THE USE OF Z-SCORE TO PREDICT UTP LOANS

Maurizio Dallocchio *, Salvatore Ferri **, Alberto Tron ***, Matteo Vizzaccaro ****

* SDA Bocconi School of Management; Department of Finance, Bocconi University, Milan, Italy
** Parthenope University of Naples, Naples, Italy
*** *Corresponding author*, Department of Finance, Bocconi University, Milan, Italy
Contact details: Department of Finance, Bocconi University, Bocconi University, Via Roentgen, 1, 20136, Milan, Italy
**** SDA Bocconi School of Management, Milan, Italy

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Abstract

The Z-Score model developed by Altman in 1968 is considered one of the more reliable predictors of bankruptcy. In contraposition to the existing literature, the paper aims to investigate the Z'-Score and Z''-Score ability to predict unlike-to-pay (UTP) loans, which is an event far earlier than insolvency. To investigate this relation, the study uses a unique sample of UTP loans, provided by a major Italian bank, and applies, as a predictive model, the Logit model, well known in academics. Final results confirm that the Z'-Score and the Z''-Score are able to forecast UTP loans. Furthermore, the findings of the papers reveal the importance of corporate governance variables in predicting financial failures.

Keywords: Financial Distress, Z-Score, Z'-Score, Predictive Modelling, Corporate Finance, Credit Risk, Bankruptcy, UTP Loans

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1. INTRODUCTION

This research investigates the accuracy of Altman's model (with particular focus on the Z'-Score and Z''-Score models) in the Italian context and, specifically, its ability to predict early signals of crisis and not just insolvency. Since the 60's with the development of analyses of a discriminating type, namely, Beaver's model (1966) and Altman's model (1968) and the diffusion of more sophisticated databases (Altman & Saunders, 1997), several empirical studies have attempted to analyze the relation between economic-financial indicators and bankruptcy.

Despite this fact, researchers still debate about the definition of crisis and the criteria to be used to determine if a company is in financial distress. Some studies link the bankruptcy to a financial event (e.g., the inability of a company to meet its current financial obligations) (Lummer & McConnell, 1989; Hotchkiss, 1995; Peterson & Rajan, 1995; Tashijian, Lease, & McConnell, 1996; Beaver & Engel, 1996, Andrade & Kaplan, 1998; Boot, 2000), while, according to other approaches, a company can be defined in crisis only when the market value of its assets falls below a certain threshold (the so-called default boundary – Black & Cox, 1976; Leland, 1994; Longstaff & Schwarts, 1995). Differently from existing literature, our approach will be unique and it will consider the entrance in the crisis status the classification as UTP position by the bank, an event that precedes the insolvency.

Many studies have highlighted the importance to anticipate the emersion of crisis since it allows a company to manage its time to elaborate a strategy to solve the situation and rebecome profitable value (Blum, 1974, Ohlson, 1980, Zmijewski, 1984, Boser, Guyon, & Vapnik, 1992, Li & Sun, 2008). Indeed, the effectiveness of the adoption of strategic actions in response to the negative dynamics of economic and financial results is strictly correlated to the promptness to anticipate the financial failure (Vašíček et al., 2017; Schivardi, Sette, & Tabellini, 2017; Brodi, 2018). Therefore, alert analysis is of particular interest for all stakeholders of a company (Warner, 1977; Charalambous, Charitou, & Kaourou, 2000; Charitou, Neophytou, & Charalambous, 2004; Davis & Karim, 2008), as also shown by the introduction of the procedures of alert in the new Italian Code of Bankruptcy (*"Codice della Crisi e dell'Insolvenza"*).

Despite the relevant importance of analyzing the conditions that can anticipate the financial distress a company, existing literature has been focused on the ability to predict bankruptcy, an event of non-return. This is also the consequence of unavailability of the data, which, in the majority of the cases, allows to recognise an insolvent company only when it becomes public, while the author, thanks to the support of a major bank operating in Italy, were able to analyze a unique database which included companies that between 2006-2016 were classified as UTP loans in the register of the bank. Therefore, the scope of this paper is to verify if Z'-Score and Z''-Score models are able to predict the classification of a company as a UTP loan. This is a discriminating element of innovation for this study since the classification as UTP is a phase that precedes the insolvency where is still possible that a company can succeed in restructuring.

The final results confirm that the Z-Score models are a valid tool for alert analysis, as it is able to predict the first signs of financial instability.

In line with the importance attributed to stakeholders' interests, the analyses carried out in the present work follow the stakeholder theory approach (Freeman, 1984; Donaldson & Preston, 1995), which considers the company from the point of view of the holders of interest in general.

2. LITERATURE REVIEW

Studies on corporate crisis can be grouped according to the following five main strands: the first is related to the causes of corporate crisis (Hedberg, Nystrom, & Starbuck, 1976; Schendel & Patton, 1976; Hambrick & D'Aveni, 1992; Gales & Kesner, 1994; Slatter & Lovett, 1999; Vašíček et al., 2017); the second to the indicators of corporate crisis (Beaver, 1966; Altman, 1968; Blum, 1969; Deakin, 1972; Wilcox, 1976; Dambolena & Khoury, 1980; Winn, 1993; Reisz & Perlich, 2007; Fiordelisi & Mare, 2013); the third to the debt analysis (Diamond, 1991; Chemmanur & Fulghieri, 1994; Aggarwal, 1995; Gilson, 1997; Mooradian & Ryan, 2005; Hotchkiss, John, Thorburn, & Mooradian, 2008; Dudley & Yin, 2018); the fourth to the evaluation of companies in crisis (Andrade & Kaplan, 1998, Eberhart, Altman, & Aggarwal, 1999; Gilson, Hotchkiss, & Ruback, 2000; Damodaran, 2009); the fifth and last, to the solutions of judicial and extrajudicial crisis and comparative economic efficiency (Berkovitch & Israel, 1998; Rasmussen, 1997; Blazy, Fimayer, & Chopard, 2008).

For the scope of this study, the causes of bankruptcy represent the key factor for the adoption of an action plan that can allow the company to regenerate value. The causes of a crisis can be endogenous or exogenous or both due to the competition among several factors (Slatter & Lovett, 1999).

