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The relevance of operating cash flow to predict bankruptcy of Brazilian listed companies

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Abstract

This article assesses whether the cash flow-to-debt ratio (OCF/TD) is relevant to predict bankruptcy of Brazilian listed companies considering the period from 2008 to 2019. The inclusion of this indicator is justified since it is a measure of a company's ability to pay its debts with cash generated from its operations. Six logistic regression models with paired samples were built for companies that went bankrupt and those that did not go bankrupt from 2008 to 2019. Three of these regressions were based on the literature (ALTMAN, 1968; SANVICENTE and MINARDI, 1998; ROCHA, 2017), and three added the OCF/TD variable to validate its significance in predicting the bankruptcy of Brazilian listed companies. Cash flow showed statistical relevance, and in general, the area under the ROC curve was larger in all models where such a variable was added, thus indicating that the inclusion of OCF/TD improves bankruptcy prediction models. The variation of the area under the ROC curve in Altman's model increases by 2.2% with the inclusion of OCF/TD; in the other models, there is a 3.8% increase. Considering two years before bankruptcy, this variation increases by at least 11%. Another contribution of the article refers to how prediction models are evaluated and compared using the ROC curve, which balances these models' sensitivity and specificity.

Keywords: Bankruptcy prediction. Brazilian companies. Operating cash flow. Logit.

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Relevância do fluxo de caixa operacional para previsão de falência das empresas brasileiras abertas

Resumo

O objetivo do artigo é avaliar se o fluxo de caixa operacional sobre passivo total (FCOPT) é relevante para melhor estimar a previsão de falência de empresas brasileiras abertas, no período de 2008 a 2019. A justificativa para a inclusão de tal indicador é baseada no fato de ele ser uma medida da capacidade das empresas de pagarem suas dívidas com o caixa gerado com suas operações. Foram construídos seis modelos de regressão logística com amostra pareada para empresas que faliram e não faliram no período: três baseados na literatura (ALTMAN, 1968; SANVICENTE e MINARDI, 1998; ROCHA, 2017) e três acrescidos da variável FCOPT para validar sua significância na previsão de falência de empresas brasileiras. O fluxo de caixa apresentou relevância estatística, e, de maneira geral, a área sob a curva ROC foi maior em todos os modelos em que a variável foi adicionada, o que indica que a inclusão de FCOPT traz uma melhor qualidade aos modelos de previsão de falência. A variação da área sob a curva ROC do modelo de Altman melhora em 2,2% com a inclusão de FCOPT; nos demais modelos, em 3,8%. Considerando dois anos antes da falência, essa variação melhora em pelo menos 11%. Outra contribuição do artigo é a forma como os modelos de previsão são avaliados e comparados, usando a curva ROC, que balanceia sensibilidade e especificidade dos modelos preditivos.

Palavras-chave: Previsão de falências. Empresas brasileiras. Fluxo de caixa operacional. *Logit*.

Relevancia del flujo de caja operativo para pronosticar la quiebra de empresas brasileñas que cotizan en bolsa

Resumen

El objetivo del artículo es evaluar si el flujo de caja operativo sobre pasivos totales (FCOPT) es relevante para estimar mejor la previsión de quiebra de las empresas públicas brasileñas, en el período de 2008 a 2019. La justificación para la inclusión de tal indicador se basa en el hecho de que es una medida de la capacidad de las empresas para pagar sus deudas con el efectivo generado por sus operaciones. Se construyeron seis modelos de regresión logística con muestra pareada para empresas que fracasaron y no fracasaron en el período: tres basados en la literatura (ALTMAN, 1968; SANVICENTE y MINARDI, 1998; ROCHA, 2017) y tres con la variable FCOPT para validar su importancia en el pronóstico de quiebra de las empresas brasileñas. El flujo de caja mostró relevancia estadística y, en general, el área bajo la curva ROC fue mayor en todos los modelos en los que se agregó la variable, lo que indica que la inclusión de FCOPT aporta una mejor calidad a los modelos de pronóstico de quiebra. La variación del área bajo la curva ROC del modelo de Altman mejora un 2,2% con la inclusión de FCOPT; y los demás modelos, un 3,8%. Considerando dos años antes de la quiebra, esta variación mejora en al menos un 11%. Otra contribución del artículo es la forma en que se evalúan y comparan los modelos de predicción, utilizando la curva ROC, que equilibra la sensibilidad y la especificidad de los modelos predictivos.

Palabras clave: Pronóstico de quiebra. Empresas brasileñas. Flujo de caja operativo. *Logit*.

INTRODUCTION

The global financial crises, such as the subprime crisis in 2008 and the debt crisis in Europe in 2009, have caused the prediction of corporate bankruptcy to gain importance both in the academic field, with the development new analysis tools, and in the real world (FEJÉR-KIRÁLY, 2015).

Since 2014, Brazil has been going through a recession, considered the longest in the country's history (CODACE, 2017). The government's actions to solve the current financial crisis, such as interest rate reduction, tax exemption, credit incentives by state-owned banks and investment in infrastructure, have led the country to present, at first, growth above the global average. However, the sharp drop in commodity prices, the extension of the world crisis and the maintenance of government incentives have produced an increase in the country's public debt and thus the need for fiscal adjustment. Besides that, the increase in inflation generated a rise in interest rates that corroborates the recessive scenario. According to B3 (The Sao Paulo Stock Exchange) data, of the 32 bankruptcies of publicly traded companies (listed on B3) that occurred in the period from 2008 to 2019, 62.5% of them (20 bankruptcies) occurred between 2014 and 2017.

The literature on corporate bankruptcy generally uses economic and financial variables of companies (FEJÉR-KIRÁLY, 2015) to assess which of them have a higher probability of bankruptcy. According to Rodríguez-Masero and López-Manjón (2020), among the most commonly used financial indexes for bankruptcy prediction are those of profitability, indebtedness and economic-financial balance. Although the cash flow-to-debt ratio (OCF/TD) represents a company's ability to pay its debts, which is related to the company's financial situation and, consequently, can be a good bankruptcy predictor, this ratio is not commonly used in articles (RODRÍGUEZ-MASERO and LÓPEZ-MANJÓN, 2020).

In the literature, the inclusion of the operating cash flow (OCF) presented the highest discriminant power in Beaver's (1966) analysis and, in a study conducted in the United Kingdom, the inclusion of this index increased the model's correct prediction rate from 54% to 83% (ALMAMY, ASTON and NGWA, 2016). Also, Rodríguez-Masero and López-Manjón (2020) show the usefulness of the OCF to predict bankruptcy in medium-sized enterprises in Spain, whereas Alves, Mata and Nunes (2015), with Portuguese data, and LeMaux and Morin (2011), with U.S. data, conclude that cash flow statements have great predictive power for bankruptcy, as they show the ability that the firm must make new investments or reduce its indebtedness. Given that the literature worldwide has concluded that cash flow is relevant when predicting bankruptcy, this article aims to analyze the relevance of the cash flow-to-debt ratio (OCF/TD) index in predicting bankruptcy of Brazilian companies listed on B3 (The Sao Paulo Stock Exchange), showing that its inclusion in a forecasting method, with the most used indexes in Brazil, improves the quality of the classification.

