Insolvency and Corporate Governance: A Forecasting Model for Brazilian Firms

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Abstract

This research aims to answer if the usage of corporate governance mechanisms by companies in the Brazilian market can help them avoid insolvency. To achieve such goal, this paper proposes an insolvency prediction model, which is based on a logistic regression that uses a dummy variable pointing whether the firm belongs or not to the categories Novo Mercado (New Market) or Nível 2 (Level 2). Besides the aforementioned variable, accounting ratios previously considered relevant in the prediction of insolvency by other researches regarding the Brazilian market are included in the model as well. The sample used in this paper includes the companies listed at BM&FBOVESPA in the period 2001-2013. However, it does not include financial institutions, companies with unavailable information, and firms whose shares were not traded in BM&FBOVESPA during the period. The model estimations presented statistically significant evidences that firms with better corporate governance practices have a lower probability of being in an insolvency situation. This research also used financial ratios as control variables to the model and found evidences, regarding their relation with insolvency, similar to other previous studies present in the literature.

Keywords

Insolvency prediction; corporate governance; accounting ratios; logistic regression.

1. Introduction

Since early 2000s, prominent companies – such as Enron, WorldCom and Lehman Brothers – were revealed as involved in huge accounting scandals that shocked investors. This increased the sense of necessity for further research and improvement in both ethics and governance issues.

As stated by Daily, Dalton and Cannella Jr (2003), governance deals with the many uses to which organizational resources are deployed and with the answer to the divergences of the many stakeholders of an organization. In accordance with the aforementioned, this paper intends to go further on governance issues, as it aims to answer if the usage of corporate governance mechanisms by companies in the Brazilian market can help them avoid insolvency. To assist in solving this issue, an insolvency prediction model based on corporate governance measures will be used here. According to Ross, Westerfield and Jaffe (2013), an insolvency situation could indicate an even more serious scenario is yet to come, since insolvency could work as the first step on a firm's path to a formal process of bankruptcy.

Due to Brazil's current situation, it might be a very suitable time to study the combination of corporate governance and corporate insolvency. The country's situation and the literature's gap contribute to show the importance of a bankruptcy prediction model for the Brazilian market.

1.1 Research Context and Relevance

The former Bolsa de Valores de São Paulo (BOVESPA) aimed to create an environment that incites both the investors' interest and the companies' value. With that in mind, BOVESPA created, in 2000, four different categories in which its listed companies were classified according to their corporate governance practices. The new categories were *Novo Mercado* (New Market), *Nível 2* (Level 2), *Nível 1* (Level 1) and *Tradicional* (Traditional). Each of these categories demands a different level of commitment on information disclosure and ownership structure rules. The former's objective was to facilitate following up and auditing companies, whereas ownership structure rules target a better balance between shareholders' rights, regardless of whether they have the companies' control or not.

As stated by BM&FBOVESPA (2009), the higher information quality provided by the companies and the increase of shareholder's rights enable a lower level of uncertainties in the investment's process of valuation. According to the same publication, less uncertainty represents a lower risk in the investment and therefore a lower cost of capital. Consequently, it would trigger a better pricing of the shares and stimulate more companies going public as another way to finance themselves. Braga-Alves and Shastri (2011) analyzed if corporate governance practices are significantly related to firm value and operating performance. They found a robust positive relation between their index and Tobin's q, a measure of firm value.

The results of these researches could lead one to think this market seems to favor companies that are more concerned with their corporate governance practices and they seem to perform better. However, can good corporate governance practices help avoid corporate insolvency?

1.2 Research Question and Objective

Prediction models of financial distress and its possible consequences (such as insolvency or bankruptcy) have been in the literature for at least half a century (ALTMAN, 1968; BAUER; AGARWAL, 2014; BEAVER, 1966; CHARITOU; NEOPHYTOU; CHARALAMBOUS, 2004; COATS; FANT, 1993; OHLSON, 1980; REISZ; PERLICH, 2007). Corporate governance has been studied as an important aspect to understand the risk of bankruptcy or insolvency. Yet, financial ratios or market-based measures have been dominant in most of the researches regarding bankruptcy and financial distress prediction models (AZIZ; DAR, 2006).