In the US, the first studies on this strands have focused on the ability of publicly available economic data to prevent business failures like in the case of Tamari (1964), which proposed an initial pioneering attempt to statistically analyse failure, Beaver (1966) and Altman (1968). Similar approaches were also adopted outside the US showing the reliability of these models notwithstanding the specificities of individual countries while random studies on bankruptcy are indeed much rarer (Altman & Narayan, 1997).

Researchers in the 90's have developed new more detailed models (Altman, 1997) which were able to identify more quickly any signal of crisis by also considering strategic variables that can also support the decision-making process (Amigoni, 1998; Eccles, 1991). In addition to the traditional predictive indicators and models of a financial nature, new multi-dimensional indicators were considered, implemented by extra-accounting measures and financial and physical techniques.

There are at least five methodological approaches to the development of risk assessment systems (scoring): 1) the linear probability model; 2) the logit model (Aziz, Emanuel, & Lawson, 1988; Platt & Platt, 1990; Salchenberger, Cinar, & Lash, 1992; Ward, 1994; Back, Laitinen, Sere, & van Wezel, 1996; McGurr & DeVaney, 1998; Kahya & Theodossiou, 1999; Beyonon & Peel, 2001; Neophytou, Charitou, & Charalambous, 2001; Lin & Piesse, 2004; Westgaard & van der Wijst, 2001; Foreman, 2003; Brockman & Turtle, 2003); 3) the probit model; 4) the discriminant analysis model (Altman, 1968, Deakin, 1977; Edmister, 1972; Blum, 1974; Libby, 1975; Moyer, 1977; Booth, 1983; Casey & Bartzack, 1984; Gombola, Haskins, Ketz, & Williams, 1987; Piesse & Wood, 1992; Coats & Fant, 1993; Back et al., 1996; Altman & Narayanan, 1997; Jo, Han, & Lee, 1997; Pompe & Feelders, 1997; McGurr & DeVaney, 1998; Yang, Platt, & Platt, 1999; Altman, Danovi, & Falini, 2013); 4) the recently developed machine learning models such as generalised boosting, AdaBoost and random forests (Jones, Johnstone, & Wilson, 2017; Zhu, Qiu, Ergu, Ying, & Liu, 2019).

Even though credit scoring models can work well in various domestic contexts and at different times, they suffer from several issues: 1) they do not take into consideration market values but are largely based on accounting data; 2) they are based on linear discriminants, while in the real world the relations are typically non-linear; 3) the predictive models shown above are often weakly correlated with the underlying theoretical models.

As suggested by Bellovary, Giacomino, and Akers (2007), the aim of future researches should be to test the efficiency of existing models rather than looking for new ones. In fact, although since 1965 approximately 150 predictive models were developed (Bellovary et al., 2007), that in the majority of the cases has shown their ability to predict insolvencies, current researches are still trying to develop new efficient models. In this sense, in more recent times, numerous empirical studies have been carried out to test the efficacy of the main models by suitably adapting or following the original formulation. Several studies have shown that existing models have diminished effectiveness in the presence of different samples (e.g., size, sector, type, legal status, area of operational interest, etc.). Part of the generalizability of the model is its applicability in periods of different observations with respect to the "test case" originally used (Grice & Dugan, 2001; Grice & Ingram, 2001; Wu, Gaunt, & Gray, 2010). Existing models have been texted also outside the original domestic contexts also outside North America or Europe (Taffler, 1984; Peel, Peel, & Pope, 1986; Altman, Hartzell, & Peck, 1998; Bottani, Cipriani, & Serao, 2004; Charitou et al., 2004; Alareeni & Branson, 2013; Altman et al., 2013; Cestari, Risaliti, & Pierotti, 2013; Celli, 2015; Giacosa, 2016; Kováčová & Kliestikova, 2017). Within these cases, it is possible to identify some relevant works focused on the Italian context (Bottani et al., 2004; Altman et al., 2013; Celli, 2015; Giacosa, Mazzoleni, Teodori, & Veneziani, 2015; Giacosa, Halili, Mazzoleni, Teodori, & Veneziani, 2016; Madonna & Cestari, 2015). Furthermore, assessments carried out over the years outside the US market have shown that the same model is efficient (Charitou et al., 2004; Alareeni & Branson, 2013).

As mentioned before, for predicting the classification of a company as a UTP position, this study uses one of the most commonly adopted and easy-to-use tools for assessing default risk, the Z-Score and Z'-Score. The Z-Score, developed by Altman in 1968, was built on a sample of 33 US manufacturing companies listed on regulated markets, it can also be applied to other industries (Al-Sulaiti & Almwajeh, 2007).

The Z-Score models aim to measure the distance – through a scoring system and with a reasonable error rate – between companies from two groups (healthy and problematic).

The model, which has a descriptive-comparative nature (Altman, 1970), is based on a formula that assigns a score using five quantitative variables. Therefore, using this score to measure the distance between companies from two groups (healthy and problematic) and to describe the financial soundness of a company by predicting its probability of default within a certain time horizon.

In analytical terms, the following linear function represents the Z-Score model:

$$Z - Score = \frac{Working\ Capital}{Total\ Assets} \times 1.2 + \frac{Retained\ Earnings}{Total\ Assets} \times 1.4 + \frac{EBIT}{Total\ Assets} \times 3.3 + \frac{Market\ Value\ of\ Equity}{Book\ Value\ of\ Total\ Liabilities} + 0.6 \times \frac{Sales}{Total\ Assets} \times 0.99 \tag{1}$$

Due to its ability to identify the tendency that links the trend of the accounting indicators in the years before insolvency for healthy companies and those in crisis, the model can be transformed into an active strategic tool aimed at preventing major financial crises (Altman & Le Fleur, 1985).

Several studies on the application of the model to samples of US companies (e.g., Timmermans, 2014) have shown a significant predictive ability of the Z-score model, up to 95% in the year previous to the insolvency of the companies analysed (year -1), to 83% two years before insolvency (year -2) and 48%, 29%, and 36%, respectively, three, four and five years before insolvency (year -3 year; year -4; year -5). Similarly, an analysis carried out on extensive databases in international contexts (32 countries including 29 European countries and 3 non-European countries – China, Colombia, and the US) has produced very positive results for the Z-Score model (Altman, Iwanicz-Drozdowska, Laitinen, & Suvas, 2017). However, some authors have criticized the predictive ability of the Z-Score (and its variants) with reference to non-US companies because the model is closely linked to the characteristics of the US market (Grice & Ingram, 2001; Grice & Dungam, 2001; Ooghe & Balcaen, 2006; Kapadia, 2011). Thus, to increase the efficiency and the effectiveness of the original model, it is appropriate to include "country-specific" estimates (Altman et al., 2017).