With the purpose of assessing the prediction of bankruptcy of Brazilian public companies from 2008 to 2019, logistic regression models are estimated with the use of explanatory variables selected according to three proposals made in Brazil: Altman (1968); Sanvicente and Minardi (1998); Rocha (2017). Data were collected from all companies listed on B3 that declared bankruptcy in the period, and a sample 53 of publicly traded companies that did not go bankrupt in the period (control group) was selected to avoid selection bias when comparing the groups, matched by sector and total assets (size).

We conclude that the addition of the OCF/TD index was relevant to the model, in all proposals, at a 5% significance level, and with an increase in the area under the ROC curve when compared to models without the addition of this variable. As the OCF/TD index captures the ability of companies to pay their debts based on cash generation from their operations, this index showed a statistical difference between bankrupt and non-bankrupt companies, thus making the models that include this indicator able to predict the future financial status more accurately by estimating the probability of bankruptcy. Therefore, this study demonstrates that the use of operating cash flow is helpful for a company's own decision-making process when it comes to management purposes, as well as for financial institutions and businesses in credit granting services.

THEORETICAL FRAMEWORK

With the economic recession experienced in Brazil throughout 2016 and the increased cost of credit, bankruptcy filings rose by 13.5% when compared to the same period of the previous year. On the other hand, Chapter 11 filings and deferred compensation agreements, also in the year 2016, registered an increase of 53.4% compared to the same period of the previous year. In May 2016, the highest growth in 12 months of bankruptcy and chapter 11 filings in the historical series of the last seven years was recorded, being 19.8% and 71.7%, respectively (Serasa Experian).

Given this scenario, bankruptcy prediction models are an important tool to help reduce financial institutions' credit risk, since they allow banks to reject loans to companies considered, early in the process, insolvent and help them sustain the profitability of their appropriate lending practices. Moreover, by forecasting an organization's future financial situation, banks can offer better terms for the company to repay its debt and help restore financial equilibrium (SOUSA and OLIVEIRA, 2014).

The initial studies on prediction of corporate bankruptcy started to be published in the mid-1930s, focusing on univariate analysis, and it lasted until the 1960s (BEAVER, 1966). From then on, more robust models came into use, such as the multivariate discriminant analysis (FEJÉR-KIRÁLY, 2015; ALTMAN, 1968). In the 1980s, new studies began to evaluate the probability of bankruptcy through logit (OHLSON, 1980) and probit (ZMIJEWSKI, 1984) regression models. Some of the advantages of using regression models are their relative simplicity of interpretation and availability in most current software. In addition, the logit model has proven to be quite robust and reliable for this purpose (AZIZ and DAR, 2006).

The use of financial indicators in bankruptcy and financial distress prediction models has been proving important since the work of Beaver (1966), who examined the predictability of 14 financial ratios and concluded that by using the operating cash flow-to-debt ratio was sufficient to predict the financial condition of companies. Then, the Z-score model created by Altman (1968) was considered by many researchers, practitioners, and managers to be an accurate tool to predict corporate bankruptcy up to three years in advance.

Several other papers have been published over time using financial indicators and a summary of them is presented in Box 1. It is important to note that the models used present good accuracy, despite dealing with different samples and contexts. In Box 1 we have the main indicators used by studies and we note, as indicated by Rodríguez-Masero and López-Manjón (2020), that cash flow is not commonly used among these financial indicators.

BOX 1

Summary of academic articles concerning business bankruptcy

Reference	Sample	Period	Variables	Methodology	Accuracy
Beaver (1966)	79 bankrupt companies and 79 non-bankrupt companies matched by industry and company size	From 1954 to 1964	• 16 financial ratios focusing on: Cash Flow, Profitability, Debt and Available Assets collected one year prior to bankruptcy.	Univariate Analysis	87,00%
Altman (1968)	33 bankrupt companies and 33 non-bankrupt companies matched by industry and company size	From 1946 to 1965	• Current Capital / Total Assets; • Retained Earnings / Total Assets; • Earnings before interest and taxes (EBIT) / Total Assets; • Market value of Equity / Book value of total liabilities; • Sales / Total Assets.	Multiple Discriminant Analysis	95,00%
Kanitz (1974)	-	-	• Current Capital / Total Assets; • Retained Earnings / Total Assets; • Earnings before interest and taxes (EBIT) / Total Assets; • Market value of Equity / Book value of total liabilities; • Sales / Total Assets.	Multiple Discriminant Analysis	-
Altman, Haldeman and Narayanan (1977)	53 bankrupt companies and 58 non-bankrupt companies matched by industry and year	From 1969 to 1975	• Working Capital / Total Assets; • Retained Earnings / Total Assets; • Standard error of earnings before interest and taxes / Total assets (normalized); • log(earnings before interest and taxes / total interest payments); • Retained Earnings / Total Assets; • Common Equity / Total Assets; • log(Total Assets).	Multiple Discriminant Analysis	92,80%
Altman, Baidya and Dias (1979)	23 insolvent and 35 solvent companies	From 1975 to 1977	• Working Capital / Total Assets; • (Noncurrent liabilities - Capital Provided by Shareholders) / Total Assets; • (Earnings before interest and taxes + Interest) / Total Assets; • Noncurrent liabilities / Total liabilities; • Sales / Total Assets.	Multiple Discriminant Analysis	88,00%