Studies that analyze the effect of corporate governance attributes on bankruptcy prediction often do not use simultaneously accounting ratios and market-based variables. Nevertheless, Darrat *et al.* (2014) published a notable exception in which they use data referring to American firms. Even though many studies – including Daily and Dalton (1994), Darrat *et al.* (2014); Elloumi and Gueyié (2001), Lee and Yeh (2004), Platt and Platt (2012) and Wilson and Altanlar (2009) – have considered corporate governance structures while studying bankruptcy, insolvency and financial distress, few use Brazilian data. The findings of those researches cannot be simply generalized to other nations, as they have different economic and regulatory environments, distinct size of capital markets, cultural differences and unequal efficiency of governance mechanisms. Thus, a model for the effect of corporate governance on situations of financial distress should be separately examined in each country, and the important factors investigated.

Business failure, financial distress, insolvency and bankruptcy are not equal and their consequences reach different levels for stakeholders. However, a notable number of authors use those terms interchangeably when describing their models. For example, even though they use "insolvency prediction model" in the title of their paper, Chung, Tan and Holdsworth

(2008) use failure as the dependent variable for their model. Moreover, they define "failure" in the page 20 of their paper as "a registered company which is insolvent, under receivership or has been liquidated". That is to say, they do not use a single exact outlining within their study. The insolvency concept used in this paper shall follow the description included in the literature review chapter.

This research aims to answer if the usage of corporate governance mechanisms in the Brazilian market can help avoid firms' insolvency. To support that, this research will use an insolvency prediction model, which will more detailed in a forthcoming chapter of this paper. Others researches have shown that financial ratios and capital market data can be used to forecast corporate insolvency in this market – including Gimenes and Uribe-Opazo (2001), Martins and Galli (2007), Minussi, Damacena and Ness Jr. (2002) and Teixeira (2014). Yet, there is a gap of examination showing the effects of also considering corporate governance attributes to insolvency prediction models as using Brazilian evidence.

2. Literature Review

This chapter is to make clear what the perspective of the concept of insolvency used in this paper is. This chapter also describes corporate governance concepts and their consequences for firm value and performance. Last, but not least, it discusses existing insolvency prediction models.

2.1 Insolvency

Insolvency may be mistook by financial distress due to some similarities in their definitions. Altman and Hotchkiss (2005) state that technical insolvency, for example, exists when the firm's is unable to meet its current obligations, which would mean a lack of liquidity. Indeed this would be a very similar definition to Ross, Westerfield and Jaffe's. (2013) definition of financial distress (as specified above). Nevertheless, those authors use less conflicting classifications as they go deeper on the theme. Altman and Hotchkiss (2005) claim that insolvency, in a bankruptcy sense, is a more definitive situation, rather than a temporary condition. In this scenario, a firm's total liabilities exceed a fair valuation of its total assets, making the firm's real net worth negative. Ross, Westerfield and Jaffe (2013) use two classifications of insolvency: stock-based insolvency and flow-based insolvency. The latter was already described in this paper, whereas the former is claimed by the authors to occur when the firm has a negative net worth in a way that its assets' value is less than the value of its debts.

In order to use a more feasible measure to identify insolvency, some authors consider those firms with negative equity as insolvent (BRAGA; FULLY BRESSAN; COLOSIMO; BRESSAN, 2006; BREWER; MONDSCHEAN, 1992). In accordance with the stock-based perspective of insolvency, Ross, Westerfield and Jaffe (2013) argue this situation would represent that the value of the firm's debt is bigger than the value of its assets.

This paper will use negative equity as a proxy for insolvency, following the aforementioned authors.

2.2 Corporate distress prediction models

Appiah, Chizema and Arthur (2015) highlight in their systematic literature review that authors used bankruptcy, liquidation, insolvency, financial distress and dissolution as synonyms for corporate failure. This was reinforced by Bellovary, Giacomino and Akers' (2007) literature review on bankruptcy, in which they include and compare studies that used words such as failure, financial distress and bankruptcy interchangeably, as if they had the same purpose of research. The confusion can also happen within a single paper and is noted in Chung, Tan and Holdsworth (2008), as described in the introduction of this paper. In this light, this section describes existing prediction models for companies in distress situations, which include insolvency, financial distress, failure or bankruptcy. Moreover, it is important to emphasize that Appiah, Chizema and Arthur's (2015) literature review, for example, includes studies that use these many definitions for corporate distress, including, then, corporate distress prediction models that use other concepts than insolvency.