In 1993, Altman introduced the Z'-Score (Altman, 1993), which consists of an adaptation of the original model for companies that are not listed in the financial markets.

In analytical terms, the following linear function represents the Z'-Score model:

$$Z' - Score = \frac{Current\ Assets - Current\ Liabilities}{Total\ Assets} \times 0.717 + \frac{Retained\ Earnings}{Total\ Assets} \times 0.847 + \frac{EBIT}{Total\ Assets} \times \times 3.107 + \frac{Book\ Value\ of\ Equity}{Book\ Value\ of\ Total\ Liabilities} \times 0.420 \times \frac{Sales}{Total\ Assets} \times 0.998 \tag{2}$$

Several studies have shown the effectiveness of the Z'-Score for analyses carried out on samples of Italian companies (Madonna & Cestari, 2015; Paoloni & Celli, 2018). Another recent study (Paoloni & Celli, 2018) on a panel of 200 companies (half of which have been subjected to bankruptcy procedures, while the other half consists of "healthy" companies) revealed the Z'-Score model's good diagnostic reliability in measuring the health of Italian manufacturing SMEs. In particular, the Z'-Score model allowed for the detection of companies under default risk.

In 1995 Altman et al. (1998) developed the Z''-Score model under the name of "double and prime score" for non-manufacturing companies and, possibly, those operating in emerging markets (with the insertion of a correction).

In analytical terms, the following linear function represents the Z''-Score model:

$$Z'' - Score = 3.25 + \frac{Current\ Assets - Current\ Liabilities}{Total\ Assets} \times 6.56 + \frac{Retained\ Earnings}{Total\ Assets} \times 3.26 + \frac{EBIT}{Total\ Assets} \times 6.27 + \frac{Book\ Value\ of\ Equity}{Book\ Value\ of\ Total\ Liabilities} \times 1.05 \quad (3)$$

Also, in this case, the model has been proven to be efficient in the Italian context. Altman et al. (2013) showed, using a sample of manufacturing enterprises under the Italian bankruptcy procedure in the period 2000-2010 showed, that the majority of the companies analysed is classified in the area of insolvency according to Z"-Score: in particular, in the last four years of the period considered, scores were always lower than 1.23.

Due to the reliability in the Italian context of Z'-Score and Z"-Score and in line with the existing literature which suggests going deeper in detail in terms of its effectiveness in different contexts, the authors chose to adopt them as an indicator of the probability of default.

The research gap that this paper aims to fill is therefore related to the timing granted by the analysis of the probability of default through Z-Scoring, which the existing literature demonstrates to be effective but not timely. In fact, from the analysis of the existing literature, it is clear that studies have been focused on answering the following question: Is the Z-Score model able to predict the state of crisis defined by the filling of the bankruptcy procedure? As mentioned before, this limitation has been caused by the unavailability of data, which allows recognising an insolvent company only when it becomes public (i.e., the procedure has been filled). Thus, our research has the scope to test not only the efficiency of the Z'-Score and Z"-Score but also their ability to predict the emersion of the crisis. This has a high impact from a managerial perspective: if the state of crisis is recognized early, it is still possible to adopt corrective actions, while when a company has filed for a bankruptcy procedure available solutions are significantly limited. Therefore, our research question can be defined as: Is the Z-Score able to predict UTP classifications?

3. RESEARCH METHODOLOGY

One of the main elements of innovation of this study is the unique samples of UTP loans that the authors were able to analyse. Historically, the reference literature on corporate crises has faced a limitation in the availability of data relating to business restructuring processes. Beyond the complete lack of available data concerning the out-of-court recovery processes (recovery plan), which are naturally private, data on so-called judicial processes (e.g., debt restructuring agreements) and qualitative information on the management of processes are particularly difficult to achieve.

Thanks to the support of a leading bank operating in Italy, the authors managed to obtain not only economic and financial data concerning companies in crisis but also the date of their inclusion in the special register of UTP positions, which for us is the event representing the crisis (while for the existing literature the event is represented by the filling of the public bankruptcy procedure). Differently from past-due-payments, UTP loans rely more on qualitative criteria that define trigger-events for the non-performing classification (paragraph 145 (b) of Annex V of Commission Implementing Regulation (EU) No. 680/2014). Banks in Italy have pre-defined automatic events – wherever possible – and annual events in place in accordance with Circular No. 272 of 30 July 2008 (12th update) of Bank of Italy (Bank of Italy, n.d.). In the case of automatic events, the exposure is automatically identified as non-performing, without any further manual inputs or need for manual confirmation. Moreover, according to paragraph 148 of Commission Implementing Regulation (EU) No. 680/2014, the classification of exposure as non-performing should be done without taking into account the existence of any collateral. Consequently, all the exposures considered in this research, even the fully collateralized ones, have been classified as non-performing in UTP situations.

The very nature of the data obliges the authors to make some further considerations. If from a legal point of view the state of crisis is assumed to begin when the company enters one of the procedures provided by bankruptcy law, from a bank's perspective, this status can be determined at a very early moment corresponding to the date on which a debtor experiences problems in the restitution of the interest or principal portion of its debt to the bank. At that time, the bank completes a special register of "unlikely to pay" positions and then takes all possible measures to protect its economic interests.

The concept of the "corporate crisis" adopted in this work, therefore, takes its cue from an unfamiliar, perhaps unique definition. This setting can considerably broaden the analytical perspective. The traditional definition adopted in literature refers to a moment of publicity of the state of crisis to conduct analysis, taking as a reference only the moment at which the company gains access to one of the procedures provided by bankruptcy law; in contrast, the definition of crisis adopted in this study allows for identification of crisis even in previous moments and even independently from the access to one of the procedures provided by the law. This perspective allows for the analysis of all cases in which credit management has a private and confidential process, where access to one of the procedures provided by bankruptcy law is only one of the possible outcomes.