Continue

Reference	Sample	Period	Variables	Methodology	Accuracy
Ohlson (1980)	105 bankrupt companies and 2,058 non-bankrupt companies	From 1970 to 1976	• Size = log (Total Assets / GNP); • Total Liabilities / Total Assets; • Working Capital / Total Assets; • 1 if liabilities > assets and 0 c.c; • Net Income / Total Assets; • Funds from operations / Total Liabilities; • 1 if NI < 0 in the last 2 years and 0 p.c.; (NIt - NIt-1)/(|NIt| + |NIt-1|).	Logistic Regression	96,12%
Zmijewski (1984)	81 bankrupt companies and 1,600 non-bankrupt companies	From 1972 to 1978	• Net Income / Total Assets; • Total Liabilities / Total Assets; • Current Assets / Current Liabilities.	Probit	98,30%
Sanvicente and Minardi (1998)	46 bankrupt companies and 46 non-bankrupt companies matched by industry sector	From 1986 to 1998	• (Current Assets - Total Liabilities) / Total Assets; • (Net Equity - Capital Stock) / Total Assets; • (Operating Income - Financial Expenses + Financial Income) / Total Assets; • Book Value of Equity / Book Value of Total Liabilities; • Earnings before interest and taxes (EBIT) / Financial Expenses.	Multiple Discriminant Analysis	80,20%
Almamy, Aston and Ngwa (2016)	90 bankrupt companies and 1,000 non-bankrupt companies	From 2000 to 2013	• Working Capital / Total Assets; • Retained Earnings / Total Assets; • Earnings before interest and taxes (EBIT) / Total Assets; • Market Value Equity / Book Value of Total Liabilities; • Sales / Total Assets; • Cash Flow from Operations / Total Liabilities.	Multiple Discriminant Analysis	82,90%
Rocha (2017)	113 insolvent companies and 87 solvent companies	From 2010 to 2015	• Working Capital / Total Assets; • log(Total Assets / IPCA); • (Total Assets - Total Liabilities) / Total Assets; • Net Revenue / receivables; • Retained earnings / Total Assets.	Logistic Regression	93,45%

Continue

Reference	Sample	Period	Variables	Methodology	Accuracy
Alaminos, Del Castillo and Fernández (2018)	220 bankrupt companies and 220 randomly chosen non-bankrupt companies. 70% was used as a training sample and 30% as a test sample	From 1990 to 2013	• Profits / Total Assets; • Current Assets / Current Liabilities; • Working Capital / Total Assets; • Retained Earnings / Total Assets; • Earnings before interest and taxes (EBIT) / Total Assets; • Sales / Total Assets; • (Current Assets + Cash Flow) / Current Liabilities; • Total Liabilities / Total Assets; • Current Assets / Total Assets; • Profit / Net worth.	Logistic Regression	94,13%
Liberman, Barbosa and Pires (2018)	37 bankrupt banks and 276 non-bankrupt banks	From 1995 to 2014	• Synthetic Basel Index; • Net Equity / Total Assets; • Net Income / Total Assets; • Net Income / Total Assets; Net Income / Total Assets; • Net Operating Income / Total Assets; • Net Assets / Total Assets; • Net Assets / (Total Assets - Net Equity); • log(Total Assets); • Among others.	Logistic Regression with panel data and Survival Analysis	-
Rodríguez-Masero and López-Manjón (2020)	71 Spanish medium-sized bankrupt companies and 71 non-bankrupt companies matched by sector and size	From 2015 to 2016	• Operating Revenue/Total Assets; • Total Liabilities/Total Assets; • Current Assets/Current Liabilities Operating Cash Flow/Total Debt.	Logistic Regression	77,48%
Bruscato, Melo and Venezuela	32 Brazilian bankrupt companies and 53 non-bankrupt companies matched by sector and size	From 2008 to 2019	• Working Capital / Total Assets; • Current Assets / Current Liabilities; • Operating Cash Flow / Total Debt; • Total Liabilities / Total Assets; • Net Equity / Total Liabilities; • Net Equity / Total Assets; • Net Revenue / Total Assets; • Earnings before interest and taxes (EBIT) / Total Assets; • Net Income / Total Assets; • Net Profit / Total Liabilities; • Retained Earnings / Total Assets; • log(Total Assets).	Logistic Regression	-

Source: Elaborated by the authors.

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As explained by Teles and Nagatsuka (2002), while on a cash basis revenues and expenses are recognized only upon receipt or payment, on an accrual basis all revenues and expenses are recorded when the taxable event occurs, regardless of having been received or paid. Therefore, it is understood that the ability to generate cash is a superior measure when compared to profit measures, which follow the accrual basis, to determine the ability to pay interest and debt, and thus to measure a company's liquidity.

The value of cash flow generated by operations consists of the financial value generated by activities directly linked to the company's operations, i.e., it excludes any cash receipts that have not been generated by the company's day-to-day activities. Examples of extraordinary receipts would be the sale of a non-operating asset or the receipt of a court-ordered indemnification. According to Braga and Marques (2001), the measure of operating cash flow divided by total debt reveals the number of years that, at the level of current cash flows, would be necessary to pay off the entire debt.

Silva, Sampaio and Gallucci Neto (2018) and Rezende et al. (2017) highlight that cash flow can indicate whether a company is in financial difficulty, which can be considered an antecedent of bankruptcy. Thus, it is to be expected that there is a relationship between cash flow and the probability of corporate bankruptcy. Throughout the world there are also studies evaluating and endorsing cash flow in bankruptcy prediction, so as to improve the accuracy of statistical models. See Gombola et al. (1987) for literature on the subject.

From the above, it is expected that the operating cash flow (OCF) is important to forecast the bankruptcies of Brazilian publicly traded companies, since it best represents liquidity, as a measurement of the company's inflows and outflows of operating resources, as evidenced in Zanolla, Gartner and Silva (2014). Some articles show that OCF brings information on the future financial conditions of companies, especially those regarding possible bankruptcy in such countries as the United Kingdom, The United States, Portugal and Spain (BEAVER, 1966; LEMAUX and MORIN, 2011; ALVES, MATA and NUNES, 2015; ALMAMY, ASTON and NGWA, 2016; RODRÍGUEZ-MASERO and LÓPEZ-MANJÓN, 2020).

Therefore, it is assumed that OCF will also bring improvement in bankruptcy prediction models for Brazilian public companies. The studies on the subject use several financial indicators, so we chose to use two studies, which use Brazilian data, by Sanvicente and Minardi (1998); Rocha (2017) and Altman (1968), as the latter is considered a seminal research in the field of bankruptcy prediction and is still widely used by professionals and scholars. The use of these publications is made only to guide the choice of the accounting variables that will be used in the model for later input of the OCF and verification of its contribution to the predictability of bankruptcies.

Almamy et al. (2016) apply Altman's Z-score model with a new variable, which is the ratio of operating cash flow and total debt. This new model was designated J-UK. Z-score correctly classified 54% of the companies and the J-UK model 82.9%.

Sanvicente and Minardi (1998) identify the most relevant accounting indexes to predict Chapter 11 of Brazilian companies. The statistical technique used was the Multiple Discriminant Analysis, which presented an overall hit rate of 79% and, according to the authors, this indicates that it has predictive power and can be applied to other samples, different from those of estimation.

Rocha (2017) replicated Ohlson's (1980) model for predicting bankruptcy of publicly traded companies in Brazil by using accounting variables one year in advance. Through the model, 93.45% of companies with accounting data of one year prior to bankruptcy were correctly classified.

