A Critical Approach to the Corporate Insolvency in Romania

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Abstract

A critical moment in the existence of an economic entity is the deterioration of its financial situation and the advent of a liquidity crisis that could lead to the establishment of debt payment incapacity. Through this paper, we analyse the financial situation of companies before the moment of entry into insolvency and during insolvency proceedings, and then we compare them with non-distressed companies. Our purpose is to debate the problem of the prediction of insolvency in terms of symptoms and methods of assessment of the risk of insolvency, taking into account a sample of companies from Romania that are listed on the Bucharest Stock Exchange Market. In order to reveal the most significant indicators that describe the distressed companies, we conducted a comparative analysis of some existing models to measure the bankruptcy riskm with a focus on testing their applicability and developing a new model appropriate for the Romanian business environment.

Keywords: *Insolvency, Insolvency Risk, Financial Information, Bankruptcy Prediction Models, Artificial Neural Networks, Romania.*

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INTRODUCTION

While companies are functioning, there could arise some difficulties or financial problems that affect their normal activity, putting their going concern in danger. Gradually these kind of problems may become bigger, taking on the form of insolvency. Even so, usually there are some suspicions and signals that indicate increased financial risks. A timely awareness of these aspects could be helpful in managing distress situations.

Intensely studied over time, the problem of insolvency and bankruptcy represents permanently a key issue for managers, stakeholders in general, and academics. As the business environment changes and faces new dimensions, these new dimensions could define the risk of insolvency as well. Furthermore, geographically thinking, factors like economic systems, financing opportunities, fiscal policies, labour conditions, markets, legislation, or national cultures can individualise businesses development. Thus, companies' activities and risks require proper study.

In this paper, the applicability of the models proposed by Altman (1968), Anghel (2002), and Robu and Mironiuc (2012) will be tested in order to detect the most representative actual symptoms of insolvency applicable to Romanian companies listed on the Bucharest Stock Exchange Market. At the end of the article, we offer useful suggestions for the everyday management of companies that are facing insolvency risk and for all parties interested in a better understanding of this topic.

CORPORATE INSOLVENCY: GENERAL ASPECTS

Changes in the global economy, changes in the national economic and business environment, new legislative approaches, and different types of companies with specific features reveal the need for reconsidering the theories and largely debated indicators of measuring the corporate insolvency risk.

Theoretical background: Theories supporting working hypotheses

Altman is one of the most representative authors who dedicated his studies to the insolvency issue. Starting in 1968 with an original z-score model, he proved in his studies the value of financial and non-financial information in the prediction of insolvency. He developed multiple discriminant prediction models for listed companies and for small and medium-sized enterprises, for which financial information is very limited (Altman, Sabato, & Wilson, 2010). This latter study was focused on UK companies and showed that non-financial and compliance information can significantly contribute to measuring the risk of insolvency in small entities. Furthermore, the results showed that the principal reasons that may explain the unexpected difficulties of companies are their insufficient capitalisation and lack of planning.

Other opinions emphasise the value of qualitative information for predicting bankruptcy. An empirical study on Canadian bankrupt companies, conducted by Fisher and Martel (2000) focuses on testing some theoretical models regarding the factors that influence the bankruptcy decision of a company by looking at the ways conflicts with creditors are managed the as well as on on reorganisation initiatives. It reveals that the structure of assets, their volume, the type of company, its ownership, and the maturity of liabilities, as well as the legal forms of the entities, affect the state of the distressed companies and the success of their reorganisation attempts.

Al-Kassar and Soileau (2014) affirmed that numerous statistical failure prediction models described in the literature were not tested in order to prove whether such methodologies work in practice. Their research demonstrates that both financial and non-financial information in the evaluation of insolvency risk is necessary.