The sample determination was carried out using analyses carried out with an information system in use at the bank that has committed (behind NDA) to provide the list of the names of past companies under the restructuring management team that had manifested a difficulty in managing their debt to the bank or they were then positively leaked from the restructuring management team for at least two years to the date that this work began. In fact, after entering the "special register" of the bank there are two outcomes of the restructuring process. The first is a complete rehabilitation of a company in its capacity to repay debts (*"in bonis"* status), and the second is the confirmed inability to repay debts because the state of crisis is too deep (*"workout"* status). Specifically, those companies were considered in the first sample:

- entered in the restructuring management team of the bank;
- were Italian companies;
- exited in the restructuring management team of the bank in August 2014;
- still "in bonis" after August 2016 (and still *"in bonis"* in 2017).

From a total of 10.143 names provided (companies and different economic entities), this process identified a total of 210 business cases. Afterward, we, specifically, identified companies that: 1) were able to repay interest or part of the principal payment; 2) were included in the "special register" of the bank; 3) had positively concluded a restructuring process at least two years before this study began. The extraction from the bank's information system allowed the authors to identify 72 companies that successfully completed the process.

Then, for each company, the following information was collected:

1) Economic and financial data: The database obtained was integrated by extracting data on profitability, solidity, business productivity considered by AIDA Bureau Van Dijk's and Amadeus databases. Data extraction concerned the three years before and the three years after the "crisis moment" (inclusion in the special register), as reported by the restructuring managers from the bank, through interviews and surveys conducted by the authors.

2) Governance data: The original database was integrated with CERVED source data to identify the evolution of corporate characteristics in terms of governance (composition and duration of the main management bodies, capital structure and turnovers within the majority of capital, average duration in the office of each body, etc.). This integration has closed the existing data gap.

Following the identification of the sample and in order to increase the efficiency of statistical analysis, two additional samples were built for the purpose of our analysis. Therefore, the final sample is composed of three sub-samples:

1) Firms in financial distress that succeeded in restructuring: The residual original sample made of 72 companies that, starting from the year 2014, have shown positive results in terms of capacity to repay their obligations to the bank. No listed company has been included.

2) Firms in a financially sound position: The first control sample that includes companies that did not show economic and financial problems during the period 2007-2016. A total of 72 companies were identified. No listed company has been included.

3) Firms which have failed: The second control sample that includes companies that ceased their operations as a consequence of bankruptcy, voluntary liquidation, judicial liquidation, or dissolution in the 2014-2016 period. A total of 76 companies were identified. No listed company has been included.

Starting from the identification of the economic and financial data of the companies in sub-sample 1, the maximum, minimum, and average values of the turnover were identified and considered as an approximation of the size of the company. The sectors of these companies were also identified using the 2007 ATECO code. Using the AIDA database, the entire population of Italian companies included in the dimensional limits of sub-sample 1 (minimum and maximum turnover limits of the sub-sample 1) and the same 2007 ATECO (Nace rev. 2) sectors were identified. This population includes 34.124 units. Using this database, the first ("healthy" companies) and the second control ("deceased" companies) samples were identified. For healthy businesses, pairwise sampling was carried out from the initial sample of rehabilitated enterprises. In particular, for each rehabilitated company, a "healthy" company has been identified with characteristics similar to that of the companies of the original sample in terms of size (revenues) and the ATECO sector. To have a balanced sampling, 72 companies were identified randomly according to these criteria through SPSS. Therefore, the number of healthy companies included in the first control sample is 72, uniform, even in terms of the number of observations, to that of rehabilitated companies (original sample). While, from the identified population, the second control sample was built through the mere identification of companies subject to termination in the period considered which led to a sample of 76 units. The final sample, including the three sub-samples, is therefore made up of 220 companies. The balance of industries included in the sample is represented in Table 1 (see Appendix), where the weight of each industry (expressed by ATECO 2007 classification) for each type of company status is reported. In Table 2 (see Appendix) descriptive statistics of corporate governance variables and Z-Score are reported.

The criteria adopted for the construction of the control samples appear consistent with the research perspective and reflect the actual health status of the companies considered (healthy, restructured, failed).

In particular, the management efficiency, expressed by the ROS, appears to be consistent with the average characteristics of the companies belonging to the clusters considered, with higher margins for healthy companies, lower for those that have been restructured (and increasing since 2014 – the year of "exit" from the crisis), generally negative for companies that have ceased trading (due to insolvency, or even voluntary liquidation). Debt ratios, in the same way, are reflecting the more or less serious financial stress.

Logit regression is then used to test our hypothesis. The authors calculated the Y variable as a dummy assuming values between 0 and 1, depending on whether the company is healthy (0), for companies in sample 2, or recovered or ceased (1), for companies in sample 1-3. This choice derives from the authors' desire to extend the number of observations in order to arrive at a more significant result through greater granularity in the considered data. Aware of the limits deriving from the attribution of a dummy variable to three different conditions, in order to check the robustness of our results, we also proceeded to verify the model for a sub-sample of companies belonging to two conditions, in order to run a traditional logit model. To run this second test, only companies included in sub-samples 1 and 2 were considered.

With regard to the independent variables included in our models, two alternative measures of Z-Score were used: Z'-Score and Z''-Score using the Altman's model already defined. Specifically, for each definition of Z-Score, we calculated the average score in three periods: 1) the period before the crisis (2007-2011); 2) the period during the crisis (2012-2014); 3) the period after the crisis (2015-2016). The authors employed as control variables the governance data downloaded from CERVED (e.g., number of sole directors, number of CEO). For the definitions of the control variables included in the model please refer to Tables 4 and 5 in Appendix.

We proceeded to the elaboration of the correlation analysis for the variables included in our analysis (Table 6, see Appendix), which provided the authors with significant results. Since the number of variables initially collected and considered is considerable, in Table 6 only those variables that show significant[1] relationships with the dummy variable are reported, with the (positive or negative) signs of their relation as highlighted in the very last column. For all the periods under analysis, there seems to be a significant negative relationship between the value of the Z-Score and the status of the company. This is consistent with the conceptual approach of the score, which involves the association of scores that are as high as the probability of company insolvency is low. The state of the company is here approximated with a dummy variable (0 = healthy company, 1 = recovered or ceased enterprise), and its relation to the score seems to confirm this hypothesis. Similarly, also the number of CEO and presidents of the board of directors in the period considered shows a negative relationship with the dummy variable.