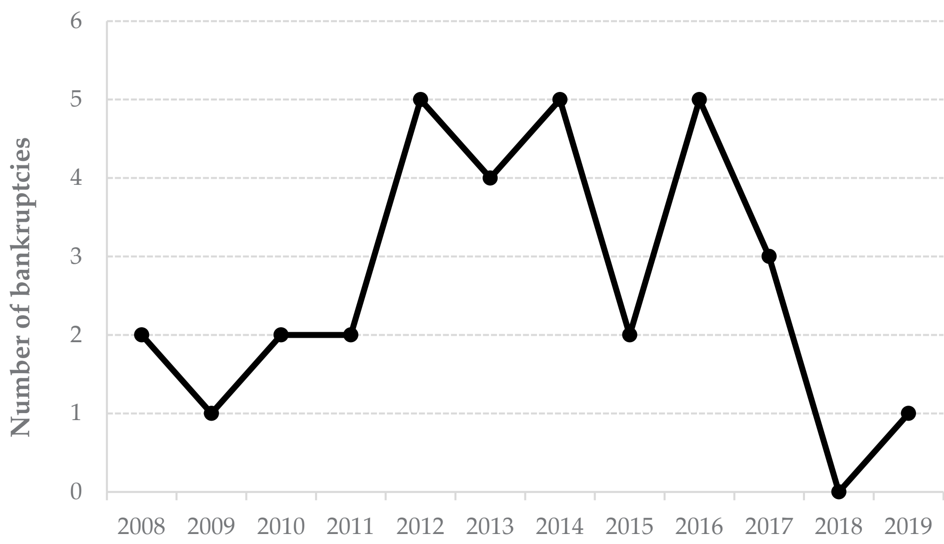
METHODOLOGY

Sample selection and data

This study used data from 32 Brazilian publicly traded companies (listed on B3), except financial institutions and state-owned enterprises, which went bankrupt in the period between 2008 and 2019. The accounting information of the companies was collected for one, two and three years before the companies went bankrupt, and the Economatica® software was used. Figure 1 illustrates the amount of bankruptcies over the years and it reveals that the highest incidence of corporate bankruptcies occurred between 2012 and 2017.

FIGURE 1

Historical distribution of the number of bankrupt companies



Source: Elaborated by the authors with information from B3.

To evaluate the relevance of operating cash flow to predict corporate bankruptcy, it is necessary to have a control group of companies, with the same profile, that did not go bankrupt during the period. Therefore, we selected a sample of 53 Brazilian publicly traded companies that did not go broke, pairing them by industry and size (measured by asset size). This type of paired sampling is common in studies of this type to reduce selection bias when comparing a small group (the occurrence of bankruptcies is small) with a much larger group (non-bankrupt companies), and the same procedure was used by Beaver (1966); Altman (1968); Sanvicente and Minardi (1998); and Rodríguez-Masero and López-Manjón (2020).

The pairing was conducted by using the nearest neighbor method, seeking to select, in general, two non-bankrupt companies closest to each bankrupt company. However, for the pairing to be properly performed, according to Stuart (2010), the standardized average difference of the distances between the bankrupt company and the non-bankrupt company (pair) should not exceed the limit of 0.25. Thus, in some cases, the pairing was made with only a single non-bankrupt company instead of two.

Description of variables and method

In this study, the nine financial variables most often cited in the literature were used as independent variables, divided into the following groups: Size, Liquidity, Indebtedness, Capitalization, Efficiency, and Profitability. A control variable describing the size of the company (in assets) was selected following Altman et al. (1977). The five variables used by Altman (1968) were selected, adapting Market Value of Equity/Book Value of Total Liabilities to Book Value of Equity/Book Value of Total Liabilities (SANVICENTE and MINARDI, 1998). In addition, the cash flow-to-debt ratio was collected due to the emphasis this variable had in the article by Beaver (1966) and Gombola et al. (1987) as the index with the greatest power to discriminate bankruptcy and its importance due to the objectives of this study. Another variable selected was inspired by the Zmijewski (1984), being a debt index (Debt/Asset ratio). Finally, a variable used by Liberman et al. (2018) was selected, representing capitalization (Equity-To-Asset ratio).

According to Liberman et al. (2018), these nine variables were divided according to the groups mentioned below:

- **Size:** Represented by the natural logarithm of Total Assets; it is being used as a control and seeks to measure the size of the institutions.
- **Liquidity:** It includes Working Capital to Total Assets ratio and cash flow-to-debt ratio. Since working capital is the difference between current assets and current liabilities, the first indicator responds to an expected effect when a company presents consistent operating losses and will have shrinking current assets in relation to total assets. The second indicator, on the other hand, is an index that measures the ability to pay the debt with the cash generated internally by the company.
- **Indebtedness:** Composed of Total Liabilities divided by Total Assets. Also known as debt/asset ratio, it is a risk indicator and it measures the percentage of third-party capital that the company has to fund corporate operations.
- **Capitalization:** the indicators in this group are related to the capital structure of the companies, measuring how much they are protected by their own capital in relation to their obligations with third parties, in the case of Net Equity divided by Total Liabilities, and Capitalization (Net Equity divided by Total Assets).
- **Efficiency:** represented by the indicator of Sales (or Net Revenue) divided by Total Assets, which measures the turnover of capital, that is, the ability to generate sales from the company's assets.
- **Profitability:** It includes the resources that measure the companies' profits in relation to the resources employed, these are: Profit before Interest and Taxes divided by Total Assets and Retained Earnings divided Total Assets. It is worth noting that this last index contemplates the company's age as an implicit variable, since a relatively young company will show a low ratio, as it has not had enough time to accumulate profit. This seems to make sense, given that the incidence of failure is higher in young enterprises.

Box 2 lists the variables to be used in the models, accompanied by their description, group, references of the main studies that used them, and the expected sign to predict the probability of bankruptcy. A negative sign indicates an expectation that an increase in the value of that variable will reduce the likelihood of company bankruptcy, while a positive sign indicates that the higher the indicator the higher the likelihood of company bankruptcy.

BOX 2

Independent (explanatory) variables

Group	Variable	Description	References	Impact
Size	**Log (Asset)**	Natural logarithm of Total Assets	Altman et al. (1977); Liberman et al. (2018)	(-)
Liquidity	**WC/TA**	Working Capital divided by Total Assets	Altman (1968); Beaver (1966); Kanitz (1974); Altman et al. (1977); Altman et al. (1979); Ohlson (1980); Almamy et al. (2016); Alaminos et al. (2018); Liberman et al. (2018)	(-)
	OCF/TD	Cash Flow-to-Debt Ratio	Beaver (1966); Almamy et al. (2016)	(-)
Indebtedness	**TL/TA**	Total Liabilities divided by Total Assets	Ohlson (1980); Zmijewski (1984); Alaminos et al. (2018)	(+)
Capitalization	**NE/TL**	Net Equity divided by Total Liabilities	Altman (1968); Kanitz (1974); Altman et al. (1979); Sanvicente and Minardi (1998); Almamy et al. (2015)	(-)
	NE/TA	Net Equity divided by Total Assets	Liberman et al. (2018)	(-)
Efficiency	**NR/TA**	Net Revenue divided by Total Assets	Altman (1968); Kanitz (1974); Altman et al. (1979); Almamy et al. (2015); Alaminos et al. (2018); Liberman et al. (2018)	(-)
Profitability	**EBIT/TA**	Profit before Interest and Taxes divided by Total Assets	Altman (1968); Kanitz (1974); Altman et al. (1977); Altman et al. (1979); Almamy et al. (2016); Alaminos et al. (2018)	(-)
	RE/TA	Retained Earnings divided Total Assets	Altman (1968); Kanitz (1974); Altman et al. (1977); Almamy et al. (2016); Rocha (2017); Alaminos et al. (2018)	(-)

Source: Elaborated by the authors.

