? *The Journal of Finance*, 53(4), 1389-1413. Available at: <https://doi.org/10.1111/0022-1082.00057>.
- Bowman, W. Y. (1997). Evaluating local government financial health: Financial indicators for Cook, DuPage, Kane, Lake, McHenry, & Will counties (Executive Summary). The Civic Federation. Retrieved from <https://www.civicfed.org>. [Accessed August 17, 2019].
- Brito, G. A., & Neto, A. A. (2008). Credit rating model for companies. *Accounting and Finance USP*, 19(46), 18-29.
- Brito, G. A., Neto, A. A., & Corrar, L. J. (2009). Credit risk rating system an application to public companies in Brazil. *Accounting & Finance Magazine - USP*, 20(51), 28-43.
- Brown, K. W. (1993). The 10-point test of financial condition: Toward an easy-to-use assessment tool for smaller cities. *Government Finance Review*, 9(6), 21-21. Cambridge University Press. (1995). Cambridge University Press. Retrieved from <https://dictionary.cambridge.org/pt/dicionario/ingles/stakeholder>. [Accessed November 04, 2019].
- Damasceno, D. L., Artes, R., & Minardi, A. M. (2008). Determining the credit rating of Brazilian companies using accounting ratios. *Administration Magazine*, 43(4), 344-355.
- Ederington, L. H. (1985). Classification models and bond ratings. *Financial Review*, 20(4), 237-262. Available at: <https://doi.org/10.1111/j.1540-6288.1985.tb00306.x>.
- Fernandino, G. F., Takamatsu, R. T., & Lamounier, W. M. (2014). Impact of accounting ratios on credit rating application in Brazilian publicly traded companies. *Accounting Vista & Revista*, 25(3), 78-94.
- Gitman, L. J. (1976). *Principles of financial management* (10th ed.). São Paulo: Pearson Universities.
- Greene, W. H. (2003). *Econometric analysis* (5th ed.). Upper Saddle River: Prentice Hall.
- Jorion, P. (2007). *Value at risk: The new benchmark for managing financial risk* (Vol. 3). New York: McGraw-Hill Companies.
- Jorion, P., Shi, C., & Zhang, S. (2009). Tightening credit standards: The role of accounting quality. *Review of Accounting Studies*, 14(1), 123-160. Available at: <https://doi.org/10.1007/s11142-007-9054-z>.
- Lima, F. G. (2018). *Risk analysis* (2nd ed.). São Paulo: Atlas.
- Lima, F. G., Fonseca, C. V., Silveira, R. L., & Neto, A. A. (2018). The determinants of credit ratings of Brazilian banks. *Contemporary Administration*, 22(2), 178-200.
- Macedo, J. D., & Corbari, E. C. (2009). Effects of the fiscal responsibility law on the debt of Brazilian Municipalities: An analysis of panel data. *Accounting and Finance USP*, 20(51), 44-60.
- Markowitz, H. (1952). Março. Portfolio selection. *The Journal of Finance*, 7(1), 77-91.
- Michel, A. J. (1977). Municipal bond ratings: A discriminant analysis approach. *Journal of Financial and Quantitative Analysis*, 12(4), 587-598. Available at: <https://doi.org/10.2307/2330334>.

- Minardi, A. M., Sanvicente, A., & Artes, R. (2006). Business unit credit determination to estimate the cost of capital for third parties. *Inspere Working Paper No. (56)*.
- Norcross, E., & Gonzalez, O. (2018). Ranking the states by fiscal condition. Mercatus research paper. Retrieved from SSRN: <https://ssrn.com/abstract=3381208> or <http://dx.doi.org/10.2139/ssrn.3381208>.
- Ohlson, J. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, 18(1), 109-131. Available at: <https://doi.org/10.2307/2490395>.
- Petersen, J. E. (1977). Simplification and standardization of state and local government fiscal indicators. *National Tax Journal*, 30(3), 299-311.
- Sales, B. F. (2006). *Development of rating methodology based on the ordered probit model*. Dissertation (Master in Finance and Business Economics), Federal University of Rio de Janeiro, Rio de Janeiro.
- Silveira, R. L., Lima, F. G., & Fonseca, C. V. (2017). *An analysis of the determinants of credit ratings: Evidence among Brazilian non-financial companies*. Paper presented at the USP Congress (FIPECAFI).
- Soares, G. O., Coutinho, E. S., & Camargos, M. A. (2012). Credit rating determinants of Brazilian companies. *Accounting Vista & Revista*, 23(3), 104-143.
- Thomas, H., & Wonnacott, R. J. (1972). *Introductory statistics for business and economics* (4th ed.). Nova Jersey, EUA: John Wiley & Sons.
- Zehms, K. M. (1991). Proposed financial ratios for use in analysis of municipal annual financial reports. *The Government Accountants Journal*, 40(1), 79-86.
- Zuccolotto, R., Ribeiro, C. P., & Abrantes, L. A. (2008). *The compose of municipal public finances in the capitals of Brazilian states*. Paper presented at the 15th Brazilian Congress on Costs.

*Views and opinions expressed in this article are the views and opinions of the author(s), International Journal of Business, Economics and Management shall not be responsible or answerable for any loss, damage or liability etc. caused in relation to/arising out of the use of the content.*