Following the correlation analysis, all the variables with significant correlations have been included in two regression models:

- The first model includes the analysis of the Z'-Score in its original formulation;
- The second model includes the analysis of the Z"-Score in its revised version.

The logit regression analysis aims to create a better understanding of the causal link between the variables.

4. RESEARCH RESULTS

Firstly, it is interesting to note that despite the inclusion of the 2007-2011 financial crisis period in our analysis, the Z-Score of this period is not actually significantly related to the status of the companies. This allows us to conclude that the financial results of that period do not distort the analyses of subsequent periods (or even that the crisis that the companies went through was not predictable through the Z-Score observable between 2007 and 2011).

Model 1

Model 1 includes the Z'-Score and the governance variables that were significant in the correlation analysis. The results are shown in Table 7 (see Appendix). The R-square value of the model is 0.315.

The Z'-Score in 2012-2014 is statistically significant at 1% level with a negative coefficient, thus, the lower the score, the higher the probability that a UTP emerges. On the contrary, the average value of Z'-Scores between 2007 and 2011 and between 2015 and 2016 are not statistically significant. Therefore, the model confirms the ability of the Z-Score tool to predict the status of a company but only using time horizons that extend to two years earlier than the occurrence of UTP. Furthermore, the importance and the efficiency of the Z'- Score in 2012-2014 is also confirmed by its standardized beta coefficient which is significantly the highest one (-0.450). Therefore, the results of the regression analysis, expressed by the level of significance, and the sign of the standardized Beta coefficient confirm the relationship between the Z'-Score and the status of the company.

The analysis reveals significant relationships with the corporate governance variables (the average term of the office of board of directors is statistically significant at 5% with a positive coefficient), included here as non-financial control variables. Therefore, the model provides suggestions for further research where non-financial variables could be used.

Model 2

Model 2 includes the Z''-Score and the governance variables that were significant in the correlation analysis (the same as Model 1). The results are shown in Table 8 (see Appendix). The R-square value of the model is 0.241. With respect to Model 1, therefore, the only variables which were substituted are those related to the Z"-Score.

The use of Z''-Score instead of Z'-Score confirms the results of Model 1. The Z"- Score in 2012-2014 is statistically significant at a 5% level, with a standardized beta of -0.356. Also, in this case, the average value of Z''-Scores between 2007 and 2011 and between 2015 and 2016 are not statistically significant.

Similarly to Model 1, also Model 2 suggests the importance of the inclusion of governance variables as control variables. In this case, the number of people who took the role of President of the Board of Directors in the period following the crisis is statistically significant at 1% with a negative coefficient.

Robustness tests

In order to check the robustness of our results, four other models were developed. The first two are based on the same of Model 1 and Model 2, with the exclusion of failed companies, therefore, only healthy or restructured companies are included (N = 144). This assessment was necessary as the dummy variable used until now (which is dichotomous) actually contains three different possible statuses related to the company (healthy, restructured, or ceased). The implemented verification grants a better matching of the conditions under which the company lies (healthy or restructured) with the values associated with the dummy variable (0 and 1). The verification was carried out both for the Z'-Score and for the Z"-Score. The results, as reported in Tables 9 and

[1] Correlation is significant at 0.01 level (two-tails).

10 (see Appendix), are confirmed both in terms of significance and signs of the relationship. In fact, the regression results using Z'-Score for only healthy and restructured companies reveals that the Z'-Score in 2012-2014 is statistically significant at 1% level, with a standardized beta of -0.433. Similarly, the regression results using Z"-Score for only healthy and restructured companies confirm the significance of the Z"-Score in 2012-2014 is. Interestingly, in both cases, corporate governance variables are not statistically significant.

Then, we run the two models again using a random sample of the original sample. Results are shown in Table 11 (Z'-Score) and 12 (Z"-Score), in Appendix. In particular, the control sample considered 51% of the observations of the original sample, selected randomly by the SPSS software. Even in this case, the results are confirmed both in terms of signs and significance of the considered variables.

5. DISCUSSION OF RESULTS

The results of Models 1 and 2 confirms the accuracy of Altman models and the efficiency of the use of Z'-Score and of Z''-Score in predicting early signals of crisis and not just insolvency. Having reached statistically significant results on a unique sample of companies, this paper confirms that the Z'-Score and Z''-Score can not only predict bankruptcy but also the inability to make earlier debt repayments, approximated by the occurrence of unlikely to pay (UTP), which is the discriminating and innovative criterion used in our study. In addition, throughout the observation period (2007-2016) healthy companies have a Z-Score level always above the medium risk threshold (1.42) and those always ceased at the high-risk level of default demonstrating the validity and predictive capability of the diagnostic model used as in Altman et al. (2013).

The outcomes of this study support the efficiency of the use of Altman's models outside the US context and in different periods, as in Paoloni and Celli (2018), contrary to the thesis of some authors (Grice & Ingram, 2001; Grice & Dungam, 2001; Ooghe & Balcaen, 2006; Kapadia, 2011) which have criticized the predictive ability of the Z-Score (and its variants) outside the US. Moreover, the outcomes of the models reveal its generalizability, and therefore its suitability for large-scale investigations as suggested by Madonna and Cestari (2015). Furthermore, our tests confirm the accuracy and the effectiveness of the original model without the necessity to include country-specific estimates (Altman et al., 2017).

However, our results as in the case of Paoloni and Celli (2018), Madonna and Cestari (2016) and Timmermans (2014), show that the Altman' models are good predictors of bankruptcy only when applied to the data from the first to the second years preceding bankruptcy, while, when applied to the data from the fourth and fifth years preceding bankruptcy, the accuracy of the models decreases drastically.

The tests also suggested the importance of the relationship between bankruptcy and governance variables. In fact, it is noted that changes in the composition of the administrative body of healthy and rehabilitated enterprises have a higher frequency than the companies that have ceased. In addition, the regression results confirm the importance of board size and turnover of its members as in Elloumi and Gueyiè (2001).