The logit model with paired sample and cross section approach will be employed in this study (see Wooldridge, 2010), changing the possible explanatory variables, so as to improve the prediction of the probability of a company going bankrupt and following the proposal of Altman (1968); Sanvicente and Minardi (1998); and Rocha (2017).

RESULT ANALYSIS

Table 1 presents the descriptive statistics of the selected explanatory variables, separated by their status as Non-Bankrupt or Bankrupt (one to three years prior). Also, considering Non-Bankrupt versus Bankrupt companies, a t-test was performed to compare mean values of the explanatory variable in question assuming unequal variances and considering a significance level of 10%.

For the variable Log Assets, there was no evidence of differences between the means at a 10% significance level. This result was to be expected, given that the matching was done by sector and asset size.

The two variables of the Liquidity group showed signs of differences between the means for all the comparisons performed, with high significance (=1%), with the exception of the Working Capital to Total Assets variable in the comparison with up to two years whose difference is at a 5% significance. Both indicators of bankrupt companies presented, on average, lower values than those of non-bankrupt companies. It is important to note that cash flow presented the highest statistical significance in differentiating bankrupt and non-bankrupt companies.

The indebtedness of bankrupt companies (from 1 to 3 years before bankruptcy) is on average different from that of non-bankrupt ones (with a significance level of up to 6% overall). Descriptively, one notes that the indebtedness of companies one year prior to their bankruptcy, on average, almost doubles the indebtedness of non-bankrupt ones.

As for the capital structure indicators, they are considerably different (descriptively, lower) in companies up to two years before bankruptcy than in non-bankrupt companies, thus reinforcing that non-bankrupt companies are not protected by equity capital with regard to their third-party debts.

In the Efficiency group, the Net Revenue to Total Assets variable presented a significant difference, with a significance level of 5%, only when comparing average values of non-bankrupt companies with those of companies one year prior to bankruptcy. And finally, in the variables describing the company's profitability, we point out that there is an average difference between non-bankrupt and bankrupt companies (considering measurements made one year before bankruptcy), with a significance level of 1% and 10% for the variables EBIT/TA and RE/TA, respectively.

As previously explained, the main objective of this study is to evaluate whether the variable cash flow-to-debt ratio (OCF/TD) is relevant to better estimate the prediction of bankruptcy of Brazilian companies when it is added to the three models presented in the literature: Altman (1968); Sanvicente and Minardi (1998); and Rocha (2017). Furthermore, we intend to verify whether the addition of the OCF/TD variable improves the forecast of these same adjusted models.

Therefore, six bankruptcy prediction models were built: three based on articles (ALTMAN, 1968; SANVICENTE and MINARDI, 1998; ROCHA, 2017) and three added the variable cash flow-to-debt ratio, whose importance is widely discussed by Beaver (1966); Gombola et al. (1987); Almamy et al. (2016); and Rodríguez-Masero and López-Manjón (2020). Also, the OCF/TD variable shows relevant discrimination between bankrupt and non-bankrupt companies (from one to three years earlier), as discussed in Table 1.

TABLE 1

Descriptive statistics of the independent variables separating companies into Bankrupt from one to three years prior and Non-bankrupt with pairing

Group	Variable	Condition	Mean	Median	Min	Max	SD	p-Value
Size	Log(Asset)	Bankrupt 1 Yr.	5.889	5.657	4.373	11.187	1.280	0.3055
		Bankrupt 2 Yr.	5.950	5.783	4.407	11.884	1.398	0.4374
		Bankrupt 3 Yr.	6.073	5.842	4.342	14.193	1.765	0.7488
		Non-bankrupt	6.193	5.806	4.113	15.810	1.690	
Liquidity	WC/TA	Bankrupt 1 Yr.	-0.590	-0.255	-3.307	0.251	0.899	**0.0001**
		Bankrupt 2 Yr.	-0.580	-0.129	-9.104	0.338	1.663	**0.0194**
		Bankrupt 3 Yr.	-0.324	-0.095	-3.102	0.435	0.752	**0.0020**
		Non-bankrupt	0.148	0.145	-0.786	0.766	0.259	
	OCF/TD	Bankrupt 1 Yr.	-0.054	-0.036	-0.596	0.333	0.175	<0.0001
		Bankrupt 2 Yr.	-0.007	-0.017	-0.183	0.175	0.076	**<0.0001**
		Bankrupt 3 Yr.	0.049	0.033	-0.082	0.331	0.102	**<0.0001**
		Non-bankrupt	0.210	0.190	-0.214	1.308	0.215	
Indebtedness	TL/TA	Bankrupt 1 Yr.	1.443	0.964	0.136	4.720	1.056	**0.0008**
		Bankrupt 2 Yr.	1.438	0.852	0.133	10.089	1.810	**0.0343**
		Bankrupt 3 Yr.	1.150	0.819	0.075	6.375	1.138	**0.0558**
		Non-bankrupt	0.714	0.535	0.192	4.485	0.667	
Capitalization	NE/TL	Bankrupt 1 Yr.	0.126	0.037	-0.788	6.344	1.212	**0.0012**
		Bankrupt 2 Yr.	0.291	0.167	-0.901	6.518	1.260	**0.0101**
		Bankrupt 3 Yr.	0.706	0.220	-0.843	12.308	2.437	0.5921
		Non-bankrupt	0.953	0.802	-0.777	4.148	0.961	
	NE/TA	Bankrupt 1 Yr.	-0.446	0.036	-3.720	0.864	1.054	**0.0009**
		Bankrupt 2 Yr.	-0.442	0.142	-9.089	0.867	1.808	**0.0367**
		Bankrupt 3 Yr.	-0.156	0.180	-5.375	0.923	1.136	**0.0606**
		Non-bankrupt	0.271	0.429	-3.485	0.795	0.665	
Efficiency	NR/TA	Bankrupt 1 Yr.	0.458	0.341	0.001	1.326	0.365	**0.0238**
		Bankrupt 2 Yr.	0.687	0.528	0.000	3.565	0.679	0.8036
		Bankrupt 3 Yr.	0.629	0.508	0.000	2.067	0.460	0.8057
		Non-bankrupt	0.654	0.512	0.004	2.431	0.495	
Profitability	EBIT/TA	Bankrupt 1 Yr.	-0.116	-0.093	-0.994	0.503	0.241	**0.0002**
		Bankrupt 2 Yr.	-0.306	-0.009	-10.350	1.704	1.865	0.2662
		Bankrupt 3 Yr.	-0.021	-0.003	-0.342	0.119	0.106	0.0003
		Non-bankrupt	0.068	0.064	-0.253	0.484	0.110	
	RE/TA	Bankrupt 1 Yr.	-1.106	-0.242	-15.025	2.542	2.792	**0.0558**
		Bankrupt 2 Yr.	-0.628	-0.087	-4.559	0.176	1.034	**0.0151**
		Bankrupt 3 Yr.	-0.580	-0.080	-6.303	0.127	1.242	**0.0631**
		Non-bankrupt	-0.111	0.093	-3.950	0.578	0.841	

