Revista de Educação e Pesquisa em Contabilidade
Journal of Education and Research in Accounting

Periódico Trimestral, digital e gratuito publicado pela Academia Brasileira de Ciências Contábeis

ISSN 1981-8610

REPeC, Brasília, v. 12, n. 3, art. 4, p. 327-348, Jul./Sep. 2018
Available online at *www.repec.org.br*
DOI: http://dx.doi.org/10.17524/repec.v12i3.1816

A Credit Risk Analysis Approach Using the Fleuriet Model

Abstract

Objective: To construct a model that can assess the credit risk in Brazilian publicly-traded companies, using indicators from Fleuriet's model of financial analysis.
Method: Methodologically, the research was defined as quantitative, with a descriptive design. The financial statements were collected from Economática and the website BM&FBOVESPA. The sample consisted of 121 companies, being 70 solvent and 51 insolvent, from different sectors.
Results: For the financial structure, working capital and working capital requirement indicators, the companies seek to achieve a constant growth model, expanding or gaining markets, in view of the continuing need for additional working capital over time. The results found for the liquidity thermometer demonstrate the importance of the financial accounts called treasury account to calculate the company's short-term corporate liquidity and solvency. Finally, financial indebtedness as a structural index contributed significantly to the model.
Contributions: This study can contribute to the Brazilian literature by evidencing that some of the indicators in Fleuriet's model are significant to assess the credit risk in Brazilian publicly traded companies.
Key words: Dynamic model, Credit risk, Bankruptcies, Financial indicators.

José Willer do Prado
Ph.D. candidate in Business Administration at Federal University of Lavras (UFLA). **Contact:** Departamento de Administração e Economia DAE/UFLA, Campus Universitário, Caixa Postal 3037. Lavras (MG), CEP: 37200-000.
E-mail: jwprado@gmail.com

Francisval de Melo Carvalho
Ph.D. in Business Administration from Presbyterian University Mackenzie (Mackenzie) and Professor at Federal University of Lavras (UFLA). **Contact:** Departamento de Administração e Economia DAE/UFLA, Campus Universitário, Caixa Postal 3037, Lavras (MG), CEP: 37200-000.
E-mail: francarv@dae.ufla.br

Gideon Carvalho de Benedicto
Ph.D. in Controllership and Accounting from University of São Paulo (USP) and Professor at Federal University of Lavras (UFLA). **Contact:** Departamento de Administração e Economia DAE/UFLA, Campus Universitário, Caixa Postal 3037, Lavras (MG), CEP: 37200-000.
E-mail: gideon.benedicto@dae.ufla.br

Valderí de Castro Alcântara
Ph.D. candidate in Business Administration at Federal University of Lavras (UFLA). **Contact:** Departamento de Administração e Economia DAE/Ufla, Campus Universitário, Caixa Postal 3037, Lavras/MG, CEP: 37200-000.
E-mail: valderidecastroalcantara@gmail.com

Antônio Carlos dos Santos
Ph.D. in Business Administration at University of São Paulo (USP) and Professor at Federal University of Lavras (UFLA). **Contact:** Departamento de Administração e Economia DAE/Ufla, Campus Universitário, Caixa Postal 3037, Lavras (MG), CEP: 37200-000.
E-mail: acsantos@dae.ufla.br

Published in Portuguese and English. Original Version in Portuguese.

Received in 3/18/2018. Ask to Revise on 6/11/2018. Resubmitted on 7/3/2018. Accepted on 7/24/2018 by Dr. Vinícius Gomes Martins (Assistant Editor) and by Dr. Orleans Silva Martins (Editor). Published on 9/6/2018. Organization responsible for the journal: Abracicon

1. Introduction

Decisions concerning the granting or not of credit play a fundamental role for the creditor institutions. The greater the volume of credit operations, the greater the risks involved, risk being an ever-present cost in credit business, making it imperative for managers to quantify it. More specifically, the idea of risk is associated to the probability that a certain result will occur in relation to the expected return, whose estimation, in turn, depends on the past (Assaf Neto, 2010). In financial activities involving credit, the aim is to find security against the risk present in operations or, at least, to transform uncertainty into measurable risk (Silva, 1983).

It is evident that the first studies in this field sought to detect if the indicators of the solvent companies were favorable and if the indicators of the insolvent companies were unfavorable. Two of the earliest (univariate) studies in the field were Fisher's Multiple Use Measurements in Taxonomic Problems (1936) and Durand's Risk Elements in Consumer Installment Lending (1941). The univariate analyses carried out in the late 1950s were replaced though as soon as academic research turned to credit scoring modeling techniques in the late 1960s (Sabato, 2009).

Seminal papers in this field were Beaver's Financial Ratios Predictors of Failure (1966) and Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy by Altman (1968). In Brazil, the first study was the article "How to predict corporate bankruptcies," published by professor Stephen Charles Kanitz. Kanitz (1974) proposed a thermometer of the business solvency situation that would become a reference for future research. Other research that would become relevant to the field was: the work "A Mathematical Model for Credit Decisions in the Commercial Bank" by Elizabetsky (1976) and "Contribution to the techniques of financial analysis: a credit grant model" by Matias (1978), among others.

Martins (2003) explains that the literature does not determine which indicators are the most significant in the assessment of insolvency. According to the author, although many indicators are used repeatedly in several studies, the choice of indicators is largely related to access to the data and the perception of the researcher.

The first study that sought to broaden the range of options in the choice of new economic/financial indicators, besides those referring to the Traditional Model of Financial Analysis, frequently used for the analysis of credit risk in Brazil, was the work of Sanvicente and Minardi (1998), by selecting indicators from the Fleuriet Financial Analysis model (also called the dynamic model) to test the dynamics of overtrading, as proposed by Fleuriet, Kehday and Blanc (1978).

Although Sanvicente and Minardi (1998) did not find better results when replacing the liquidity index with indicators of overtrading dynamics, they opened up possibilities for new work to explore other indicators. The objective of this study is to build a model capable of evaluating credit risk in Brazilian publicly traded companies using the Fleuriet model of financial analysis.

2. Theoretical Framework

2.1 Credit risk

Garcia, Guijarro and Moya (2013) and Prado, Alcântara, Carvalho, Vieira, Machado and Tonelli (2016) point out that credit risk assessment has been the subject of a series of in-depth studies in recent years; it is the main focus of the financial and banking areas mainly due to the recent international financial crisis, which had a severe effect on many financial organizations. In addition, Akkoç (2012), Finlay (2011) and Oreski and Oreski (2014) emphasize that credit risk is one of the most important issues for the banking sector and has gained increasing attention in recent years.

Garcia, Gimenez and Guijarro (2013) elucidate that credit risk management is a key issue for any company at any time. The authors note that there are currently several methods that aim to predict the probability of default by debtors, many of them using logit analysis or discriminant analysis for classification.

Harris (2013) and Yu, Wang and Lai (2008) note that increased competition in the financial service industry has led many companies to find innovative ways to deal with risk in order to achieve and/or maintain a competitive advantage. As a result of the current economic and business environment, financial institutions face greater risk of losses associated with non-compliant credit approval in decisions. Kou and Wu (2014) argue, however, that the main purpose of credit risk analysis is to classify customer samples as "good" or "bad" payers (solvent or insolvent).

2.2 The Fleuriet model

In predicting insolvency, the financial literature does not definitively establish which are the best indicators to be used. Various researchers have repeatedly used several indicators, but the choice process usually depends on the data availability and the researcher's intuition.

According to Assaf Neto (2010), the traditional model of analysis of financial statements is one of the most important studies of financial management. A better understanding of this method can be achieved by means of economic and financial indicators, classified into four groups: liquidity and activity, indebtedness and structure, profitability and stock analysis.

In this respect, Fleuriet, Kehday and Blanc (2003) argue that the traditional presentation structure, which groups several asset and liability accounts horizontally and, according to the terms of these accounts, in a decreasing order of availability, is erroneous. The authors emphasize that the assets and liabilities accounts should be considered in relation to the dynamic reality of the companies and classified according to their cycle, i.e. the time it takes to accomplish a turn.