If companies could take a glance into the future, they probably could take a big advantage against their competitors and ensure their own survival. Even though we cannot be certain of everything happening in the future, an effort has been made to, at least, understand the odds of one's business continuity.

According to Bellovary, Giacomino and Akers (2007), the initial studies using ratio analysis for bankruptcy prediction focused on individual ratios (univariate). The authors defined those as important groundwork for multivariate studies. For instance, Altman (1968) used that foundation to propose a five-factor multivariate discriminant model, which became very popular, as literature suggests.

Since then, many models for bankruptcy prediction have been created and they mainly use the following methods: multivariate discriminant analysis (MDA), logit analysis, probit analysis and neural networks. As stated by Aziz and Dar (2006), a MDA model is a linear combination of specific discriminatory variables that will result in a score. This bankruptcy score is then used to classify firms into non-bankrupt and bankrupt, as per their individual characteristic. Logit analysis and probit analysis consider the probability that the firm will go bankrupt as a dichotomous dependent variable. The latter requires non-linear estimation, which the former does not (BELLOVARY; GIACOMINO; AKERS, 2007). Neural networks use an approach similar to brain process to perform classification tasks. Each "neuron" is a node with weighted interconnections, which are structured in layers. Each node in the input layer will receive input signals – information about firms, in the bankruptcy prediction context – from different source objects that will be transformed into a single output signal. This output signal will either be accepted as a classification decision or re-transmitted as an input signal to other nodes (it might include itself). This procedure continues until a classification decision is attained and it satisfies the pre-specific criteria (AZIZ; DAR, 2006).

Along with the method, an important aspect to take notice is the number of factors. Bellovary, Giacomino and Akers' (2007) findings suggest that having a larger number of factors in the model does not ensure its accuracy is higher. They observe that models with only two factors could be as precise as a 21 factor model.

Besides the number of factors, other elements should also be taken into account when considering a corporate distress prediction model. After analyzing 83 selected studies on bankruptcy prediction based on a systematic literature review, Appiah, Chizema and Arthur (2015) laud the results in studies using one-year financial data prior to failure. Yet, the results from these models were not as good as when utilizing data 2-5 years prior to failure, according to them.

Concluding their study, the authors agreed they could repeat the inference of Charitou, Neophytou and Charalambous (2004), which criticize that many bankruptcy prediction researches were not based on an economic theory in choosing the variables for distinguishing between failing and non-failing firms. Appiah, Chizema and Arthur (2015) continue their conclusion suggesting the link between corporate failure and theoretical arguments should be considered in future studies. Next, they propose that using corporate governance lens to theoretical arguments may contribute for a better understanding in the corporate failure process.

Although some studies targeted to clarify the impact of corporate governance elements on bankruptcy (Daily and Dalton (1994) and Fich and Slezak (2008), among others), few of them used data from the Brazilian market. For instance, Appiah, Chizema and Arthur's (2015) systematic literature review had its final selected studies originated from 11 countries, with 53% of the studies utilizing dataset from US and only 1% from Brazil.

Most of the insolvency prediction researches based on the Brazilian market do not use any corporate governance variables. On the other hand, the literature offers many studies based on Brazilian evidence relating corporate governance attributes with performance and firm's value. This could be the closest to bankruptcy, since one thing can lead to the other.

In 1979, one of the first Brazilian papers on the theme was published by Altman, Baidya and Dias. They utilized a sample of 58 firms and the MDA in order to identify companies that would be in financial distress or not. Only financial measures were used in this study – all of them were calculated from firms' balance sheet. The authors posited their predictions would be 88% precise for the data regarding 1-year prior to the distress recognition and 78% correct for the data that would forfeit three years ahead.

In 2003, Castro Júnior used Brazilian companies in insolvency prediction models that were based on three different statistics techniques: discriminant analysis, logistic regression and neural networks. His goal was to compare them in terms of predictive capabilities. The author's results confirmed a considerable advantage for the neural network models, since its accuracy reached at least 90% among the three built models in his research. In order to estimate those models, Castro Júnior used different mixes of variables of distinct types. Those types could be classified in capital structure, liquidity indicators, profitability variables and inventory related variables. None of the variables used in Castro Junior's study was related to corporate governance either.

3. Methodology

This chapter describes the methodology used in this paper, including the data gathering process, its treatment and application to the model. A short review on the logit function and regression are done as well, since they are used to produce the insolvency prediction model.