Note: P-value considering t-test for two independent samples (Bankrupt versus Non-bankrupt) assuming unequal variances. Bold p-value shows conclusion for different means between groups, considering significance level up to 10%.
Source: Elaborated by the authors.

Box 3 indicates which explanatory variables will be used in each model to be fitted with data from bankrupt and non-bankrupt firms jointly.

BOX 3

Explanatory variables used in each model fitted considering data from non-bankrupt and bankrupt firms from one to three years earlier jointly

Model via studies by:	Log (Asset)	WC/TA	OCF/TD	TL/TA	NE/TL	NE/TA	NR/TA	EBIT/TA	RE/TA
Altman (1968)	-	YES	Proposed in this article	-	YES	-	YES	YES	YES
Sanvicente and Minardi (1998)	-	-		YES	YES	YES	YES	YES	-
Rocha (2017)	YES	YES		-	-	YES	YES	-	YES

Source: Elaborated by the authors.

Table 2 presents the correlations between the independent variables and the intention is to analyze if the models that will be herein proposed consider variables without having high correlations, aiming to avoid a high degree of multicollinearity. Considering the models described in Box 3, it can be seen that the variables TL/TA and NE/TA are strongly and inversely correlated and both were used in the model of Sanvicente and Minardi (1998); the variables WC/TA and NE/TA have strong correlation and both were used in the model of Rocha (2017); and, finally, the variable cash flow-to-debt ratio (OCF/TD) presents the most moderate correlation (less than 0.70, in absolute value) with all other explanatory variables, and thus may be widely tested in the different models.

TABLE 2

Correlation matrix between the independent variables considering data from Non-bankrupt and Bankrupt companies one to three years earlier jointly

Group		Log (Ativo)	WC/TA	OCF/TD	TL/TA	NE/TL	NE/TA	NR/TA	EBIT/TA	RE/TA
Size	**Log (Asset)**	1								
Liquidity	**WC/TA**	0.07	1							
	OCF/TD	0.12	0.48	1						
Indebtedness	**TL/TA**	-0.06	-0.85	-0.44	1					
Capitalization	**NE/TL**	-0.03	0.52	0.56	-0.62	1				
	NE/TA	0.06	0.85	0.44	-0.99	0.62	1			

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Group		Log (Ativo)	WC/TA	OCF/TD	TL/TA	NE/TL	NE/TA	NR/TA	EBIT/TA	RE/TA
Efficiency	**NR/TA**	0.28	0.12	0.10	-0.11	-0.03	0.12	1		
Profitability	**EBIT/TA**	0.09	0.50	0.66	-0.45	0.31	0.45	0.12	1	
	RE/TA	0.21	0.48	0.29	-0.52	0.33	0.52	0.14	-0.01	1

Source: Elaborated by the authors.

Table 3 presents the results of six models estimated for a sample of bankrupt companies one year prior to bankruptcy, matched by sector and asset size pairing, with non-bankrupt companies. Tables 5 and 6 present the same models, but with data for bankrupt companies two and three years earlier, respectively. Before interpreting these tables, the following are the measures calculated to compare the performance of the fitted models.

It is commonly found in the literature the use of a 50% cutoff point, which defines that an estimated probability above 50% classifies the company as 'bankrupt' and, if not, it classifies it as 'non-bankrupt'. With these classifications to be obtained from the model with a 50% cutoff compared to the true classifications, three useful percentages are usually calculated for model performance analysis: accuracy - percentage of total model hits; sensitivity - percentage of true positives (for bankrupt companies, the percentage of hits is calculated); and specificity - percentage of true negatives (for non-bankrupt companies, percentage of hits is calculated).

Another widespread measure for performance analysis is the area under the ROC curve (Receiver Operating Characteristic), whose result can be interpreted as the probability that any given company will be correctly classified. An ROC curve is constructed by the ordered pairs (1-specificity, sensitivity), calculated by considering several cutoff point values between 0 and 1 under a particular estimated model. It is worth noting that if the ROC curve is the bisector, the area under this curve (under the bisector) will be equal to 0.50, and in this case the model does not allow to distinguish the groups well.

Also, as the objective of this study is to indicate a model for prediction, cross validation is important to evaluate the performance of each proposed model in its assertiveness of classification under a new set of data and hence the leave-one-out method (Stone, 1974) was chosen, in which one observation at a time is removed from the sample and the model is estimated without the removed observation, and then this estimated model is used to calculate the area under the ROC curve. This process is repeated for each of the sample observations.

By initially analyzing the results in Table 3, Altman's (1968) model with the addition of the cash flow-to-debt ratio variable causes the probability of a company's correct classification (area under the ROC curve) to increase by 1.87% when the OCF/TD variable is added to the model, increasing from 90.60% to 92.29%. Another positive point of note is that this variable proved to be relevant for predicting corporate bankruptcy at a 5% significance level. The other variable that also measures liquidity, Working Capital to Total Assets, also proved to be essential in the models with or without the presence of OCF/TD. However, the variable Earnings before Interest and Taxes to Total Assets (EBIT/TA) had its estimate significant at 5% only in the model without the presence of OCF/TD.

In the model of Sanvicente and Minardi (1998), the inclusion of OCF/TD increases the area under the ROC curve by 3.39%. Also, this variable is highly relevant to predict corporate bankruptcy at a 5% significance level. However, the Net Equity to Total Assets variable of debt also proved to be relevant only when there is the presence of OCF/TD in the model. There was no relevant variable for predicting corporate bankruptcy when the OCF/TD variable was not added to the model (at a 10% significance level).