2.2.1 The Balance Sheet in the Fleuriet model

Padoveze and Benedicto (2010) point out that Law 6.404/1976 (Brazil, 1976), the Brazilian Corporate Law, which presents the basic structure of the financial statements in Brazil, has undergone countless updates, deriving from Law 11.638/07 of December 28, 2007 and Law 11.941 of May 27, 2009 (Brazil, 2007, 2009). On this basic presentation structure of the financial statements, the model proposed by Fleuriet et al. (1978) suggests a reclassification to a completely dynamic and functional standard, in order to satisfactorily address the financial management of the organization. According to Fleuriet et al. (2003, p.7):

> For a better understanding of the financial analysis model to be defined, the assets and liabilities accounts should be considered in relation to the dynamic realities of the companies, in which the accounts are classified according to their cycle, i.e. the time it takes to make a turn.

Fleuriet et al. (2003) present the classification of the accounts within the Balance Sheet, according to its model, as can be observed in Figure 1.

			ASSETS	LIABILITIES			
CURRENT ASSETS	ERRATIC ACCOUNTS	Financial	*Current* Cash, Bank accounts, Securities.	*Current* Discounted Trade Receivables, Short-Term Bank Loans, Dividends Payable, Income Tax Payable etc.	Financial	ERRATIC ACCOUNTS	CURRENT LIABILITIES
	CYCLICAL ACCOUNTS	Operational	Receivables, Inventories of Finished Goods, Inventories of Production in process Inventories of Raw Material, Advance to suppliers etc.	Raw Material Suppliers, Wages and Social Charges, Taxes and Fees.	Operational	CYCLICAL ACCOUNTS	
NON-CURRENT ASSETS	NON-CYCLICAL ACCOUNTS	Fixed	*Non-Current Assets* Loans to third parties Securities receivable etc. Investments, Real estate	*Non-Current Liabilities* Long-Term Liabilities, Bank Loans, Debentures, Financing etc. Net Equity Social Capital Reserves, Accumulated profits or losses.	Fixed	NON-CYCLICAL ACCOUNTS	NON-CURRENT LIABILITIES

Figure 1. The cycles in the Balance Sheet

Source: adapted from Fleuriet *et al*. (2003, p. 8).

According to Fleuriet et al. (2003), Santos and Francisco (2016) and Vieira (2008), some accounts show a slower movement, when analyzed separately, in relation to other Balance Sheet accounts, and can be called “non-cyclical” or “permanent” (Fixed). Other accounts are directly influenced by the turnover (production and sales) and characteristics of the operating cycle (conditions of receipt and payment, storage period), and can be classified as “cyclical” or “operational” because they are related to the operational cycle of the business (Assaf Neto & Silva, 2012).

And finally, as Fleuriet et al. (1978) argue, there are accounts that do not necessarily have a direct link with the operational cycle of the company, varying according to the conjuncture and the risk of more or less liquidity that the company wishes to assume, presenting a ‘discontinuous and erratic’ movement. They are called erratic or financial. According to Fleuriet et al. (2003: 7): “Erratic, from the Latin erraticu. Wandering, bumbling, erratic, random, walking out of the way. That is, it implies the non-connection of these accounts with the Operational Cycle of the company “.

2.2.2 Main indicators in the model

Rasoto, Ishikawa, Rasoto, Stankowitz, Pietrovski and Carvalho (2017) and Viera, Brito, Santana, Sanches and Galdamez (2017) emphasize that, from this new segmentation of the Balance Sheet, the indicators of the Fleuriet model arise: Working Capital Requirement (WCR), Working Capital (WC) and Cash Balance (CB). These new indicators are used in the economic-financial analysis of companies no longer in a static way, but understanding the organization as a 'living organism' (Assaf Neto & Silva, 2012; Braga, 1991; Fleuriet et al., 1978; Jones and Jacinto, 2013; Melo and Coutinho, 2007; Padoveze & Benedicto, 2010; Silva, 2012).

Considering the three indicators, the overtrading effect can be analyzed, the Liquidity Thermometer, which results from the relationship between the Cash Balance and the Working Capital Requirement (CB/WCR), and also evaluate the types of financial structure. The next topic brings further detail on the indicators and their analyses.

2.2.2.1 Working Capital Requirement (WCR)

Fleuriet *et al.* (2003) describe the Working Capital Requirement (WCR) as follows: within the financial cycle of companies, cash outflows (production expenses) occur before cash inflows (sales revenues). The company's operations, therefore, create a need for permanent fund application (called working capital requirements), which is evidenced in the balance sheet by a positive difference between the value of the operational/cyclical accounts of the asset (Operational Assets - OA) and operational/cyclical liabilities (Operational Liabilities - OL).

$$WCR = OA - OL \tag{1}$$

Melo and Coutinho (2007) clarify that the Fleuriet model can be used as a joint solvency and profitability indicator. The authors affirm that, for WCR, low values are expected as a positive sign for the company, that is, the higher this indicator, the greater will be the possibility of using short-term financial resources to finance it, without guarantees of renewal, increasing the risk of insolvency.

2.2.2.2 Working Capital (WC)

According to Vieira (2008), working capital represents a source of long-term resources that can be used to finance the company's working capital requirement. If negative, however, the working capital represents a lack of long-term resources, forcing the company to finance its activities with short-term resources. The calculation is:

$$WC = NCL - NCA \tag{2}$$

Fleuriet *et al.* (2003, p. 11) clarify that: "the Working Capital Requirement, when positive, reflects a permanent application of funds that normally needs to be funded with the permanent resources the company uses. When the WCR is funded with short-term resources [...] the risk of insolvency increases".

2.2.2.3 Cash Balance (CB)

Silva (2012) clarifies that the Cash Balance (CB) can be higher or lower than zero but, when lower, it means that the company has short-term debts in financial institutions, or other short-term debts not related to the operational cycle, and higher than its short-term resources. Araújo, Costa and Camargos (2013) affirm that the cash balance is measured through the confrontation between the financial asset (FA) and financial liability (FL) accounts, and can also be obtained by the difference between WC and WCR.

$$T = FA - FL \quad \text{or} \quad T = WC - WCR \tag{3}$$

Melo and Coutinho (2007) explain that, in view of the analysis of business solvency, the cash balance can be interpreted by analysts as a favorable indicator for a company when it presents higher or positive values, because the lower (or negative) it is , the more short-term financial resources the company will need to finance its activities, increasing the risk of insolvency, and the renewal of these resources is not guaranteed (Silva, Lopes, Pederneiras, Tavares, & Silva, 2016).

2.2.2.4 Overtrading

Sanvicente and Minardi (1998) observe that the Overtrading Effect is a relevant factor for predicting bankruptcies in Brazil. In this same line, Carvalho (2004) affirms that, when a company presents, for several consecutive years, a growth in Working Capital Requirements (WCR) higher than its Working Capital (WC), we can say that it coexists with the so-called Overtrading Effect, which will be identified by a growing negative Cash Balance (CB).

Brazil and Brazil (2008), within this same theoretical domain, affirm that the pathology of the Cash Balance management is the Overtrading Effect, which arises from an excessive reliance on short-term loans, which makes company liquidity critical. The authors point out that any credit cut that occurs as a result of a slowdown in the economy and, consequently, a drop in sales, can lead the company to a state of insolvency quickly, as the delay with suppliers is inevitable in these conditions.

2.2.2.5 Liquidity Thermometer (LT)

Another indicator that can be analyzed in the Fleuriet model is the Financial Situation Thermometer (TSF) or Liquidity Thermometer (TL). According to Fleuriet *et al.* (2003), the liquidity thermometer demonstrates the magnitude of the negative cash balance in relation to the WCR and its trend over time and, depending on the signs of the two indicators involved, it shows the share of the short-term capital from third parties that finance the WCR.

$$LT = \frac{CB}{WCR} \tag{4}$$

Vieira (2008) emphasizes that the WCR is an operational demand for resources that, in view of its strong link with the operations, is permanent or long-term. Due to this characteristic, its funding source should be similar, preponderantly deriving from long-term sources.

2.3.2.6 Types of financial structure

Marques and Braga (1995) argue that the affinity between the cash balance (CB), the working capital requirement (WCR) and the working capital (WC) permits the identification of six specific funding structures. It should be observed that, in the initial study by Fleuriet *et al.* (1978), only four types of financial structures were considered: I, II, III and IV (Fleuriet *et al.*, 2003). In this study, as can be observed in Table 1, the authors ignored conditions in which CB, WCR and WC were equal to zero.