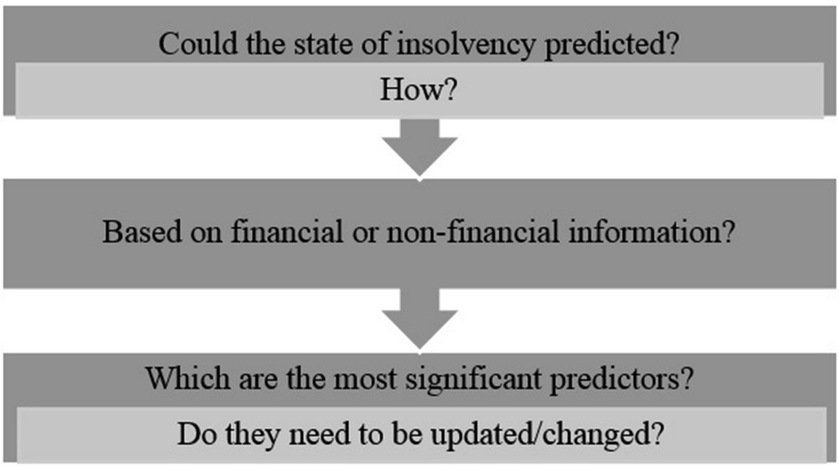
Šarlija and Jeger (2011) stated that macroeconomic conditions as well as market dynamics have changed over the period of their study. Financial ratios that were less important in one period became more important in the next period. According to them, in complex business conditions, mathematical and statistical models have become a necessity, but despite the fact that many studies reported high predictive power for their ratios, a unique perfect combination of financial ratios has not been found. Furthermore, financial distress prediction models lose their predictive power over time.

The performance of bankruptcy prediction models in the recent financial crisis context was tested by a study of Cimpoeru (2014), in which it was applied to Romanian companies. It compared classic score models such as those used by Altman and Taffler and logistic regression methods. The results were in line with the literature; in a financial crisis context, classical models have to be reestimated and financial ratios reconsidered (Cimpoeru, 2014).

Robu, Balan and Jaba (2012) estimated the going concern ability of Romanian companies to continue their activity within a predictable time horizon, without becoming insolvent or bankrupt. According to this study, the activity field (e.g., industry, commerce, services) and the level of structural ratios of the balance assets and liabilities (normal/high) were distinguished as determinant factors of influence on the survival time of the companies.

In general, all these studies present the problem of insolvency starting from the following research questions, as can be seen from Figure 1.

Figure 1. *Approaches of the problem of insolvency existing in literature*



Source: Author's processing

Existing studies of the insolvency problem launched and emphasised the question of the predictability of state of insolvency by valuation of financial and non-financial data. Opinions are diverse, and a complete and stable model has not been validated through a time test. Under these circumstances, we proposed to reanalyse the subject from the perspective of today's business environment, according to the following working hypotheses:

- *H1:* Corporate insolvency can be predicted and described by specific indicators, especially by certain financial ratios.

- *H2:* The significance of insolvency risk predictors can be influenced by the analysed period.

Methods and models of measuring the insolvency risk

Different statistical methods were used for developing predictive models of bankruptcy. These were refined during time and retested in order to prove their compliance to the changes of the business environment. Regression analysis, score models and discriminant analysis, logistic regression, artificial neural networks, expert systems, and other methods were applied in studies such as those by Altman (1968), Altman, Sabato, and Wilson (2010), Al-Kassar and Soileau (2014), Chung, Tan, and Holdsworth (2008), Fisher and Martel (2000), Hamdi (2012), Laitinen, Lukason, and Suvas (2014), Ramayah (2010), and Wilson (2014).

In addition, Romanian authors such as Anghel (2002), Bircea (2012), Robu and Mironiuc (2012), Cimpoeru (2014), and others conducted studies focusing on the financial problems of Romanian companies.

As insolvency may have multiple causes, the questions that arise are which information could best describe this state of crisis and what is its value relevance? Financial ratios offer the advantage of a numerical measurement of the state of companies' financial position and performance, assessing the efficiency of the activity, indebtedness, liquidity, solvency, and profitability, as well as making a distinction between current operating activity, investments initiatives, and financial activities. On the other hand, these are considered historical data with questionable accuracy and predictive power. However, additional details could be useful in assessing the status of enterprises (for example, corporate governance-related factors; *the* size, type and age of enterprises; features of the activity field and industry prospects; intellectual capital indicators; macroeconomic indicators; management style; etc.). A hybrid model could be expected to achieve a more accurate prediction of corporate financial distress (Lin, Liang, & Chu, 2010).

AN ANALYSIS OF THE INSOLVENCY OF ROMANIAN COMPANIES LISTED ON THE BUCHAREST STOCK EXCHANGE

In order to validate the mentioned hypotheses, firstly, we focused on performing an empirical study that includes a comparative analysis of three exiting statistical models of bankruptcy prediction. Seconldy, we proposed a new approach relevant in evaluating the insolvency risk, with the purpose of confirming the results and indicating the most representative symptoms of the financial difficulties that Romanians companies face.