3.1 Logit function and regression

The methodology used in this paper is quantitative. The proposed research uses a logit model to express the probability of failure of a firm as a dichotomous dependent variable that is a function of a vector of explanatory variables. However, the dichotomous dependent variable, as a logit model assumes, is the logarithm of the odds (probability) that an event (fail or not) will occur. Hence, we can see a logistic regression as a mathematical approach usually employed to explain the relationship of several independent variables to a dichotomous dependent variable (KLEINBAUM; KLEIN, 2010).

Thus, the distribution used shall be a logistic cumulative distribution function. An application of it would represent that a result of 0.5 would mean equals chances of the company being insolvent or not. This research suggests an insolvency prediction model based on a dummy variable for the firm's level of corporate governance, as well as financial and accounting ratios.

3.2 Choice of variables

Using Brazilian market (BM&FBOVESPA) data, Stüpp (2015) compared the insolvency prediction power of 29 of the main financial and accounting ratios used in the literature. It included measures of liquidity, indebtedness, capital structure, average periods and profitability. One of his paper's goals, according to the author, was to identify the most relevant independent variables for the insolvency prediction process. After taking into account MDA and logistic analysis, the writer claims the most significant variables, in decreasing order, were: total liabilities/total assets, return on equity, current ratio, EBIT/net debt, non-current assets/equity, debt-equity ratio, debt composition, cash conversion cycle, acid-test ratio and asset turnover.

To reach this conclusion, the author used two different approaches: first, he used all of the 29 variables and afterwards he used the stepwise method (selecting the variables with the greatest classification capacity).

As this paper is based on companies listed on the BM&FBOVESPA exchange, it uses the categories of corporate governance created by this stock exchange. Those categories take into account information disclosure and ownership structure rules, as well as other board composition requirements that go beyond the Brazilian law demands. The four main categories – *Novo Mercado* (New Market), *Nível 2* (Level 2), *Nível 1* (Level 1) and *Tradicional* (Traditional) – were explained in the introduction of this paper. This research uses a dummy independent variable marking 1 if the company is either classified as Novo Mercado or Nível 2, or 0 if the firm is not in either one of these two categories. As companies in these two categories are theoretically the ones with the best governance practices, this could be an interesting criterion to represent the effect of corporate governance practices.

Accordingly, the corporate governance level dummy and those ten variables from Stüpp (2015) – used as control variables – are the variables to be used in the model. A similar one testing the insolvency prediction power of governance mechanisms has not been described for the Brazilian market in the literature.

As for the dependent variable, this paper considers firms as insolvent when they present a negative equity, following Braga *et al.* (2006) and Brewer and Mondschean (1992). This definition of insolvency should be a more feasible measure to identify insolvency in the data set. Hence, as a logistic regression demands for its dependent variable, a dummy will be set as 1 for companies with negative equity, whereas it will be set as 0 in any distinct scenario.

3.3 Data Gathering

In order to have a more detailed access to information, this research includes only data from companies that have been listed in BM&FBOVESPA from 2001 to 2013. Economática's database was the chosen source of financial and accounting information. Moreover, firms' classification of corporate governance was obtained through BM&FBOVESPA's website. Since the exchange started structuring its process of classifying companies in governance levels only in the year 2000, data collection starts in the following year, 2001.

Moreover, the sample used in this paper does not include financial institutions, companies with unavailable information, and firms whose shares were not traded in BM&FBOVESPA during the period. This resulted in an observation of 527 firms through 13 years, that is to say, 6,851 firm-year observations per variable. However, because the database had some missing information and those observations had to be disregarded; those data shall compose an unbalanced panel with a final number of 3,934 firm-year observations per variable.

3.4 Sample assessment

The software used to generate the logistic model, as well all the other statistical calculations was Eviews. The software presented that three independent variables of the logistic model (Total liabilities/total assets, Non-current assets/Equity and Debt-Equity Ratio) had their capacity to explain firms' insolvency restricted due to lack of variance within the employed context of maximum likelihood. This is suggested by the fact that those three regressors had each a separating value from which all their other observations, above or below it, were linked to the same result in the dependent variable (insolvent or solvent). Thus, those variables were excluded from the model because of this lack of variance.