Table 1
Types of financial structure and situation

Type	WC	WCR	T	Situation
I	+	–	+	Excellent
II	+	+	+	Solid
III	+	+	–	Unsatisfactory
IV	–	+	–	Bad
V	–	–	–	Very Bad
VI	–	–	+	High Risk

Source: Adapted from Marques and Braga (1995) and Fleuriet *et al*. (2003, p. 8)

Brazil and Brazil (2008, p.31) explain that "these three variables WCR, WC and CB permit the definition of the companies' conjunctural and structural profile, linked, respectively, to the adopted financial policy (level of risk) and to the business". Fleuriet et al. (2003) note that Type I companies, although they appear less frequently, deserve to be evaluated because they have an excellent financial position with respect to their high level of liquidity. Type II shows a solid financial situation, having a positive CB that allows it to face temporary increases in WCR, as mentioned by Fleuriet et al. (2003).

In Type III, the WCR is higher than the WC and, therefore, the CB is negative. The company finances part of its WCR with short-term credits. This condition is not severe when the WCR is temporarily high. In Type IV, "it configures a typical financial structure of a company that fights to survive" (Fleuriet et al., 2003, p.16). Marques and Braga (1995) show that, in the Type V structure, the financial condition is very bad. In addition to the negative WC, which suggests that short-term sources are used to finance long-term assets, the value of the WCR, also negative, is higher than the WC. Finally, Marques and Braga (1995) comment that, in the situation of high risk originating from the use of the Type VI structure, WC and WCR remain negative. The WCR is lower than the WC though. This scenario allows for a positive CB, which indicates that the company is not performing its operations properly.

2.2.3 Studies on credit analysis using the Fleuriet model

Fleuriet et al. (2003, p. 75) state that the "three categories of liquidity indicators [immediate liquidity, dry liquidity and current liquidity] present a major drawback: they do not provide any indication of the liquidity situation of the company because, in the long-term liabilities, there is no distinction between renewable financing and exceptional financing". Padoveze and Benedict (2010, p.262) clarify that:

> Considering the differentiated nature of the cash accounts, there is a reclassification of working capital: cyclical accounts are classified as cash and, consequently, total cyclical assets less total cyclical liabilities indicates *net working capital requirement* (NWCR). The other accounts, financial and not linked to operations, are called treasury accounts, and only with them should the company's short-term liquidity and solvency capacity be calculated.

In the light of the method developed by Fleuriet in 1978, some studies on liquidity, solvency and/or credit using the Fleuriet model can be found in the literature as presented in Table 2.

Table 2
Synthesis of studies that used the Fleuriet model.

Authors / Year	Dimension Sample	Period	Model and Accuracy	Conclusion/Observations
Sanvicente and Minardi (1998)	Total sample 81 companies 44 solvent 37 insolvent	1986 until 1997	DA* Best forecast: 81.8%	First study to test the dynamics of overtrading in credit risk analysis in Brazil. In total, 14 independent indicators were tested.
Minussi, Damacena and Ness Junior (2002)	323 companies 168 solvent 155 insolvent	1998 until 2000	LR* 95%	49 financial indicators were selected for the solvency analysis, 45 of which belong to the traditional financial analysis model and 4 to the Fleuriet model. Of the five significant indicators for the final model, two refer to the Fleuriet model.
Eifert (2003)	51 companies 30 solvent 21 insolvent	1996 and 1997	DA and LR Best models: DA 92.7% LR 100%	174 indicators were tested, 64 of which referred to the most recent statement (period t), 55 to the one but last statement (period t-1) and 55 to the three years-previous statement (period t-2). With the groups of indicators (t), (t and t-1) and (t, t-1 and t-2), the stepwise method was used for DA as well as for LR to produce 6 models. According to the author, the superiority of LR over DA is clearly perceived in all aspects.
Carvalho (2004)	100 companies 50 solvent 50 insolvent	2000 until 2002	DA Best model 96%	Five models of insolvency prediction were developed. The author affirms that, in the elaboration of his study, the importance of the dynamics of overtrading can be highlighted as highly valuable in the construction of an insolvency prediction model for commercial companies.

(*) DA = Discriminant Analysis; LR = Logistic Regression.

Source: elaborated by the authors based on the studies cited.

3. Research Method

Regarding the ends, this study can be classified as descriptive (Marconi & Lakatos, 2011); as for the means, it can be characterized as *ex post facto* (Vergara, 2008); and as to the form of approach, this research is qualified as quantitative.

With regard to the sampling, first, the solvency concept used in the study had to be defined. In order to define insolvency, the Bankruptcy Law - Law 7.661, dated June 21, 1945 (Brazil, 1945) was used, which was revoked by Law 11.101 of February 2005 (Brazil, 2005), valid for all current bankruptcy and bankruptcy cases.

It should be taken into account that, in order to collect the indicators of insolvent companies, the date of one year before the company announced bankruptcy was used (year previous to the event, time t-1). In order to complete the sample, however, at least one solvent company is selected for each insolvent company, that is, for each company determined as insolvent, at least one solvent company belonging to the same industry will be selected and, where possible, with assets proportionate to that of the insolvent institution. This method is based on previous studies developed by Altman (1968), Brito, Assaf Neto and Corrar (2009) and Sanvicente and Minardi (1998) to match the sample. The database was prepared based on Economática. And, for the preparation of this study, the sample was composed of 121 companies, being 70 companies considered solvent and 51 insolvent.

3.1 Definition of indicators

For the selection of the indicators of the Fleuriet model of financial analysis, the initial work of Fleuriet et al. (1978) was used, as well as the main works presented, which demonstrate the importance of identifying future insolvency problems in companies. The definition of the indicators is based on Pereira, Domínguez and Ocejo (2007), in which the authors affirm that empirical evidence has indicated that the choice of indicators that presented satisfactory results in previous research offers high potential for new research. Table 3 shows the indicators from the Fleuriet model that were used.

Table 3
Notation of Indicator Calculation Formulae

Fleuriet Model			
Cod.	**Indicators**	**Formula**	**Authors**
X1	WC over Assets	WC / AT	Presented in this study
X2	WC over Net Income	WC / NI	
X3	WCR over Assets	WCR / AT	Brito, Assaf Neto and Corrar (2009), Carvalho (2004), Minussi, Damacena and Ness Junior (2002) and Sanvicente and Minardi (1998)
X4	WCR over Net Income	WCR / NI	
X5	Cash Balance over Assets	CB / AT	Brito, Assaf Neto and Corrar (2009), Carvalho (2004), Eifert (2003), Horta (2010), Minussi, Damacena and Ness Junior (2002) and Sanvicente and Minardi (1998)
X6	Cash Balance over Net Income	CB / NI	
X7	Financial Liabilities over Current Assets	FL / CA	Eifert (2003)
X8	Type of Financial Structure	TFS	Melo and Coutinho (2007)
X9	Liquidity Thermometer - LT	CB / (|WCR|)	Horta (2010) and Vieira (2008)
X10	Cash Balance	CB=FA–FL	Melo and Coutinho (2007)
X11	Working Capital Requirement	WCR = OA – OL	Melo and Coutinho (2007)
X12	Working Capital	WC = NCL – NCA	Melo and Coutinho (2007)
X13	Financial indebtedness	(FL + NCFL) / TA	Brito, Assaf Neto and Corrar (2009)

Legend: CA = Current assets; FA = Financial assets; OA = Operational assets; NCA = Non-current assets; TA = Total assets; WC = Working capital; FL = Financial liabilities; NCL = Non-current liabilities; NCFL = Non-current financial liabilities; OL = Operational liabilities; WCR = Working capital requirement; NI = Net Income; CB = Cash balance; TFS = Type of financial structure; LT = Liquidity thermometer.

Source: elaborated by the authors based on the studies cited.

3.2 Discriminant Analysis - DA

For this study, the Discriminant Analysis model was used, as it permits verifying the impact of each indicator on insolvency through its coefficients. For the development of the model, the software SPSS (Statistical Package for Social Sciences) was used.

Virgillito and Famá (2008) point out that, with two groups of companies, solvent (A) and insolvent (B), two measures V1 and V2 (their observations, indicators), the ellipses A and B (drawn with small and large dots , see Figure 2) being their universes; Z being the axis determined by its discriminant function, which in turn consists of indicators. If we draw a straight line through the intersection area of the two ellipses and project this line into a new Z axis, according to Hair et al. (2009), the overlapping area between the two univariate distributions A and B (represented by the shaded area, see Figure 2) will be the smallest among all other possible straight lines to be drawn through the overlapping area of the two ellipses.