Despite the results, the work suffers from several problems. Firstly, our sample includes only not listed Italian companies, which is a peculiar and specific sample since Italian companies have lower dimensions and lower transparency in governance than their European competitors, thus our data may suffer from distortions.

Secondly, companies are selected through a criterion adopted by one specific bank, which acts as a partner in this project. Specifically, it adopted a group perspective. A "group" may have a number of subsidiaries within it that have (or may not) have difficulty managing credit. Thus, there is the risk of a potential research gap: risk of result distortions in quantitative analyses carried out due to the fact that the results of a "legal entity" may be less relevant by adopting a "group" perspective. However, we believe it is a low-risk case: the significance of the results obtained allows us to conclude that these would be even more robust by adopting a "legal entity" perspective.

In addition, other financial institutions could adopt different criteria for the identification of UTP loans. However, these circumstances should in any case have a limited effect, in consideration of the common rules to which banks and companies are subject at the European level.

Finally, the size of the sample used is another limitation that can be solved by future research. However, in the absence of publicly available data on UTP, the use of confidential information, both important and limited, becomes necessary. This problem, we believe, is likely to be common to any research that wants to investigate the characteristics of companies that are classified among UTPs within the banking information system.

6. CONCLUSION

Despite the low diffusion and use of adequate predictive indicators in managerial and banking practice, this work confirms the predictive ability of one of the existing models, specifically Altman's Z'-Score and Z''-Score. The study shows also the fundamental practical implications of early signs of crisis. From an economic and financial point of view, stakeholders should monitor financial indicators: there are thresholds beyond which the probability of success/failure of a turnaround is considerably increased. From a management point of view, lower turnover of top roles (and therefore a greater turnover and a shorter period of time in office) corresponds to a lower probability of a crisis. Furthermore, 42% of the rehabilitated companies increased their social capital which confirms that the contribution of "fresh" capital as equity decreases the likelihood of a crisis.

Due to the limitation of this work and existing literature, the aim of future researches should be to test the efficiency of existing models (such as Z-Score) in predicting events far earlier than insolvency by also analysing different contexts, with companies and banks of other countries. Of particular interest could be to analyse companies and UTP in the US context and compare results with EU context. However, the availability of data is another issue that could limit also future researches. In order to solve this issue, future researches could adopt machine learning models, such as random forests, which do not suffer from lack of observations, like the logit model, and have shown to be in some cases more accurate (Jones et al., 2017).

Finally, with particular reference to the corporate governance variables, included in our study as control variables, we found a number of interesting relationships. Further research should investigate the role of different uses customs and laws on corporate governance variables. The topic has strong relevance given the limited literature on the matter (Baysinger & Butler, 1985; Denis, Denis, & Sarin, 1997; Himmelberg, Hubbard, & Palia, 1999; Elloumi & Gueyiè, 2001; Huson, Malatesta, & Parrino, 2004; Fahlenbrach & Stulz, 2007). Therefore, there is a research gap to be filled by further research focused on corporate governance within corporate restructuring processes.

REFERENCES

1. Aggarwal, R. (1995). Microstructure of world trading markets: Hans R. Stoll, Norwell, MA: Kluwer Academic Publishers, 1993, 154 pp. *International Review of Economics & Finance, 4*(3), 311-313. https://doi.org/10.1016/1059-0560(95)90048-9
2. Alareeni, B., & Branson, J. (2013). Predicting listed companies' failure in Jordan using Altman models: A case study. International *Journal of Business and Management, 8*(1), 113-126. https://doi.org/10.5539/ijbm.v8n1p113
3. Al-Sulaiti, K. I., & Almwajeh, O. (2007). Applying Altman Z-Score model of bankruptcy on service organizations and its implications on marketing concepts and strategies. *Journal of International Marketing and marketing research, 32*(2), 59-74.
4. Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance, 23*(4), 589-609. https://doi.org/10.1111/j.1540-6261.1968.tb00843.x
5. Altman, E. I. (1970). Ratio analysis and the prediction of firm failure: A reply. *The Journal of Finance, 25*(5), 1169-1172. https://doi.org/10.2307/2325591
6. Altman, E. I. (1983). Exploring the road to bankruptcy. *Journal of Business Strategy, 4*(2), 36-41. https://doi.org/10.1108/eb039018
7. Altman, E. I. (1988). *The prediction of corporate bankruptcy. A discriminant analysis.* New York, NY: Garland Publishing Inc.
8. Altman, E. I. (1993). *Corporate financial distress and bankruptcy* (2nd ed.). New York, NY: Wiley & Sons.
9. Altman, E. I. (2002). Revisiting credit scoring models in a Basel 2 environment. In M. K. Ong (Ed.), *Credit rating: Methodologies, rationale and default risk.* London, UK: Risk Book.
10. Altman, E. I., & Le Fleur, J. K. (1985). I modelli di previsione delle insolvenze: Le loro applicazioni alla gestione d'impresa. *Finanza, Marketing, Produzione, 4,* 77-93. Retrieved from http://www.biblio.liuc.it/scripts/essper/ricerca.asp?tipo=scheda&codice=10037013
11. Altman, E. I., & Narayanan, P. (1997). An international survey of business failure classification models. *Financial Markets, Institutions and Instruments, 6*(2), 1-57. https://doi.org/10.1111/1468-0416.00010
12. Altman, E. I., & Saunders, A. (1997). Credit risk measurement: Developments over the last 20 years. *Journal of Banking & Finance, 21*(11-12), 1721-1742. https://doi.org/10.1016/S0378-4266(97)00036-8
13. Altman, E. I., Danovi, A., & Falini, A. (2013). Z-score model's application to Italian companies subject to extraordinary administration. *Journal of Applied Finance, 23*(1), 1-10. Retrieved from http://people.stern.nyu.edu/ealtman/BOZZA%20ARTICOLO%2017.pdf
   Altman, E. I., Hartzell, J., & Peck, M. (1998). Emerging markets corporate bonds: A scoring system. In *Emerging market capital flows* (pp. 391-400). https://doi.org/10.1007/978-1-4615-6197-2_25
14. Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K., & Suvas, A. (2017). Financial distress prediction in an international context: A review and empirical analysis of Altman's Z-score model. *Journal of International Financial Management & Accounting, 28*(2), 131-171. https://doi.org/10.1111/jifm.12053
15. Amendola, A., Restaino, M., & Sensini, L. (2015). An analysis of the determinants of financial distress in Italy: A competing risks approach. International *Review of Economics and Finance, 37,* 33-41. https://doi.org/10.1016/j.iref.2014.10.012
16. Amigoni, F. (1998). *Manuale di organizzazione.* Turin, Italy: UTET.
17. Anderson, R. W., & Sundaresan, S. (1996). Design and valuation of debt contracts. *The Review of Financial Studies, 9*(1), 37-68. https://doi.org/10.1093/rfs/9.1.37
18. Andrade, G., & Kaplan, S. N. (1998). How costly is financial (not economic) distress? Evidence from highly leveraged transactions that became distressed. *The Journal of Finance, 53*(5), 1443-1494. https://doi.org/10.1111/0022-1082.00062
19. Asquith, P., Gertner, R., & Scharfstein, D. (1994). Anatomy of financial distress: An examination of Junk-Bond issuers. *The Quarterly Journal of Economics, 109*(3), 625-658. https://doi.org/10.2307/2118416
20. Aziz, A., Emanuel, D. C., & Lawson, G. H. (1988). Bankruptcy prediction – An investigation of cash flow based models. *Journal of Management Studies, 25*(5), 419-437. https://doi.org/10.1111/j.1467-6486.1988.tb00708.x
21. Back, B., Laitinen, T., Sere, K., & van Wezel, M. (1996). *Choosing bankruptcy predictors using discriminant analysis, logit analysis, and genetic algorithms* (Turke Centre for Computer Science, Technical Report No. 40). Retrieved from http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.28.4162
22. Bank of Italy. (n.d.). *Circular No. 272 of 30 July 2008 (12th update, 17 September 2019).* Retrieved from https://www.bancaditalia.it/compiti/vigilanza/normativa/archivio-norme/circolari/c272/CIRC272_12agg.pdf
23. Baysinger, B. D., & Butler, H. N. (1985). Corporate governance and the board of directors: Performance effects of changes in board composition. *The Journal of Law, Economics and Organization, 1*(1), 101-124. https://doi.org/10.1093/oxfordjournals.jleo.a036883

24. Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research, 4,* 71-111. https://doi.org/10.2307/2490171
25. Beaver, W. H., & Engel, E. E. (1996). Discretionary behavior with respect to allowances for loan losses and the behaviour of security prices. *Journal of Accounting and Economics, 22*(1-3), 177-206. https://doi.org/10.1016/S0165-4101(96)00428-4
26. Bellovary, J. L., Giacomino, D. E., & Akers, M. D. (2007). A review of bankruptcy prediction studies: 1930 to present. *Journal of Financial Education, 33,* 262-298. Retrieved from https://epublications.marquette.edu/cgi/viewcontent.cgi?article=1025&context=account_fac
27. Berkovitch, E., & Israel, R. (1998). The bankruptcy decision and debt contract renegotiations. *Review of Finance, 2*(1), 1-27. https://doi.org/10.1023/A:1009738110075
28. Beyonon, M. J., & Peel, M. J. (2001). Variable precision rough set theory and data discretisation: An application to corporate failure prediction. *Omega, 29*(6), 561-576. https://doi.org/10.1016/S0305-0483(01)00045-7
29. Bijnen, E. J., & Wijn, M. F. C. M. (1994). *Corporate prediction models. Ratios or regression analysis* (Tilburg University Working Paper No. 658). https://doi.org/10.2139/ssrn.1340
30. Black, F., & Cox, J. C. (1976). Valuing corporate securities: Some effects of bond indenture provisions. *The Journal of Finance, 31*(2), 351-367. https://doi.org/10.1111/j.1540-6261.1976.tb01891.x
31. Blazy, R., Fimayer, A., & Chopard, B. (2008). Bankruptcy law: A mechanism of governance for financially distressed firms. *European Journal of Law and Economics, 25,* 253-267. https://doi.org/10.1007/s10657-008-9048-8
32. Blum, M. (1974). Finding company discriminant analysis. *Journal of Accounting Research, 12*(1), 1-25. https://doi.org/10.2307/2490525
33. Blum, W. J. (1969). *Materials on reorganization, recapitalization and insolvency.* Boston, MA: Little Brown.
34. Boot, A. W. A. (2000). Relationship banking: What do we know? *Journal of Financial Intermediation, 9*(1), 7-25. https://doi.org/10.1006/jfin.2000.0282
35. Booth, A. (1983). A reconsideration of trade union growth in the United Kingdom. *British Journal of Industrial Relations, 21*(3), 377-391. https://doi.org/10.1111/j.1467-8543.1983.tb00142.x
36. Boser, B. E., Guyon, I. M., & Vapnik, V. N. (1992). A training algorithm for optimal margin classifiers. *Proceedings of the 5th Annual Workshop on Computational Learning Theory* (pp. 144-152). https://doi.org/10.1145/130385.130401
37. Bottani, P., Cipriani, L., & Serao, F. (2004). Il modello di analisi Z-Score applicato alle PMI. *Amministrazione & Finanza, 19*(1), 50-53. Retrieved from http://newsletter.sirio-is.it/files/allegati/Allegato1_1615.pdf
38. Brockman, P., & Turtle, H. J. (2003). A barrier option framework for corporate security valuation. *Journal of Financial Economics, 67*(3), 511-529. https://doi.org/10.1016/S0304-405X(02)00260-X
39. Brodi, E. (2018). *Tempestiva emersione e gestione della crisi d'impresa. Riflessioni sul disegno di un efficiente "sistema di allerta e composizione"* (Questioni di Economia e Finanza, Occasional Paper No. 440). Retrieved from https://www.bancaditalia.it/pubblicazioni/qef/2018-0440/QEF_440_18.pdf
40. Casey, C. J., & Bartczak, N. J. (1984). Cashflow – It's not the bottom line. *Harvard Business Review.* Retrieved from https://hbr.org/1984/07/cash-flow-its-not-the-bottom-line
41. Celli, M. (2015). Can Z-score model predict listed companies' failures in Italy? An empirical test. *International Journal of Business and Management, 10*(3), 57-66. https://doi.org/10.5539/ijbm.v10n3p57
42. Cestari, G., Risaliti, G., & Pierotti, M. (2013). Bankruptcy prediction models: Preliminary thoughts on the determination of parameters for the evaluation of effectiveness and efficiency. *European Scientific Journal, 9*(16), 265-290. https://doi.org/10.19044/esj.2013.v9n16p%25p
43. Charalambous, C., Charitou, A., & Kaourou, F. (2000). Comparative analysis of artificial neural network models: Application in bankruptcy prediction. *Annals of Operations Research, 99*(1-4), 403-425. https://doi.org/10.1023/A:1019292321322
44. Charitou, A., Neophytou, E., & Charalambous, C. (2004). Predicting corporate failure: Empirical evidence for the UK. *European Accounting Review, 13*(3), 465-497. https://doi.org/10.1080/0963818042000216811
45. Chemmanur, T. J., & Fulghieri, P. (1994). Investment bank reputation, information production, and financial intermediation. *The Journal of Finance, 49*(1), 57-79. https://doi.org/10.1111/j.1540-6261.1994.tb04420.x
46. Christensen, I., & Li, F. (2014). Predicting financial stress events: A signal extraction approach. *Journal of Financial Stability, 14,* 54-65. https://doi.org/10.1016/j.jfs.2014.08.005
47. Coats, P. K., & Fant, L. F. (1993). Recognizing financial distress patterns using a neural network tool. *Financial Management, 22*(3), 142-150. https://doi.org/10.2307/3665934
48. Dambolena, I. G., & Khoury, S. J. (1980). Ratio stability and corporate failure. *The Journal of Finance, 35*(4), 1017-1026. https://doi.org/10.1111/j.1540-6261.1980.tb03517.x
49. Damodaran, A. (2009). *Valuing distressed and declining companies.* https://doi.org/10.2139/ssrn.1428022
50. Davis, E. P., & Karim, D. (2008). Comparing early warning systems for banking crises. *Journal of Financial Stability, 4*(2), 89-120. https://doi.org/10.1016/j.jfs.2007.12.004
51. Deakin, E. B. (1972). A discriminant analysis of predictors of business failures. *Journal of Accounting Research, 10*(1), 167-179. https://doi.org/10.2307/2490225
52. Deakin, E. B. (1977). Business failure prediction: An empirical analysis. In E. I. Altman, & A. W. Sametz (Eds.), *Financial crisis, institutions and markets in a fragile environment* (pp. 72-98). New York, NY: John Wiley and Sons.
53. Denis, D. J., Denis, D. K., & Sarin, A. (1997). Agency problems, equity ownership, and corporate diversification. *The Journal of Finance, 52*(1), 135-160. https://doi.org/10.1111/j.1540-6261.1997.tb03811.x
54. Diamond, D. W. (1991). Debt maturity structure and liquidity risk. *The Quarterly Journal of Economics, 106*(3), 709-737. https://doi.org/10.2307/2937924
55. Donaldson, T., & Preston, L. E. (1995). The stakeholder theory of the corporation: Concepts, evidence, and implications. *The Academy of Management Review, 20*(1), 65-91. https://doi.org/10.2307/258887
56. Dudley, E., & Yin, Q. E. (2018). Financial distress, refinancing, and debt structure. *Journal of Banking & Finance, 94,* 185-207. https://doi.org/10.1016/j.jbankfin.2018.07.004
57. Eberhart, A. C., Altman, E. I., & Aggarwal, R. (1999). The equity performance of firms emerging from bankruptcy. *The Journal of Finance, 54*(5), 1855-1868. https://doi.org/10.1111/0022-1082.00169
58. Eccles, R. G. (1991). The performance measurement manifesto. *Harvard Business Review, 69*(1). Retrieved from https://hbr.org/1991/01/the-performance-measurement-manifesto