Test of models in Altman (1968), Anghel (2002), and Robu and Mironiuc (2012)

Chung, Tan, andHoldsworth (2008) indicate that the models might not specifically tell the managers what is wrong, but they may be useful instruments in problem identification. We subscribe to this opinion, and in order to verify the applicability of some existing models of bankruptcy prediction, we conducted an empirical study on 12 Romanian entities listed on the Bucharest Stock Exchange. Seven of them had entered into insolvency proceedings, and five of them were without insolvency-related antecedents. The companires were operating in the metallurgical and electrical industries, agriculture, construction, and transportation services. In total, we assessed 93 financial statements over the period of 2004 to 2013, covering nine to ten years of assessmnet for distressed enterprises and five years of assessment for non-distressed enterprises.

The selected models for this test are the initial Altman model, recognised as a reference model in the literature, and two score models developed for Romanian enterprises by the Romanian authors Anghel and Robu and Mironiuc. Those models were developed in different periods, but their analysis helps us to prove if their accuracy can be trusted over time. By this test of applicability and accuracy, we prove if they can still be applicable to Romanian companies listed on the Bucharest Stock Exchange.

The Altman model was developed for manufacturing companies from the US with a distinct economic and reporting profile. The Romanian models were built during periods with different reporting norms and intense political and economic changes.

As can be remarked from the equation of the models, there are few representative financial indicators that significantly contribute to the score results. These are total assets turnover, determined by dividing the annual sales to total assets of the company (representative in the Altman model); net profit ratio in total income, the proportion of cash-flow in total assets, and debt ratio (representative in the Anghel model); and return on assets ratio (according to the Robu and Mironiuc model).

According to the Altman model, an assessment of the predictive power of these models in the years before the distressed companies entered into insolvency proceedings indicates that all cases are considered as facing high bankruptcy risk. The decreasing trend of the Z-scores for companies in insolvency proves the intensification of the state of the crisis, but the application of this model in today's Romanian business environment is questionable.

Table 2. *Accuracy of the tested models during the period of 2004 to 2013*

		Model		
Period	**Cases**	**Altman**	**Anghel**	**Robu & Mironiuc**
N-10	2	100%	50%	50%
N-9	4	100%	25%	0%
N-8	6	100%	67%	0%
N-7	6	100%	67%	0%
N-6	6	100%	67%	17%
N-5	6	100%	83%	17%
N-4	7	100%	86%	14%
N-3	8	100%	75%	25%
N-2	8	100%	75%	25%

N-1	7	100%	100%	71%
N	5	100%	100%	40%
N+1	3	100%	100%	100%
Total	68	100%	76%	26%
N - year of the company’s entry into insolvency proceedings				

Source: Author’s processing

As seen in Table 2, he same status of high insolvency risk was obtained by all three models in 22 percent of the cases. High insolvency risk was evaluated simultaneously by the Anghel and Robu and Mironiuc models in 48 percent of the cases, with the remark that the Anghel model is more restrictive, predicting a more increased risk two to three years in advance of Robu and Mironiuc model. At the same time, for enterprises without financial difficulties, the Robu and Mironiuc model showed more restrictive results than the Anghel model in eight percent of the cases.

In general, the overall results of the conducted tests reveal that the evaluation models have predictive power. In the years before the instauration of insolvency, they identify the high risk level, but as long as their results are different and their accuracy differs, the need of updates should not be neglected.

Selection of variables

The previous analysis revealed that there are some significant ratios that influence the results of the models. Considering them as a reference point for continuing our study and taking into account the overall structure of the financial accounts of the companies, we selected the financial ratios presented in Table 3 as the main relevant indicators for insolvency risk detection.

Table 3. Financial ratios suggested for statistical analysis

Ratios	Calculus formula	Meaning
Debt ratio	Total liabilities/Total assets	Degree of indebtedness
Return on assets	Net result/Total assets	Return on activity/Profitability
Total assets turnover	Sales/Total assets	Efficiency of the activity
Quick ratio	(Current asset Inventory)/ Current liabilities	Assessment of liquidity

Source: Author's processing

This combination of financial ratios is expected to be appropriate for a complex evaluation of the insolvency risk because it addresses the level of liquidity and indebtedness as well as the performance and efficiency of the activity. As a pre-test of the value relevance of these ratios, we compared their range of values and their mean values for the same sample of companies as in the previous test of the Altman (1968), Anghel (2002), and Robu and Mironiuc (2012) models. The results of this analysis are systematised in Table 4.