The overlapping area in Figure 2, which is projected on the Z-axis, can be interpreted as the discrimination between the two groups, which are the indicators of insolvent and solvent companies. Thus, the smaller the overlapping area, the smaller will be the number of insolvent companies classified as solvent and vice versa. Consequently, the lower the probability will be of granting credit to an insolvent company.

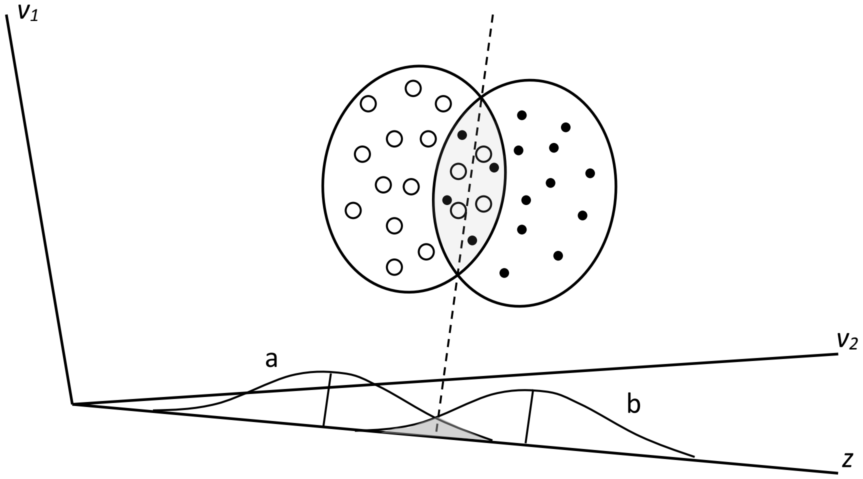

Figure 2. Graphical representation of discriminant analysis of two groups

Source: adapted from Hair *et al.* (2009, p. 230).

It is important to observe that, in the Discriminant Function by Fisher, also known as Classification Function, the constant *a* (intercept) is not used, which simplifies the interpretation of the values produced for $W_{i,}$ because these approach the actual values when intercept *a* is not present in the function. Through this method, the observations for the (independent) variables are inserted in Fisher's function and a classification score for each group is calculated for that observation, so it is classified in the group with the highest classification score (Hair, Black, Babin, Anderson & Tatham; Corrar, Paulo & Dias Filho, 2014).

4. Results and discussion

Firstly, through the descriptive statistical analysis, we aim to better understand the characteristics of the sample used, because two groups represent the sample: solvent companies (2) and insolvent companies (1). In this sense, to verify if the indicators present statistically significant differences, to distinguish between solvent and insolvent groups, the One-Way Anova test was performed to compare the individual means of the groups and to verify the discrimination power of each indicator. The Anova Z test points out that there is a difference between the groups and, when the variances are not equal and the groups have unequal sizes (as in the present case), a more robust statistic like the Brown-Forsythe test is required to measure the means of the groups.

Table 4 presents the descriptive statistics per group, as well as the Z test and the Brown-Forsythe test, which validate the Anova process for all indicators, that is, the indicators have different intergroup means, which makes it statistically possible to create rules to identify solvent and insolvent companies.

Table 4
Descriptive Statistics of Indicators and One-Way ANOVA test

Descriptions		N	Mean	Standard Deviation	Minimum	Maximum	Anova			
							Z test		Brown-Forsythe2	
							Statistics	Sig.	Statistics	Sig.
X1) WC / TA	Insolvent	51	-0.302	0.381	-1.009	0.266	79.110	0.000	65.264	0.000
	Solvent	70	0.166	0.189	-0.213	0.728				
	Total	121	-0.031	0.367	-1.009	0.728				
X2) WC / NI	Insolvent	51	-0.505	1.274	-2.621	2.980	21.109	0.000	16.473	0.000
	Solvent	70	0.251	0.450	-0.929	2.980				
	Total	121	-0.068	0.966	-2.621	2.980				
X3) WCR / TA	Insolvent	51	-0.077	0.257	-0.659	0.365	49.228	0.000	40.930	0.000
	Solvent	70	0.175	0.132	-0.031	0.519				
	Total	121	0.069	0.231	-0.659	0.519				
X4) WCR / NI	Insolvent	51	-0.114	0.439	-0.998	0.874	38.266	0.000	31.374	0.000
	Solvent	70	0.258	0.211	-0.060	0.864				
	Total	121	0.101	0.374	-0.998	0.874				
X5) CB / TA	Insolvent	51	-0.231	0.261	-0.901	0.200	40.414	0.000	34.334	0.000
	Solvent	70	0.007	0.148	-0.322	0.465				
	Total	121	-0.094	0.235	-0.901	0.465				
X6) CB / NI	Insolvent	51	-0.547	0.925	-2.649	0.997	20.785	0.000	16.145	0.000
	Solvent	70	-0.005	0.315	-1.499	0.994				
	Total	121	-0.233	0.697	-2.649	0.997				
X7) FL / CA	Insolvent	51	1.378	1.029	0.057	3.785	50.849	0.000	39.216	0.000
	Solvent	70	0.442	0.329	0.031	1.726				
	Total	121	0.837	0.848	0.031	3.785				
X8) TFS = Structure	Insolvent	51	4.294	1.082	1.000	6.000	89.117	0.000	83.331	0.000
	Solvent	70	2.614	0.873	1.000	5.000				
	Total	121	3.322	1.273	1.000	6.000				
X9) LT = CB / (|WCR|)	Insolvent	51	-5.871	9.580	-26.496	6.996	27.091	0.000	20.210	0.000
	Solvent	70	0.254	1.986	-5.328	6.986				
	Total	121	-2.328	7.052	-26.496	6.996				
X10) CB = FA – FL	Insolvent	51	-246350	549517	-1557441	1422049	9.121	0.003	8.410	0.005
	Solvent	70	20658	423002	-1557441	1422049				
	Total	121	-91883	496220	-1557441	1422049				
X11) WCR = OA – OL	Insolvent	51	23671	196769	-286261	784853	24.427	0.000	27.289	0.000
	Solvent	70	251798	283467	-167550	905259				
	Total	121	155645	274100	-286261	905259				
X12) WC = NCL – NCA	Insolvent	51	-209052	547758	-1466833	1465732	20.692	0.000	19.370	0.000
	Solvent	70	201269	443412	-1466833	1465732				
	Total	121	28324	528644	-1466833	1465732				
X13) (FL + NCFL) / TA	Insolvent	51	0.627	0.464	0.117	1.757	33.325	0.000	25.976	0.000
	Solvent	70	0.281	0.162	0.020	0.720				
	Total	121	0.427	0.366	0.020	1.757				

[2]Robust Tests of Equality of Means. (sig. < 0.05).

Source: research data.

As statistically significant results were obtained for the indicators, we can proceed with the analyses for the sample. To select the best indicators for the model, we chose to use the stepwise method, which helps to eliminate less significant indicators (based on an F statistic) (Charnet, Freire, Charnet & Bonvino, 2008). This process selected only five out of 13 indicators tested. Next, the results found for the Discriminant Analysis model are presented.

For Discriminant Analysis, indicators are considered significant if the significance ratio is equal or inferior to 0.05 (sig. < 0.05). Thus, based on the observation of Table 5, it can be concluded that the five indicators separated for this study can distinguish the groups and can be used in the analysis.

Furthermore, Wilks' Lambda is presented, which statistically represents that, the lower the indicator and its significance level, the better its power to distinguish among the groups (Hair *et al.*, 2009). As observed, the two indicators that best present this function were Type of Financial Structure (X8- TFS = Types of Financial Structure), corresponding to 0.622 and Working Capital (X1- WC / TA) equal to 0.626.

Table 5
Tests of equality of group means

	Wilks' Lambda	Z	df1	df2	Sig.
X1) WC / TA	**0.626**	52.680	1	88	0.000
X4) WCR / NI	0.784	24.223	1	88	0.000
X8) TFS = Structure	**0.622**	53.586	1	88	0.000
X9) LT = CB / (|WCR|)	0.784	24.308	1	88	0.000
X13) (FL + NCFL) / TA	0.797	22.463	1	88	0.000

Source: research data.