The model of Rocha (2017) with the addition of the OCF/TD variable also shows an increase by 3.17% in the area under the ROC curve. Still, this variable is also relevant for the prediction of corporate bankruptcy at a 5% significance level. The variable Working Capital to Total Assets (WC/TA), which also measures liquidity, was relevant with or without the presence of OCF/TD in the model. However, the NE/TA variable had its estimate significant at 10% only in the model without the presence of OCF/TD.

Table 3 presents a descriptive analysis of the various areas under the ROC curve, calculated with the omission of each observation in the six fitted models. In general, these results show that, on average, the area under the ROC curve remains larger when the OCF/TD variable is present in the model. Considering Altman's (1968) model, the 5% quantile (92.02%) when the OCF/TD variable is added to the model is better (higher) than the 95% quantile (91.62%) calculated when this variable is not added to the model. Finally, another comparison that highlights a better performance of the fit when there is the presence of the cash flow-to-debt ratio variable is given when comparing that the smallest area under the ROC curve in the Altman model with the OCF/TD variable (91.92%) is larger than the 95% quantile of the area under the ROC curve in the Altman model without the variable in question (91.62%). The same interpretations occur when comparing the results of the models of Sanvicente and Minardi (1998) and Rocha (2017), in the contexts with and without the OCF/TD variable.

TABLE 3

Estimates from the logit model with data matched to bankrupt companies one year earlier

Group	Variables	Altman (1968)		Sanvicente and Minardi (1998)		Rocha (2017)	
		With OCF/TD	Without OCF/TD	With OCF/TD	Without OCF/TD	With OCF/TD	Without OCF/TD
Size	**Log (Asset)**					0.139 (0.280)	-0.246 (0.300)
Liquidity	**WC/TA**	-4.660** (2.032)	-4.415** (1.936)			-5.663** (2.180)	-6.823*** (1.774)
	OCF/TD	-6.818** (3.214)		-8.144** (2.896)		-7.589** (3.299)	
Indebtedness	**TL/TA**			17.852* (9.174)	20.621 (13.206)		
Capitalization	**NE/TL**	0.043 (0.360)	0.043 (0.360)	-0.722 (1.535)	-0.722 (1.535)		
	NE/TA			17.719* (9.385)	20.374 (13.672)	1.085 (0.699)	0.843* (0.496)

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Group	Variables	Altman (1968)		Sanvicente and Minardi (1998)		Rocha (2017)	
		With OCF/TD	Without OCF/TD	With OCF/TD	Without OCF/TD	With OCF/TD	Without OCF/TD
Efficiency	**NR/TA**	-0.649	-0.639	-0.888	-1.091	-0.827	-0.693
		(1.493)	(1.287)	(0.954)	(0.789)	(1.497)	(1.127)
Profitability	**EBIT/TA**	-0.679	-5.817**	-2.734	-6.540		
		(3.915)	(2.610)	(2.702)	(4.027)		
	RE/TA	0.306	0.097			0.190	0.243
		(0.259)	(0.225)			(0.179)	(0.185)
	Constant	-0.363	-0.795	-17.288*	-20.264	-1.119	0.546
		(0.745)	(0.702)	(9.036)	(13.206)	(1.405)	(1.746)
Including all observations	**Log likelihood**	-30.906	-33.508	-35.362	-39.640	-29.951	-34.919
	***Pseudo* R^2**	0.485	0.442	0.411	0.339	0.501	0.418
	Area on the ROC curve	92.29%	90.60%	89.35%	86.42%	92.49%	89.65%
	% Variation	1.87%		3.39%		3.17%	
Descriptive Area under the ROC curve (areas obtained with each 1 observation omitted from the model)	**Mean**	92.39%	90.63%	89.47%	86.59%	92.52%	89.6%
	Standard Deviation	0.46%	0.49%	0.75%	0.99%	0.39%	0.38%
	Min	91.92%	90.17%	88.99%	85.95%	92.07%	88.99%
	Max	95.00%	93.46%	95.27%	94.54%	94.34%	91.3%
	Quantile 5%	92.02%	90.27%	88.99%	86.00%	92.18%	89.28%
	Quantile 50%	92.22%	90.51%	89.24%	86.41%	92.37%	89.49%
	Quantile 95%	93.29%	91.62%	90.38%	87.36%	93.31%	90.58%

Note: Robust standard error in parentheses, *p<0.1, **p<0.05, ***p<0.01.
Source: Elaborated by the authors.

For the models described in Table 4, the percentages of the area under the ROC curve obtained in the fits with the inclusion of the cash flow-to-debt ratio variable were higher when compared within their respective percentages.

TABLE 4

Estimates from the logit model with data matched to bankrupt companies 2 years earlier

Group	Variables	Altman (1968)		Sanvicente and Minardi (1998)		Rocha (2017)	
		With OCF/TD	Without OCF/TD	With OCF/TD	Without OCF/TD	With OCF/TD	Without OCF/TD
Size	**Log (Asset)**					0.095 (0.181)	-0.261 (0.251)
Liquidity	**WC/TA**	-3.797* (2.020)	-4.654** (1.874)			-3.905** (1.905)	-4.819*** (1.434)
	OCF/TD	-14.855** (5.246)		-14.193** (5.108)		-15.122** (6.335)	
Indebtedness	**TL/TA**			15.48** (6.704)	20.279* (10.545)		
Capitalization	**NE/TL**	0.006 (0.433)	0.006 (0.433)	-0.554 (1.146)	-0.554 (1.146)		
	NE/TA			15.579** (6.742)	19.715* (11.144)	-0.146 (1.061)	1.028 (1.199)
Efficiency	**NR/TA**	-0.110 (1.155)	-0.144 (0.832)	0.021 (0.834)	-0.432 (0.527)	-0.039 (0.901)	-0.262 (0.758)
Profitability	**EBIT/TA**	0.604 (1.683)	-1.567 (1.493)	-0.308 (0.262)	-1.092 (1.91)		
	RE/TA	1.220 (0.7600)	0.410 (0.481)			1.287 (1.242)	-0.21 (1.136)
	Constant	0.608 (0.607)	-0.633 (0.565)	-14.956** (6.565)	-20.174* (10.545)	0.020 (0.985)	0.668 (1.66)
Including all observations	**Log likelihood**	-32.112	-44.099	-35.535	-49.530	-32.101	-43.780
	***Pseudo* R²**	0.454	0.250	0.396	0.158	0.454	0.256
	Area on the ROC curve	92.54%	81.83%	90.32%	81.88%	92.90%	82.45%
	% Variation	13.09%		10.31%		12.67%	
Descriptive Area under the ROC curve (areas obtained with each 1 observation omitted from the model)	**Mean**	92.46%	81.11%	90.36%	81.89%	92.91%	82.48%
	Standard Deviation	1.28%	4.17%	0.44%	0.65%	0.34%	0.59%
	Min	80.49%	55.2%	89.93%	80.92%	92.54%	81.4%
	Max	94.40%	86.35%	93.02%	85.45%	95.09%	85.07%
	Quantile 5%	92.27%	78.87%	90.03%	81.24%	92.64%	81.82%
	Quantile 50%	92.42%	81.87%	90.23%	81.72%	92.79%	82.32%
	Quantile 95%	93.19%	83.07%	91.18%	83.34%	93.48%	83.38%

Note: Robust standard error in parentheses, *p<0.1, **p<0.05, ***p<0.01.
Source: Elaborated by the authors.