According to Brooks (2014), when two explanatory variables are presented as having a very high correlation, we are facing a multicollinearity situation and it should be avoided. Hence, in order to check the presence of multicollinearity in the proposed model, the correlation between the eight explanatory variables (first round) are tested using the software Eviews. The results shown in Table 2 exhibit a high correlation between the ROE and Asset Turnover explanatory variables. Thus, the ROE variable is excluded and the correlation between the remaining variables in the model is retested (second round). The results are presented in Table 3 show the model is now set free from multicollinearity problems.

Table 1: Correlation coefficients (first round)

	CG Dummy	Return on Equity	Current Ratio	EBIT/Net Debt	Debt Composition	Cash Conversion Cycle	Acid-test Ratio	Asset Turnover
Corporate Governance	1.000							
Return on Equity	-0.006	1.000						
Current Ratio	0.094	0.430	1.000					
EBIT/Net Debt	0.001	-0.146	-0.059	1.000				
Debt Composition	-0.054	0.036	-0.002	0.000	1.000			
Cash Conversion Cycle	-0.008	0.000	0.000	0.102	-0.035	1.000		
Acid-test Ratio	0.053	0.568	0.775	-0.085	0.294	-0.004	1.000	
Asset Turnover	-0.010	0.984	0.434	-0.150	0.042	-0.001	0.574	1.000

Source: Created by the author

Table 2: Correlation coefficients (second round)

	CG Dummy	Current Ratio	EBIT/Net Debt	Debt Composition	Cash Conversion Cycle	Acid-test Ratio	Asset Turnover
Corporate Governance	1.000						
Current Ratio	0.094	1.000					
EBIT/Net Debt	0.001	-0.059	1.000				
Debt Composition	-0.054	-0.002	0.000	1.000			
Cash Conversion Cycle	-0.008	0.000	0.102	-0.035	1.000		
Acid-test Ratio	0.053	0.775	-0.085	0.294	-0.004	1.000	
Asset Turnover	-0.010	0.434	-0.150	0.042	-0.001	0.574	1.000

Source: Created by the author

3.4.1 Model Development

In order to avoid problems with the heteroscedasticity of the standard error estimates, the Huber/White estimator (HUBER, 1967; WHITE, 1982) was employed during the regression estimation.

The logistic regression achieved its maximum likelihood, through quadratic hill climbing, after 10 iterations for the binary logit as using the remaining explanatory variables, which were: corporate governance dummy (X_1), current ratio (X_2), EBIT/Net Debt (X_3), debt Composition (X_4), cash conversion cycle (X_5), acid-test ratio (X_6) and asset turnover (X_7).

As mentioned before, this was obtained through the usage of Eviews software using an unbalanced panel, since not all information was available in every analyzed period. The logistic regression to the probability that the firm is insolvent is then given by the equation:

$$logit\ P_i = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 x_5 + \beta_6 X_6 + \beta_7 X_7 + \mu_i$$

Brooks (2014) reminds us that we cannot simply assume that, in a logit model, a 1-unit increase in one x_{4i} (variable chosen arbitrary just for the sake of the example) causes a $\beta_{4i}\%$ increase in the probability that the firm is insolvent. This would be incorrect because the form of the function in a logit model is $P_i = F(\alpha + \beta_1 x_1 + \cdots + \beta_k x_k + \mu_i)$. Therefore, to get hold of the exact relationship between changes in x_{4i} and P_i, the required proceeding would be to diferentiate F with respecto to x_{4i}.

4. Result Analysis

Table 4 shows the descriptive statistics for the seven explanatory variables of the model.

Table 3: Descriptive Statistics

	Corporate Governance	Current Ratio	EBIT/Net Debt	Debt Composition	Cash Conversion Cycle	Acid-Test Ratio	Asset Turnover
Mean	0.204626	1.735446	-20.89182	0.511340	5456813.	1.159037	1.301807
Median	0.000000	1.338973	20.70824	0.491337	54.86478	0.859695	0.656240
Maximum	1.000000	57.60000	287153.9	1.000000	2.15E+10	57.60000	2023.705
Minimum	0.000000	0.000604	-262500.0	0.000988	-517541.8	0.000372	-0.008181
Std. Dev.	0.403480	2.045319	9236.815	0.227872	3.42E+08	1.566326	32.25913
Skewness	1.464318	10.37732	5.017424	0.224753	62.69769	15.30904	62.65797
Kurtosis	3.144227	200.3809	665.5486	2.322797	3932.000	458.7697	3928.678
Jarque-Bera	1409.308	6456673.	71971114	108.2931	2.53E+09	34203422	2.53E+09
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	805.0000	6827.243	-82188.41	2011.612	2.15E+10	4559.652	5121.310
Sum Sq. Dev.	640.2758	16453.03	3.36E+11	204.2231	4.61E+20	9649.129	4092883.
Observations	3934	3934	3934	3934	3934	3934	3934