Another important fact is the Multicollinearity test for the indicators in the Discriminant model. In this sense, as Field (2013) highlights, the Multicollinearity test can be applied by means of different criteria, including the Tolerance and VIF. Thus, "a tolerance coefficient inferior to 0.1 probably indicates a severe collinearity problem. [...] a VIF score superior to 10 is a reason for concern" (Field, 2013, p. 257). It can be observed in Table 6 that both the Tolerance and VIF coefficients present favorable statistics against the presence of multicollinearity.

Table 6
Multicollinearity Coefficients

Indicators	Collinearity statistics	
	Tolerance	VIF
X1) WC / TA	0.260	3.849
X4) WCR / NI	0.661	1.513
X8) TFS = Structure	0.414	2.418
X9) LT = CB / (|WCR|)	0.767	1.303
X13) (FL + NCFL) / TA	0.496	2.017

a. Dependent Variable: Situation 1 and 2.

Source: research data

The analysis of the Coefficients in the classification function permits knowing a bit more about the importance of each indicator in the Discriminant function (Corrar *et al.*, 2014). Based on the data in Table 7, it can be concluded that the coefficients (of the indicators) with negative values for the discriminant function will contribute (the higher the indicator) for the company to be ranked below the cut-off point and, consequently, to be considered insolvent. On the other hand, the positive coefficients will contribute (the higher the indicator) for the company to be considered in the group of solvent companies.

Table 7

Canonic discriminant function coefficients (non-standardized coefficients).

Indicators	Function
X1) WC / TA	0.899
X4) WCR / NI	0.971
X8) TFS = Structure	- 0.444
X9) LT = CB / (|WCR|)	0.055
X13) (FL + NCFL) / TA	- 0.980
(Constant)	1.887

Source: research data

After obtaining the coefficients of the non-standardized canonic discriminant function, the function can be elaborated for the Discriminant Analysis, that is, the Credit Scoring can be represented by Equation 5.

$$Z = 1.887 + 0.899.\left(\frac{WC}{TA}\right) + 0.971.\left(\frac{WCR}{NI}\right) - 0.444.\,(\text{Type of Structure}) \\ +0.055.\left(\frac{CB}{WCR}\right) - 0.980.\left(\frac{FL + NCFL}{TA}\right) \quad (5)$$

After establishing the Discriminant Analysis function, the cut-off point can be calculated based on the centroids of each group. The centroids are the means obtained with the individual distribution of the groups. The weighted average between the centroids of each of the distributions will be the cut-off point of the discriminant function. The result obtained for the optimal cut-off point is -0.0641 and this value will serve to classify the companies by means of their discriminant score. That is, companies that rank the cut-off point have been classified as belonging to group "1" (insolvent) and companies that have a discriminant score above the cut-off point will be classified as part of group "2" (solvent).

Another method used in the interpretation of the results obtained by the Discriminant Function is the application of a classification scale as used by Silva (2012) or by Kanitz (1978) in his Insolvency Thermometer. This scale can be obtained after calculating the standard deviations and means of each group (Corrar et al., 2014), as shown in Figure 3.

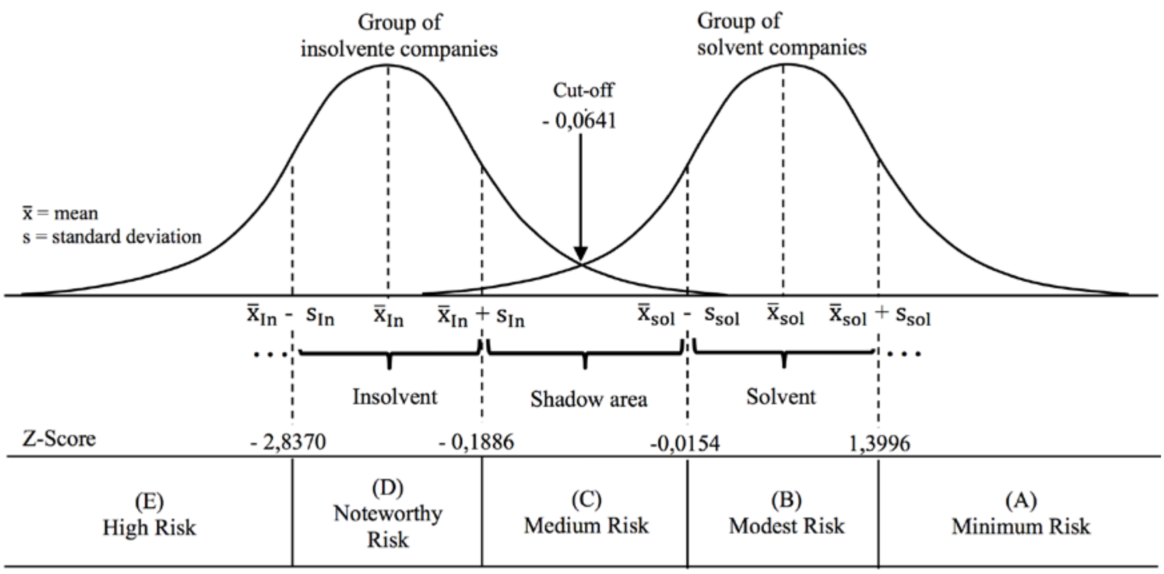

Figure 3. Risk classification scale

Source: elaborated based on the studies by Kanitz (1974, p. 13), Hair et al. (2009, p. 230), Silva (2012, p. 356) and Corrar et al. (2014, 239).

As shown in Figure 3, the company whose Z-Score (discriminant score) calculation ranges between -0.0154 and -0.1886 will be considered in the shadow area and will be classified in an indefinite situation, so that an average risk can be attributed. Companies that rank between -0.1866 to -2.8370 will be classified as insolvent and will be assigned a preoccupying risk due to their status. A company that has a value lower than -2.8370 will be considered insolvent, with a High Risk. Therefore, these companies inspire greater care in the granting of credit. Statistically, one may say that the statistical model has no basis to assert any classification in this shady interval (Kanitz, 1974). Therefore, one solution is to create a scale of risk classification from the ranges found by the two distributions studied, that is, solvent companies and insolvent companies.

The results found through the classification for the discriminant analysis are displayed in Table 8. The correctly grouped original cases represent a 90.9% success rate, while the cases selected for the cross-validation (Lachenbruch's test) confirm the result with the same level of accuracy. Finally, by testing the function for the unselected cases, to generate the function, we obtained 90.9% accuracy. The discriminant function achieved the same level of accuracy for the cases that were used for its creation as well as for the external cases that did not participate in its construction.

Table 8
Results of the classification[a,b,d]

Classg			**Situation**	**Association with expected group**		**Total**
				Solvent	Insolvent	
Selected cases	Original	Count	Solvent	53	3	56
			Insolvent	11	23	34
		%	Solvent	94.6%	5.4%	100%
			Insolvent	32.4%	67.6%	100%
	With cross-validation[c]	Count	Solvent	53	3	56
			Insolvent	11	23	34
		%	Solvent	94.6%	5.4%	100%
			Insolvent	32.4%	67.6%	100%
Non-selected cases	Original	Count	Solvent	14	0	14
			Insolvent	4	13	17
		%	Solvent	100%	0%	100%
			Insolvent	23.5%	76.5%	100%

a. 84.4% of selected original grouped cases classified correctly

b. 87.1% of non-selected original grouped cases classified correctly

c. The cross-validation is only done for the analysis cases. In the cross-validation, each case is classified according to the function deriving from all cases different from this case

d. 84.4% of selected cases grouped with cross-validation classified correctly

Source: research data.

Due to the fact that the Discriminant Analysis is a linear technique, the global precision level of the model for correctly classified companies is satisfactory, as the main objective here is to verify the impact of the Fleuriet model indicators.

4.1 Working Capital over Assets (X1- WC / TA)

The indicator Working Capital over Assets was representative for the Discriminant Analysis model. The sample presented positive coefficients for the solvent companies (0.166) and negative coefficients for the insolvent companies (-0.302), with a total average of -0.031 (Table 9). The Discriminant Analysis presented a positive sign (+) for the coefficient, which indicates that, within the discriminant function, the higher the coefficient of the working capital indicator, the greater the probability of the company being solvent.