Table 4. Pre-test of the financial ratios suggested for statistical analysis

	Non-distressed companies				**Insolvent companies**			
Ratios	Range		Trend	Mean	Range		Trend	Mean
Debt ratio	0,12	1,21	slowly up	0,43	0,15	2,90	Up	0,75
Return on assets	-0,18	0,10	slowly down	-0,01	-0,34	0,13	down	-0,05
Assets turnover	0,26	1,51	slowly down	0,76	0,02	1,72	down	0,80
Quick ratio	0,33	4,25	down	1,15	0,07	4,47	down	0,79

Source: Author's processing

First, it is evident that the indebtedness of insolvent companies is very high. This seems to be the result of the accumulated liabilities over time. Even though the same tendency of increasing debt ratio is noticed among non-distressed companies, the range and mean values are considerably different. For the non-distressed companies, in general, the total liabilities represent around 43 percen the total assets, while for insolvent companies their level grows up to 75 percent. In terms of profitability, it seems that these Romanian companies are facing problems in valuing their products and services, as they are registering net losses during the analysed period. Nevertheless, the losses are more accentuate among insolvent enterprises. The same slight differences were registered for assets turnover ratio, showing a possible destabilisation of the market demand or a high level of improperly used assets. Coming to quick ratio comparison, even though the trend has the same tendency, the mean values highlight the lack of liquidity among insolvent firms.

Looking at the previous results, we could be tempted to eliminate the return on assets ratio and the assets turnover ratio from further empirical study. However, the evidence from the comparison of the Altman (1968), Anghel (2002), and Robu and Mironiuc (2012) models as well as the results of a previously conducted study (Mironiuc & Taran, 2015) and the principles of the Du-Pont system of ratio analysis (Gitman & Zutter, 2011) sustain the relevance of these ratios. Furthermore, behind the state of the liquidity crisis, the most expected causes are the performance and efficiency of the activity disruptions. Thus, we consider it appropriate to include all of the four selected financial indicators in the further empirical study.

Method of analysis

As we have seen from the literature review, plenty of methods have been used in insolvency and bankruptcy studies, each of them having its own particularities. Without restrictive assumptions, the artificial neural networks method is appropriate for evaluating the importance of financial indicators that describe different groups of entities.

Zhang, Hu, Patuwo, and Indro (1999) studied the role of artificial neural networks in bankruptcy prediction and concluded that neural networks are significantly more accurate methods of prediction of bankruptcy than logistic regression models, due to the former's nonlinear nonparametric adaptive-learning properties. Huang, Chiu, and Wang (2012) have the same opinion. They affirmed that artificial neural networks analysis is able to predict the possibility of financial distress two to three years in advance. However, their study proves that neural networks analysis is not appropriate for all information, and this fact could be understandable because the method imitates the operating mode of the human brain and is therefore able to learn and to generalise from experience (Hamdi, 2012).

As a complementary source of evidence, we will focus as well on the descriptive statistics of the analysed sample.

Description of data

The further analysis is realised on a sample of 25 Romanian companies listed on the Bucharest Stock Exchange. The sample is composed of:

- 10 companies not facing financial problems and without any records in the official reports of insolvency proceedings analysed for the 2009-2013 period;
- 7 entities listed on the secondary market of the Bucharest Stock Exchange and registered officially as being in insolvency proceedings for the 2004-2012 or 2004-2013 periods;
- 8 companies listed on the principal market of Bucharest Stock Exchange, suspended from trading and having entered into insolvency proceedings, analysed for the 2009-2013 period.

The collected data are from the Bucharest Stock Exchange official website or directly from the financial statements of the companies as published on their official websites.

Results of the empirical study

Our empirical study of the indicators of insolvency for Romanian companies was realised using the SPSS statistics software, version 20. At the beginning, we prepared the comparative descriptive statistics analysis, consisting in presenting the extreme values of the subgroups of the sample, as well as mean values and standard deviation, as can be seen in Table 5.