Source: Created by the author

With the explanatory variables more detailed in the table above, we can now proceed to the logistic regression with the insolvency dummy as the dependent variable. The sample contained 413 observations of insolvency (negative equity) from a total of 3,934 firm-year examinations. Table 5 shows the results from the logistic regression to the probability that the firm is insolvent and each explanatory variables' coefficient. It is worth noticing that the corporate governance variable is presented with a negative sign, associating firms with better governance practices with a lower chance of becoming insolvent. The variable's p-value is low enough to found statistical significance at even a 1% level.

Table 4: Logistic Regression to the Probability the Firm is Insolvent

$$logit\ P_i = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 x_5 + \beta_6 X_6 + \beta_7 X_7 + \mu_i$$

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.187482	0.280719	4.230141	0.0000*
Corporate Governance Dummy	-2.260787	0.369970	-6.110738	0.0000*
Current Ratio	-0.459637	0.304522	-1.509374	0.1312
EBIT/Net Debt	-3.50E-06	3.00E-06	-1.163673	0.2446
Debt Composition	2.884938	0.563004	5.124189	0.0000*
Cash Conversion Cycle	-9.12E-06	1.95E-06	-4.685706	0.0000*
Acid-Test Ratio	-7.681342	0.591481	-12.98664	0.0000*
Asset Turnover	0.227760	0.011437	19.91432	0.0000*

McFadden R-squared	0.533160	Mean dependent var	0.104982
S.D. dependent var	0.306569	S.E. of regression	0.218961
Akaike info criterion	0.317685	Sum squared resid	188.2273
Schwarz criterion	0.330450	Log likelihood	-616.8858
Hannan-Quinn criter.	0.322214	Deviance	1233.772
Restr. deviance	2642.815	Restr. log likelihood	-1321.407
LR statistic	1409.043	Avg. log likelihood	-0.156809
Prob(LR statistic)	0.000000		
Obs with Dep=0	3521	Total obs	3934
Obs with Dep=1	413		

* Indicates statistical significance at the 1% level

Source: Created by the author

The variables Current Ratio and Acid-Test Ratio are measures of liquity. Theorericaly then, the higher their numbers, the better for firms' financial and operacional health. Considered as return measaures, the ratios EBIT/Net Debt and Asset Turnover would have higher values in better scenarios. As the Debt Composition ratio considers how much of the firm's libiabilities is on the short-tem, it would be reasonable to assume that lower values would mean less obligations for the firm's cash flow in the short-term and, therefore, less chances to become insolvent in the short-term. Following the definition of the Cash Conversion Cycle, it would be expected lower numbers (less days) for the solvent firms, but the model estimation found an inverse relationship between insolvency and the aforementioned variable. However, the same result was found in Stüpp

(2015), in which he analyzes public Brazilian firms as well. As a return measure, one could expect the variable Asset Turnover to have a negative sign on the estimated logistic regression shown above. This would mean that, the higher the revenue a company can generate from its total assets, the lower would be the firm's chance to be in an insolvency situation. However, the opposite relation is presented in the estimated regression. Also using a Brazilian sample, Sanvicente and Minardi (1998) found a similar association between insolvency and Asset Turnover. They suggest that firms would face financial distress due to their growth without a relevant amount of equity or long-term debt to finance it. According to them, if this continues to go on, the firm would then become dependent on expensive shot-term credits, increasing its risk of insolvency.

This insolvency prediction model seems to corroborate with evidences that the use of corporate governance mechanisms can bring benefits to the companies.

In order to test the prediction efficiency of the model, Table 6 is exhibited containing the percentage of correct classifications using the estimated equation. This in-sample prediction used a cutoff of 0.5 to designate the classification of the firm as insolvent or not, according with the probability that comes out from the equation in each case. The model based on the estimated equation obtained a precision of 93.39% when predicting firm's insolvency.