Table 9
Summary of results for the indicator Working Capital over Assets (X1- WC / TA)

Comparison	Descriptive Statistics		
Literature: The higher the better, Melo and Coutinho (2007).	Situation	N	Mean
	Insolvent	51	-0.302
DA = (X1) (+) sign of the indicator, the higher the more solvent.	Solvent	70	0.166
	Total	121	-0.031

Source: elaborated by the authors.

As Olinquevitch and Santi Filho (2009: 85) argue, "in analytical terms, the mere availability of WC is not sufficient to indicate good economic and financial health: the available own resources need to be adapted to the needs." From the perspective of solvency analysis, however, experts expect high WC as a positive indicator for the firm. Being a source of long-term resources, the WC, when sufficiently high, i.e. higher than the Working Capital Requirement, brings peace of mind regarding the renewal of short-term financing terms from external sources (Melo & Coutinho, 2007).

4.2 Working Capital Requirement (X4-WCR / NI)

Nascimento, Espejo, Voese and Pfitscher (2012) note that the Working Capital Requirement (WCR) can be positive or negative. For Olinquevitch and Santi Filho (2009, p.13), the positive sign of WCR indicates that Working Capital (WC) applications are higher than the sources of WC, "expressing that the company is investing resources in the business turnover" . When the WCR sign is negative, however, it indicates that WC sources are higher than applications in WC, "expressing that the company is obtaining (financing its activities with) resources from the business turnover" (Olinquevitch & Santi Filho, 2009, p.13).

Analyzing the WCR on Net Income, as can be observed in Table 10, the average of the sample of solvent companies was positive, while the average for insolvent companies was negative. This is confirmed by the Discriminant Analysis model, presenting values that indicate that, the higher the value for WCR, the greater the probability that the company will be solvent.

Table 10
Summary of results for the indicator Working Capital Requirement (X4- WCR/NI)

Comparison	Descriptive Statistics		
Literature: Positive or Negative, Padoveze and Benedicto (2010).	Situation	N	Mean
	Insolvent	51	-0.114
AD = (X3) (+) sign* of the indicator, the higher the more solvent.	Solvent	70	0.258
		121	0.101

Source: elaborated by the authors.

Empirically, these results differ from those presented by Minussi, Damacena and Ness Junior (2002, p. 122), who, when investigating companies in the industrial sector, found coefficients for the indicator WCR over Net Income ("NCG / Net Sales - Variable X2") with averages of 0.80 for the group of solvent companies and an average of 3.50 for insolvent companies. This contradiction has a possible explanation when we analyze the situation more closely through the company's Financial Structure Type, as will be discussed in the following topic.

4.3 Type of Financial Structure (X8- TFS = Balance sheet structure)

As can be observed in Table 11, the divergent result found in relation to the work by Minussi, Damacena and Ness Junior (2002), presented in the previous topic, is due to the fact that only four of the solvent companies in the sample possess the Type 1 Financial Structure 'Excellent', that is, they have positive WC and CB positive and negative WCR, while the majority of the solvent companies presented a Type 2 Financial Structure 'Solid' (32 companies, positive WC, WCR and CB), or Type 3 'Unsatisfactory' (22 companies, positive WC and WCR and negative CB), in which the WCR is positive, which directly influences the positive average WCR for solvent companies (0.258).

On the other hand, what justifies the negative average WCR of insolvent companies (-0.114) is the fact that 27 insolvent companies, more than half of the sample, are classified under Type 5 Financial Structure 'Very bad' (24 firms, negative WC, WCR and CB) and Type 6 'High risk' (3 companies, negative WC and WCR and positive CB. In these two types of structures, companies have negative WCR (Table 11).

Table 11
Clustering of companies per types of structure and financial situation

Type	WC	WCR	T	Situation	Solvent Companies	Insolvent Companies	Total Sample
I	+	–	+	Excellent	4	1	5
II	+	+	+	Solid	**32**	3	35
III	+	+	–	Unsatisfactory	**22**	6	28
IV	–	+	–	Bad	11	14	25
V	–	–	–	Very bad	1	**24**	25
VI	–	–	+	High risk	0	**3**	3
				Total	**70**	**51**	**121**

Source: adapted from Braga (1991, p. 10); Marques and Braga (1995, p. 56); Fleuriet *et al*. (2003, p. 15)

In this sense, the results presented are in accordance with Padoveze and Benedicto (2010, p.264), who emphasize that, "in general, companies seek to perform a model of constant growth, gaining or expanding markets. Within this premise, there is always an additional requirement of working capital over time", because it represents the resource necessary for the performance of the company's operations. Fleuriet and Zeidan (2015) also point out that not planning the growth of working capital requirements can lead to severe cash flow difficulties. Olinquevitch and Santi Filho (2009, p.13) also state that:

> The variable Net Working Capital Requirement (NWCR) is the main determinant of the companies' financial situation. Its value reveals the level of resources needed to keep the business spinning. Unlike the investments in permanent assets, which involve long-term decisions and slow recovery of capital, the accounts that comprise the Net Working Capital Requirement (NWCR) express short-term operations with quick effects. Changes in storage policy, credit policy and purchasing policy have immediate effects on cash flow.

In Table 11, it is important to note that none of the solvent companies was classified under Type VI 'High Risk'. Nevertheless, the company OGX Petróleo, defined as insolvent in the sample, was classified under Type I 'Excellent', although the discriminant analysis model classified the company as insolvent. In the evaluation by type of structure only, the financial situation of OGX Petroleum would have gone by unnoticed.

As shown in Table 11, the Types of Financial Structure were proposed by Fleuriet et al. (1978) and then expanded by Braga (1991) with two more levels. The indicator used in this study represents a proxy equal to 1 for type 1, rising up to 6 for type 6, that is, companies classified as 1 are ranked under 'Excellent', while companies classified as 6 rank under 'High risk'.

Therefore, the indicator Type of Financial Structure presented a coefficient for the indicator in accordance with the literature. The values obtained by the study sample also presented the same behavior (Table 12).

Table 12
Summary of results for the indicator X8 – Type of Financial Structure

Comparison	Descriptive Statistics		
Literature: The smaller the better, Marques and Braga (1995).	Situation	N	Mean
	Insolvent	51	4.294
DA = (-) sign of the indicator, the larger the more insolvent.	Solvent	70	2.614
		121	3.322

Source: elaborated by the authors.

It should be noted that, in the discriminant analysis model, the Wilks' lambda test for the indicator was the most significant, with the lowest coefficient (0.622).

4.4 Liquidity thermometer (X09- LT)

Horta (2010) states that the Liquidity Thermometer confirms a financial reserve to cope with the occasional expansions of the WCR, especially for seasonal growths. In this sense, the temporary needs for investment in cash, when not covered by long-term financing, can be sustained by the limit of the existing balance (Padoveze & Benedicto, 2010).

In the sample, the Liquidity Thermometer presented negative values for insolvent companies and positive values for solvent ones. The positive value for solvent companies was confirmed by the Liquidity Thermometer, in the Discriminant Analysis model, with a positive sign, indicating that, the higher its value, the more likely that the company will have to be solvent (Table 13). This is in accordance with Padoveze and Benedicto (2010, p.262), for whom it is "by means of financial accounts (treasury accounts) that one should "calculate the company's liquidity and solvency capacity in the short term".

Table 13
Summary of results for the indicator Liquidity thermometer (X09- LT)

Comparison	Descriptive Statistics		
Literature: The higher the better, Fleuriet et al. (2003).	Situation	N	Mean
	Insolvent	51	-5.871
DA = (X9) (+) sign of the indicator, the higher the more solvent.	Solvent	70	0.254
		121	-2.328

Source: elaborated by the authors.

Empirically, the results found for the Liquidity Thermometer are in accordance with Horta (2010), when using the Liquidity Thermometer to evaluate several sectors: basic materials sector (solvent = 0.011 and insolvent = -0.003); cyclical consumption goods (solvent = 0.010 and insolvent = -0.032); non-cyclical consumption goods (solvent = 0.002 and insolvent = -0.047); industrial goods (solvent = -0.133 and insolvent = -0.133); construction and transport (solvent = 0.004 and insolvent = -0.219); information technology and telecommunications (solvent = -0.007 and insolvent = -0.385).