Table 5. *Descriptive statistics of the groups of companies*

Ratios	Non-distressed companies				Insolvent companies			
	Range		Mean	Standard deviation	Range		Mean	Standard deviation
Debt ratio	0,02	1,15	0,42	0,30	0,00	3,44	0,78	0,56
Return on assets	-0,20	0,10	-0,01	0,07	-0,69	0,13	-0,08	0,13
Asset turnover	0,07	2,07	0,81	0,44	0,02	2,89	0,70	0,52
Quick ratio	0,17	5,23	1,14	1,02	0,02	8,01	0,94	1,09
Ratios	**Before entering into insolvency**				**During insolvency proceedings**			
	Range		Mean	Standard deviation	Range		Mean	Standard deviation
Debt ratio	0,00	2,90	0,71	0,45	0,10	3,44	1,02	0,80
Return on assets	-0,33	0,08	-0,06	0,10	-0,69	0,13	-0,14	0,20
Asset turnover	0,03	2,89	0,80	0,54	0,02	1,21	0,36	0,25
Quick ratio	0,03	8,01	0,94	1,08	0,02	5,42	0,96	1,14

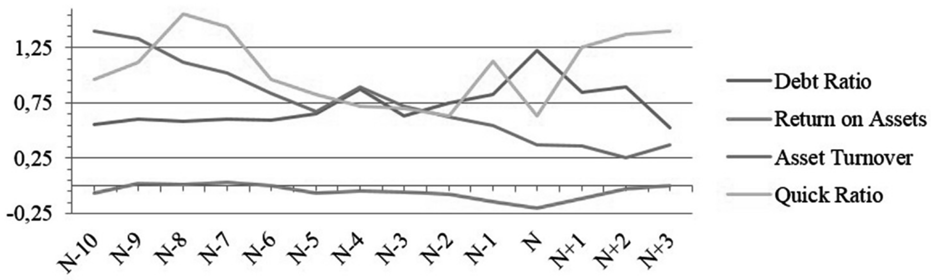
Source: Author's processing

Our first classification was the general one, between companies without financial difficulties and insolvent companies. At this level of analysis, the group of insolvent companies was formed by the financial results of the companies that had entered into insolvency, including a few years before, during and even after the insolvency proceedings period. This explains the fact that the range of values of selected ratios for insolvent companies is partially overlapping the range of values for non-distressed companies. The mean values of the ratios are significantly different, showing a high level of indebtedness among insolvent firms; a higher negative mean value of the return of assets ratio –indicating net losses and a smaller level of assets turnover explained most likely by a decrease of the turnover; and a quick ratio indicating the lack of liquidity of the current assets, except inventories, in order to pay the current liabilities of insolvent firms.

Looking at the level of indicators before entering into insolvency proceedings in comparison with the beginning of the insolvency proceedings period, it is relevant to highlight the considerable increase of indebtedness among the insolvent firms, as well the increase of their losses and the decrease of efficiency of their assets usage. In terms of liquidity, the mean values of the quick ratio are almost similar, showing a slight increase during the insolvency proceedings period and, actually, the first proof of trial to solve the financial problems of those entities.

One of the presumptions of our study was that the state of insolvency could be foreseen based on a staged deterioration of the financial position and performance of enterprises. Figure 2 presents the mean values of the debt ratio, the return on assets ratio, the assets turnover ratios, and the quick ratio for the insolvent companies from our sample, covering the period from 10 years before entering into insolvency proceedings and until the fourth year of proceedings.

Figure 2. *Mean values of the analysed ratios for the insolvent companies, before and during the insolvency proceedings*



Source: Author's calculations

As shown in Figure 2, the year N (meaning the year of official entry into insolvency proceedings) is a breakpoint for the analysed ratios, showing the highest medium level of indebtedness, the highest lack of liquidity, and the biggest losses. In terms of assets turnover, the year of entering into insolvency registered a considerable inefficiency of the usage of assets, which stayed stable during the first year of insolvency and decreased again in the second year before increasing at the level of the year N in the next period. Generally, this analysis shows that the state of crisis did not come on suddenly and that all ratios were affected over time. In the last five years before insolvency, variations of the indicators seem to explain a trial of the companies to face the arisen financial difficulties, but the overall trends show the destabilisation of their financial position and performance. The encouraging evidence is the fact that during the insolvency proceedings period, the situation of the firms became more favourable and the level of the debt ratio, the return on assets, and the quick ratio became similar to that from eight to nine years before the onset of the insolvency problem. Years three and four after the moment of entry into insolvency proceedings represent in fact the moment of exit from the proceedings, in the case that the recovery programme was successfully accomplished.