In Table 5, the percentages of the area under the ROC curve adjusting the models with bankrupt companies three years earlier are the lowest when compared to the respective percentages obtained in the adjustments with bankrupt companies one year and two years earlier, even though the percentages of variation in the area under the ROC curve have increased between 3.85% and 10.47%, due to the addition of the OCF/TD variable in the adjustments of the three proposals.

TABLE 5

Estimates from the logit model with data matched to bankrupt companies 3 years earlier

Group	Variables	Altman (1968)		Sanvicente and Minardi (1998)		Rocha (2017)	
		With OCF/TD	Without OCF/TD	With OCF/TD	Without OCF/TD	With OCF/TD	Without OCF/TD
Size	Log (Asset)					-0.022 (0.158)	-0.04 (0.144)
Liquidity	WC/TA	-3.411** (1.390)	-3.747** (1.372)			-3.17** (1.215)	-3.824*** (1.123)
	OCF/TD	-6.808** (3.395)		-8.001** (3.338)		-7.391** (3.719)	
Indebtedness	TL/TA			11.602 (7.543)	9.752 (7.56)		
Capitalization	NE/TL	0.170 (0.155)	0.170 (0.155)	0.019 (0.179)	0.019 (0.179)		
	NE/TA			11.514 (7.527)	9.381 (7.525)	0.527 (1.238)	0.674 (1.231)
Efficiency	NR/TA	-0.090 (0.932)	-0.225 (1.033)	0.039 (0.668)	-0.21 (0.637)	-0.154 (0.904)	-0.444 (0.706)
Profitability	EBIT/TA	-1.178 (5.857)	-7.581 (6.806)	-0.846 (4.237)	-7.555** (3.612)		
	RE/TA	0.894 (0.627)	0.821 (0.628)			0.52 (1.205)	0.01 (1.238)
	Constante	0.032 (0.534)	-0.503 (0.496)	-11.491 (7.420)	-10.179 (7.560)	0.195 (1.038)	-0.477 (1.021)

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Group	Variables	Altman (1968)		Sanvicente and Minardi (1998)		Rocha (2017)	
		With OCF/TD	Without OCF/TD	With OCF/TD	Without OCF/TD	With OCF/TD	Without OCF/TD
Including all observations	Log likelihood	-40.830	-43.553	-44.013	-48.322	-41.248	-46.192
	Pseudo R^2	0.259	0.210	0.201	0.123	0.251	0.162
	Area on the ROC curve	83.70%	80.60%	80.54%	76.52%	83.07%	75.20%
	% Variation	3.85%		5.25%		10.47%	
Descriptive Area under the ROC curve (areas obtained with each 1 observation omitted from the model)	Mean	83.65%	80.57%	80.63%	76.68%	83.11%	75.21%
	Standard Deviation	0.58%	0.59%	0.61%	0.97%	0.59%	0.63%
	Min	82.57%	79.52%	79.46%	74.27%	82.21%	73.67%
	Max	86.60%	82.93%	83.1%	81.97%	85.61%	77.25%
	Quantile 5%	83.02%	79.74%	79.92%	75.82%	82.62%	74.32%
	Quantile 50%	83.52%	80.48%	80.36%	76.52%	82.87%	75.12%
	Quantile 95%	84.63%	81.56%	81.80%	77.96%	84.22%	76.47%

Note: Robust standard error in parentheses, *p<0.1, **p<0.05, ***p<0.01
Source: Elaborated by the authors.

An important check to be made on the results of all models fitted in the last three tables (Tables 3 to 5), is to analyze whether the sign of the significant coefficients in these models behaved as expected (see Table 1). Most variables behaved as expected, except for Net Equity to Total Assets (NE/TA), which was estimated with a positive sign (significant at 10%) whereas a negative one was expected, i.e., increasing the value of this variable was expected to reduce the probability of the company going bankrupt. In the model of Sanvicente and Minardi (1998), this certainly occurred due to the almost perfect inverse correlation of this variable with TL/TA, also relevant to the model. In Rocha's (2017) model, on the other hand, there is a strong correlation between NE/TA and WC/TA, which is highly relevant to the model.

CONCLUSION

In order to better predict the bankruptcy of Brazilian public companies, the variable cash flow-to-debt ratio (OCF/TD) was added to models containing explanatory variables under the proposal of three different papers: Altman (1968); Sanvicente and Minardi (1998); and Rocha (2017). Additionally, we sought to study the performance in predicting bankruptcy considering logit regression models with a cross section approach and performing cross validation by using the leave-one-out method.

Considering companies bankrupt two years earlier (see Table 4), the models adjusted with the presence of OCF/TD presented the highest percentages of the area under the ROC curve (92.54%, 90.32% and 92.90%), when compared to these measures obtained for bankrupt companies one year earlier (92.29%, 89.35% and 92.49%, see Table 3) and when compared to these measures obtained in the adjustments for companies three years earlier (83.70%, 80.54% and 83.07%, see Table 5). These values obtained for the area under the ROC curve are considered excellent (HOSMER JUNIOR, LEMESHOW and STURDIVANT, 2013) for predicting the bankruptcy or non-bankruptcy condition of a company according to the relevant variables in each model.

Moreover, in each proposition discussed in Table 4, the relevant variables are exactly the same when comparing the adjustments with and without the OCF/TD variable, allowing us to understand that the improvement in model performance with OCF/TD is a consequence of its inclusion. This conclusion can be made only for the models adjusted with data from bankrupt companies two years earlier.

Overall, the area under the ROC curve was larger in all models where OCF/TD was added. In the leave-one-out cross-validation, the descriptive analysis obtained with the calculated values for the area under the ROC curve when omitting each observation from the model shows that the smallest area for the models with OCF/TD is larger than the 95% quantile of these areas for the models without OCF/TD. This occurs for all three models we ran in this study, showing that the presence of OCF/TD provides higher probabilities of correctly classifying any given company.

An important limitation on this study was the sample size of bankrupt companies. Despite using data from all publicly traded companies that went bankrupt from 2008 to 2019, we only have 32 bankruptcies, which compromises the estimation of the models. For future research, it is worth considering longer periods, since there was a reduced amount of Brazilian public companies that went bankrupt with accounting data available for consultation.

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