4.5 Financial indebtedness (X13- [FL + NCFL] / TA)

The indicator of Financial Indebtedness (X13) is presented in Brito, Assaf Neto and Corrar (2009). Even though it is not exactly one of the indicators that assess the financial situation of the company through a dynamic analysis, it was chosen because it is an indicator of structure that evaluates the degree of indebtedness of the company from a financial perspective.

As Fleuriet *et al.* (1978) argue, there are accounts that do not necessarily have a direct link with the operational cycle of the company, varying according to the conjuncture and the risk of higher or lower liquidity the company wishes to assume, presenting a 'discontinuous and erratic' movement. They are called "erratic" or "financial" and, in this sense, the use of a structure indicator that is based on this view is welcome in the model.

Table 14 presents the measures for the Financial Indebtedness indicator (X13). It is observed that insolvent companies obtained higher averages (0.627), while solvent companies showed lower averages (0.281). On the other hand, the discriminant analysis showed a negative sign, demonstrating that, the higher the value of the indicator, the greater the likelihood of insolvency.

Table 14
Summary of results for the indicator Financial indebtedness (X13- [FL + NCFL] / TA)

Comparison	Descriptive Statistics		
	Situation	N	Mean
Literature: The lower the better, Brito, Assaf Neto and Corrar (2009).	Insolvent	51	0.627
AD = (X9) (-) sign of the indicator, the higher the more insolvent.	Solvent	70	0.281
	Total	121	0.427

Source: elaborated by the authors.

These considerations are in agreement with the literature regarding the risk of insolvency linked to the high degree of indebtedness. The results also corroborate the results found by Brito, Assaf Neto and Corrar (2009, p. 35): "the greater the value of this indicator, the greater the likelihood of the company becoming insolvent".

5. Final Considerations

The objective of this study was to construct a model capable of assessing credit risk in Brazilian publicly-traded companies, using indicators from the Fleuriet model of financial analysis. Methodologically, the research was defined as quantitative and, by nature, it is descriptive. The financial statements were collected through Economática and the BM & FBOVESPA website. The sample consisted of 121 companies, 70 of which were solvent and 51 insolvent in several sectors.

With the sample and the indicators of the study, a descriptive analysis of the data was performed, as well as a one-way Anova, which presented a satisfactory result for the proposed indicators, meaning that the indicators were significant to classify solvent and insolvent companies. Regarding the final indicators used to compose the Credit Risk model, the contribution of the method proposed by Fleuriet applied to grant credit is clearer. The indicators selected for the model were: working capital, working capital requirement, type of financial structure, liquidity thermometer, financial indebtedness.

For the indicators Type of Financial Structure, Working Capital and Working Capital Requirement, one may say that companies seek to perform a constant growth model, expanding or gaining markets, as there is always a need for additional working capital to over time. The results found for the Liquidity Thermometer demonstrate the importance of financial accounts called treasury accounts to calculate the company's liquidity and solvency capacity in the short term. Finally, financial indebtedness as a structure index contributed significantly to the model.

This study may contribute to the Brazilian literature by showing that some of the indicators of the Fleuriet model are significant to assess credit risk in Brazilian publicly-traded companies. Thus, through our study, some of the characteristics of the insolvent companies for the present sample can be elucidated. These contributions are fundamental for credit risk research and contribute to the development of the method of reclassifying the balance sheet through the Fleuriet model. Finally, in the light of the above, it is concluded that the indicators of the Fleuriet model effectively contribute to predict corporate insolvency.

References

Akkoç, S. (2012). An empirical comparison of conventional techniques, neural networks and the three stage hybrid Adaptive Neuro Fuzzy Inference System (ANFIS) model for credit scoring analysis: The case of Turkish credit card data. *European Journal of Operational Research, 222*(1), pp.168-178. doi: https://dx.doi.org/10.1016/j.ejor.2012.04.009

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The journal of finance*, *23*(4), pp. 589-609. doi: https://dx.doi.org/10.1111/j.1540-6261.1968.tb00843.x

Araújo, E. A. T., de Oliveira Costa, M. L. & de Camargos, M. A. (2013). Mapeamento da produção científica sobre o Modelo Fleuriet no Brasil. *Gestão Contemporânea*, *14*(1).

Assaf Neto, A. (2010). *Finanças corporativas e valor* (5ª ed.). São Paulo: Atlas.

Assaf Neto, A. & Silva, C. A. T. (2012). *Administração do capital de giro* (4ª ed.). São Paulo: Atlas.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of accounting research*, *4*(3), pp. 71-111. doi: https://dx.doi.org/10.2307/2490171

Braga, R. (1991). Análise avançada do capital de giro. *Caderno de estudos FIPECAFI*, *3*(3), pp. 1-34. doi: https://dx.doi.org/10.1590/S1413-92511991000100003

Brasil (1945). *Decreto-Lei nº 7.661*, de 21 de junho de 1945. Presidência da República. Brasília, DF, Brasil.

Brasil (1976). *Lei nº 6.404, de 15 de dezembro de 1976*. Dispõe sobre as sociedades por ações. Diário Oficial da União. Brasília, DF: Exército Brasileiro.

Brasil (2005). *Lei nº 11.101, de 9 de fevereiro de 2005*. Regula a recuperação judicial, a extrajudicial e a falência do empresário e da sociedade empresaria. Diário Oficial da União. Brasília, DF: Exército Brasileiro.

Brasil (2007). *Lei nº 11.638, de 28 de dezembro de 2007*. Altera e revoga dispositivos da Lei n°. 6.404, de 15 de dezembro de 1976, e da Lei n. 6.385, de 7 de dezembro de 1976, e estende às sociedades de grande porte disposições relativas à elaboração e divulgação de demonstrações financeiras. Diário Oficial da União. Brasília, DF: Exército Brasileiro.

Brasil (2009). *Lei nº 11.941, de 27 de maio de 2009*. Altera a legislação tributária federal relativa ao parcelamento ordinário de débitos tributários; concede remissão nos casos em que especifica; institui regime. Diário Oficial da União. Brasília, DF: Exército Brasileiro.

Brasil, H. V. & Brasil, H. G. (2008). *Gestão financeira das empresas: um modelo dinâmico* (4ª ed.). Rio de Janeiro: Qualitymark.

Brito, G. A. S., Assaf Neto, A. & Corrar, L. J. (2009). Sistema de classificação de risco de crédito: uma aplicação a companhias abertas no Brasil. *Revista Contabilidade & Finanças*, *20*(51), pp. 28-43. doi: https://dx.doi.org/10.1590/S1519-70772009000300003

Carvalho, A. T. (2004). *Modelo de previsão de insolvência para empresas comerciais*. Dissertação de Mestrado, Universidade Federal de Santa Catarina, Florianópolis, SC, Brasil.

Charnet, R. , Freire, C.A.L., Charnet, E.M.R. & Bonvino, H. (2008). *Análise de modelos de regressão linear com aplicações* (2ª ed.). Campinas: Unicamp.

Corrar, L. J. , Paulo, E. & Dias Filho, J.M. (2014). *Análise multivariada: para os cursos de administração, ciências contábeis e economia*. São Paulo: Atlas.

Durand, D. (1941). Risk elements in consumer installment lending. *Studies in consumer installment financing, 8, pp.* 1-101.

Eifert, D. S. (2003). *Análise quantitativa na concessão de crédito versus inadimplência: um estudo empírico*. Dissertação de mestrado, Universidade Federal do Rio Grande do Sul, Porto Alegre, RS, Brasil.

Elizabetsky, R. (1976). *Um modelo matemático para decisão no banco comercial*. Dissertação de mestrado, Universidade de São Paulo, São Paulo, SP, Brasil.

Field, A. (2013). *Descobrindo a estatística usando o SPSS*. Porto Alegre: Artmed.

Finlay, S. (2011). Multiple classifier architectures and their application to credit risk assessment. *European Journal of Operational Research, 210*(2), pp. 368-378. doi: https://dx.doi.org/10.1016/j.ejor.2010.09.029

Fisher, R. A. (1936). The use of multiple measurements in taxonomic problems. *Annals of Eugenics*, *7*(2), pp. 179-188. doi: https://dx.doi.org/10.1111/j.1469-1809.1936.tb02137.x

Fleuriet, M., Kehday, R. & Blanc, G. (1978). *A dinâmica financeira das empresas brasileiras: um método de análise, orçamento e planejamento financeiro*. Belo Horizonte: Fundação Dom Cabral.