Table 5: Expectation-Prediction Evaluation for Binary Specification

Success cutoff: C = 0.5

	Estimated Equation			Constant Probability		
	Dep=0	Dep=1	Total	Dep=0	Dep=1	Total
P(Dep=1)<=C	3438	177	3615	3521	413	3934
P(Dep=1)>C	83	236	319	0	0	0
Total	3521	413	3934	3521	413	3934
Correct	3438	236	3674	3521	0	3521
% Correct	97.64	57.14	93.39	100.00	0.00	89.50
% Incorrect	2.36	42.86	6.61	0.00	100.00	10.50
Total Gain*	-2.36	57.14	3.89			
Percent Gain**	NA	57.14	37.05			

*Change in "% Correct" from default (constant probability) specification
**Percent of incorrect (default) prediction corrected by equation
Source: Created by the author

Similar, but not equal to insolvency, the literature presents studies showing the effects of corporate governance mechanisms in the prediction of bankruptcy, financial distress, default and corporate failure as using data from other countries than Brazil – including Daily and Dalton (1994), Darrat *et al.* (2014); Elloumi and Gueyié (2001), Lee and Yeh (2004), Platt and Platt (2012) and Wilson and Altanlar (2009). Still, none of those use an index or any measure that assembles exactly the same corporate governance carachteristics in one number. Therefore, those results are not exactly comparable with the ones found in this paper.

Nevertheless, we have an example that associates firms' financial health with good governance practices. Lee and Yeh (2004) used the percentage of directors occupied by controlling shareholder, the percentage the controlling shareholders pledged for bank loans and the deviation in control away from the cash flow rights. They used Taiwanese listed firms in their sample and state that, on the whole, those firms associated with weak corporate governance measures are vulnerable to economic downturns and more susceptible to falling into financial distress.

5. Conclusion

This research aimed to answer if the usage of corporate governance mechanisms in the Brazilian market can help avoid firms' insolvency. A logit model measuring the probability of insolvency for Brazilian firms was used in order to try to answer that question. The model estimations presented statisticaly significant evidences that firms with better corporate governance practices have a lower probability of being in a insolvency situation. Those evidences arise from a logistic regression that used data from companies listed in BM&FBOVESPA from 2001 to 2013. This paper also used financial ratios as control variables to the model and found evidences, regarding their relation with insolvency, similar to other previous studies present in the literature.

Nevertheless, the high correlation found between the variables Asset Turonover and ROE was not deciphered in this paper and its meaning or reason stands as a suggestion for future studies. The same is valid for the three variables that had their capacity to explain firms' insolvency restricted due to lack of variance within the employed context of maximum likelihood (Total liabilities/total assets, Non-current assets/Equity and Debt-Equity Ratio).

The original idea for this paper was to study the relation of firms' bankruptcy with corporate governance measures. However, this idea was abandoned due to the difficulty of getting precise information regarding the bankruptcy of Brazilian firms. Insolvency, on the other hand, could be interpreted from an accounting perspective and it was, therefore, more feasible to obtain data and study it. Hence the choice for insolvency.

In addition, an important point to take notice is the amount of authors using interchangeably the terms business failure, financial distress, insolvency and bankruptcy. As described in the literature review chapter of this paper, they are not precisely the same and their consequences reach different levels for all the stakeholders. This research employed caution on the usage of each one of those terms. In this context, the present literature describes no similar model testing the insolvency prediction power of governance mechanisms for the Brazilian market in the literature. This paper could then represent a relevant contribution to the literature regarding corporate governance and corporate insolvency, as weel as to all stakeholders of the firms listed on BM&FBOVESPA.

A study limitation that could be noticed in this reserach is the usage of the dummy variable that considers the two top levels of B&MFBOVESPA's classification of corporate governance as representing a whole package of governance carachteristics. It was, indeed, interesting and useful in order to understand the relation between insolvency and corporate governance as whole. Yet, it could be appealing to analyze the realation between specific measures of corporate governance – such as board size, proportion of inside directors and board diversity – and insolvency (or failure) in the Brazilian market. The literature currently shows a gap of evidences picturing that relation, even though this could be interesting to scholars and firms' stakeholders. Nevertheless, this could represent a tremendous challenge considering the availabilty of data concerning Brazilian firms.

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