Our study continued with the Multilayer perceptron option of the artificial neural networks method, revealing the importance of those ratios in each one of the three classifications that we did. Its results are presented in Table 6.

Table 6. *Normalised importance of the selected variables*

Ratios	2 groups	3 groups	Yearly groups
Debt ratio	100,00%	100,00%	80,30%
Return on assets	25,80%	35,80%	100,00%
Assets turnover	44,10%	77,90%	91,10%
Quick ratio	29,10%	14,80%	14,80%

Source: Author's processing

In the first discriminating test between healthy and insolvent firms, the debt ratio was considered the most representative indicator of the imminent financial problems, being followed by the assets turnover ratio and the other ratios, which registered a significantly lower percentage of importance. From the classification among non-distressed and insolvent companies both before and during the insolvency proceedings periods, the debt ratio registered again the absolute percentage of importance. The assets turnover ratio also registered at a considerable level of importance, showing that efficiency of the activity is the second indicator of insolvency, which presents a significant deterioration during time. When trying to make a distinction only among insolvent companies in order to highlight their yearly performance during the analysed period, the most important indicator was the return on assets ratio, explaining that in the short-term, the profitability is that which reflects the potential problems of the companies, being as it is a sensitive indicator of the overall performance. The efficiency of activity seems to be very important as well for comparing the results on a yearly basis, explaining also the quick destabilisation of companies caused by problems with their sales. The level of indebtedness is important also, but it is more stable liabilities especially long-term ones being accumulated over time. The quick ratio does not make a significant distinction, which means that it may represent a potential and temporary problem for all companies during each moment of their business cycles.

The level of confidence in these results might be affected by the accuracy of the built models. According to the artificial neural networks analysis methodology, the training step is more important and requires more cases for analysing and building the classification algorithm. The accuracy of this step was also higher for our cases, as can be seen from Table 7. For the distinction between healthy firms and insolvent ones, it obtained the highest level of confidence 80.6 percent during the training step and 80 percent during testing. The chances of misclassification were higher in the case of discriminating among non-insolvent companies and insolvent entities during the pre-insolvency period and insolvency period. Questionable results were registered for the yearly grouping of the insolvent firms.

Table 7. *Accuracy of the artificial neural networks classifications*

Classification	**Training**	**Testing**
2 groups	80,60%	80,00%
3 groups	71,10%	59,10%
Yearly groups	38,00%	22,90%

Source: Author's processing

These results confirm our expectations and validate the stated working hypotheses of our study. There are financial ratios that make a considerable distinction in measurement of the insolvency risk and between the categories of companies. Their importance is relative, and they can be ranked according to the stage of classification and to the analysed period. Thus, the discriminatory power of these ratios is different from 10 years before insolvency proceedings to five years before, the representative indicators of insolvency being affected since the last five years before the entry into the state of crisis. Even the evoked crisis is, first of all, a liquidity crisis. Factors like indebtedness, profitability, and efficiency are more decisive. Based on them, the liquidity problems may be avoided, solved, postponed, or intensified.

CONCLUSION

Even though the issue of insolvency has been intensively studied, the updated and actual remarks about this problem serve as useful instruments of managerial decisions, credit risk assessment, and validation of going concern assumption, as well as the basis for further research.

Different studies were conducted and different methods were used, but their accuracy became questionable over time. By testing the Altman (1968), Anghel (2002), and Robu and Mironiuc (2012) models on a sample of Romanian companies, we noticed that their results were not similar and, in fact, Altman model is much more restrictive than the others. From here, the need for improving the studies and adapting them to the present reality is relevant evidence.

By studying the value relevance of a new combination of ratios for assessing the insolvency risk, and by discriminating between healthy and insolvent companies by conducting an artificial neural networks analysis, we observed that the indebtedness of companies which iscontinuously increasing over time is the most important factor that predicts the imminence of insolvency. In addition, the assets usage efficiency is a problem faced by insolvent andnon-distressed companies alike. Since five years before, financial ratios deterioration seems to indicate insolvency imminence. From the yearly classification of insolvent companies, the quick ratio was regarded as the most sensitive indicator with variations over time. However, it cannot be considered a relevant predictor of insolvency as long as its evidences are variable.

These results are suggestive for understanding the main issues that predict and describe the state of insolvency, even if limitations like restrictions concerning data availability or the size of the selected sample require future extensions in order to enhance its relevance.

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