Fleuriet, M., Kehday, R. & Blanc, G. (2003). *O Modelo Fleuriet: a dinâmica financeira das empresas brasileiras: um método de análise, orçamento e planejamento financeiro* (3a ed.). Rio de Janeiro: Campus.

Fleuriet, M. & Zeidan, R. (2015). *O modelo dinâmico de gestão financeira*. Riode Janeiro: Alta Books.

Garcia, F., Gimenez, V. & Guijarro, F. (2013). Credit risk management: A multicriteria approach to assess creditworthiness. *Mathematical and Computer Modelling, 57*(7-8), 2009-2015. doi: https://dx.doi.org/10.1016/j.mcm.2012.03.005

Garcia, F., Guijarro, F. & Moya, I. (2013). Monitoring credit risk in the social economy sector by means of a binary goal programming model. *Service Business, 7*(3), pp. 483-495. doi: https://dx.doi.org/10.1007/s11628-012-0173-7

Hair, J. F.,Black, W.C., Babin, B.J., Anderson, R.E. & Tatham, R.L. (2009). *Análise multivariada de dados*. 6ª. ed. Porto Alegre: Bookman, 2009.

Harris, T. (2013). Quantitative credit risk assessment using support vector machines: Broad versus Narrow default definitions. *Expert Systems with Applications, 40*(11), pp. 4404-4413. doi: https://dx.doi.org/10.1016/j.eswa.2013.01.044

Horta, R. A. M. (2010). *Uma metodologia de mineração de dados para a previsão de insolvência de empresas brasileiras de capital aberto*. Tese de doutorado, Universidade Federal do Rio de Janeiro, Rio de Janeiro, RJ, Brasil.

Jones, G. D. C. & Jacinto, A. C. O. (2013). Management analysis of working capital investments by fleuriet model in an agribusiness: A case study. *Revista em Agronegocio e Meio Ambiente*, *6*(1), pp. 9-30.

Kanitz, S. C. (1974). Como prever falências de empresas. *Revista Negócios em Exame*, pp. 95-102.

Kanitz, S. C. (1978). Como prever falências. São Paulo: McGraw-Hill do Brasil.

Kou, G. & Wu, W. (2014). An Analytic Hierarchy Model for Classification Algorithms Selection in Credit Risk Analysis. *Mathematical Problems in Engineering*, *2014*(2014), pp. 1-7. doi: https://dx.doi.org/10.1155/2014/297563

Marconi, M. A. & Lakatos, E. M. (2011). *Metodologia do trabalho científico: procedimentos básicos, pesquisa bibliográfica, projeto e relatório, publicações e trabalhos científicos* (7ª ed.) São Paulo: Atlas.

Marques, J. A. V. C., & Braga, R. (1995). Análise dinâmica do capital de giro: o Modelo Fleuriet. *Revista de Administração de Empresas*, *35*(3), pp. 49-63. doi: https://dx.doi.org/10.1590/S0034-75901995000300007

Martins, M. S. (2003). *A previsão de insolvência pelo modelo de Cox*: uma contribuição para a análise de companhias abertas brasileiras. Dissertação de mestrado, Universidade Federal do Rio Grande do Sul, Porto Alegre, RS, Brasil.

Matias, A. B. (1978). *Contribuição às técnicas de análise financeira: um modelo de concessão de crédito*. Dissertação de mestrado, Universidade de São Paulo, São Paulo, SP, Brasil.

Melo, A. C. & Coutinho, E. S. (2007). O modelo Fleuriet como indicador conjunto de solvência e rentabilidade. *Anais do EnANPAD*, Rio de Janeiro, RJ, Brasil, 31.

Minussi, J. A., Damacena, C. & Ness Jr., W. L. (2002). Um Modelo de Previsão de Solvência Utilizando Regressão Logística. *Revista de Administração Contemporânea*, *6*(3), pp. 10-128. doi: https://dx.doi.org/10.1590/S1415-65552002000300007

Nascimento, C., Espejo, M. M. D. S. B., Voese, S. B. & Pfitscher, E. D. (2012).Tipologia de Fleuriet e a crise financeira de 2008. *Revista Universo Contábil*, *8*(4), pp. 40-59. doi: https://dx.doi.org/10.4270/ruc.2012430

Olinquevitch, J. L. & Santi Filho, A. (2009). *Análise de balanços para controle gerencial: demonstrativos contábeis exclusivos do fluxo de tesouraria* (5ª ed.) São Paulo: Atlas.

Oreski, S. & Oreski, G. (2014). Genetic algorithm-based heuristic for feature selection in credit risk assessment. *Expert Systems with Applications*, *41*(4), pp. 2052–2064. doi: https://dx.doi.org/10.1016/j.eswa.2013.09.004

Padoveze, C. L. & Benedicto, G. C. (2010). *Análise das demonstrações financeiras* (3ª ed.). São Paulo: Cengage Learning.

Pereira, J. M., Domínguez, M. Á. C. & Ocejo, J. L. S. (2007). Modelos de previsão do fracasso empresarial: aspectos a considerar. *Tékhne-Revista de Estudos Politécnicos*, *7*, pp. 111-148.

Prado, J. W., Alcântara, V.C., Carvalho, F.M., Vieira, K.C., Machado, L.K.C. & Tonelli, D.F. (2016). Multivariate analysis of credit risk and bankruptcy research data: a bibliometric study involving different knowledge fields (1968–2014). *Scientometrics*. doi: https://dx.doi.org/10.1007/s11192-015-1829-6

Rasoto, A., Ishikawa, G., Rasoto, V.I., Stankowitz, R.F., Pietrovski, E.F. & Carvalho, H.A. (2016). *Business competitiveness: Model of computerized financial planning*. In *IAMOT 2016 - 25th International Association for Management of Technology Conference, Proceedings: Technology - Future Thinking*, pp. 1191-1203.

Sabato, G. (2009). Modelos de Scoring de risco de crédito. *Revista Tecnologia de Crédito*, *1*(68), pp. 29-47.

Santos, G. T. & Francisco, J. R. D. (2016). Liquidity indicators versus dynamic model: application in period pre and post-crisis banking segment. *Revista Contabilidade e Controladoria*, *8*(2), pp. 8-22. doi: https://dx.doi.org/10.5380/rcc.v8i2.37471

Sanvicente, A. Z. & Minardi, A. M. A. F. (1998). *Identificação de indicadores contábeis significativos para a previsão de concordata de empresas*. São Paulo: Instituto Brasileiro de Mercado de Capitais,Working Paper.

Silva, G. R., Lopes, J. E. D., Pederneiras, M. M. M., Tavares, M. F. N. & Silva, E. E. D. (2016). A study on Fleuriet model applied in financial management of electric companies listed on the BM & FBOVESPA. *Revista Ambiente Contábil*, *8*(2), pp. 92-109.

Silva, J. P. (1983). *Administração de crédito e previsão de insolvência*. São Paulo: Atlas.

Silva, J. P. (2012). *Análise financeira das empresas* (11ª ed.) São Paulo: Atlas.

Vergara, S. C. (2008). *Projetos e relatórios de pesquisa em administração* (9ª ed.). São Paulo: Atlas.

Vieira, M. V. (2008). *Administração estratégica do capital de giro* (2ª ed.). São Paulo: Atlas.

Viera, L. B., Brito, S. S., Santana, J. R. B., Sanches, S. L. R. & Galdamez, E. V. C. (2017). The effects of mergers and acquisitions on financial ratios of Brazilian publicly traded companies. *Rege-Revista De Gestao, 24*(3), pp. 235-246. doi: https://dx.doi.org/10.1016/j.rege.2016.08.003

Virgillito, S. B. & Famá, R. (2008). Estatística multivariada na construção de modelos para análise do risco de crédito e previsão de insolvência de empresas. *Revista Integração*, *53*(13), pp. 105-118.

Yu, L., Wang, S. & Lai, K. K. (2008). Credit risk assessment with a multistage neural network ensemble learning approach. *Expert Systems with Applications, 34*(2), pp. 1434-1444. doi: https://dx.doi.org/10.1016/j.eswa.2007.01.009