59. Edmister, R. O. (1972). An empirical test of financial ratios analysis for small business failure prediction. *The Journal of Finance and Quantitative Analysis, 7*(2), 1477-1493. https://doi.org/10.2307/2329929
60. Elloumi, F., & Gueyiè, J.-P. (2001). Financial distress and corporate governance: An empirical analysis. *Corporate Governance, 1*(1), 15-23. https://doi.org/10.1108/14720700110389548
61. Ezzamel, M., Brodie, J., & Mar-Molinero, C. (1987). Financial patterns of UK manufacturing companies. *Journal of Business Finance & Accounting, 14*(4), 519-536. https://doi.org/10.1111/j.1468-5957.1987.tb00110.x
62. Fahlenbrach, R., & Stulz, R. M. (2007). *Managerial ownership dynamics and firm value* (NBER Working Paper No. 13202). https://doi.org/10.3386/w13202
63. Fiordelisi, F., & Mare, D. S. (2013). Probability of default and efficiency in cooperative banking. *Journal of Financial Markets, Institutions and Money, 26,* 30-45. https://doi.org/10.1016/j.intfin.2013.03.003
64. Foreman, R. D. (2003). A logistic analysis of bankruptcy within the US local telecommunications industry. *Journal of Economics and Business, 55*(2), 135-166. https://doi.org/10.1016/S0148-6195(02)00133-9
65. Freeman, R. E. (1984). *Strategic management: A stakeholder approach.* https://doi.org/10.1017/CBO9781139192675
66. Gales, L. M., & Kesner, I. F. (1994). An analysis of board of director size and composition in bankrupt organizations. *Journal of Business Research, 30*(3), 271-282. https://doi.org/10.1016/0148-2963(94)90057-4
67. Giacosa, E. (2016). *Il fenomeno della crisi aziendale. Modello di percezione della crisi d'impresa.* Milan, Italy: Franco Angeli.
68. Giacosa, E., Halili, E., Mazzoleni, A., Teodori, C., & Veneziani, M. (2016). Re-estimation of company insolvency prediction models: Survey on Italian manufacturing companies. *Corporate Ownership & Control, 14*(1-1), 159-174. https://doi.org/10.22495/cocv14i1c1p1
69. Giacosa, E., Mazzoleni, A., Teodori, C., & Veneziani, M. (2015). Insolvency prediction in companies: An empirical study in Italy. *Corporate Ownership & Control, 12*(4-1), 232-250. https://doi.org/10.22495/cocv12i4c1p6
70. Gilson, S. C. (1997). Transactions costs and capital structure choice: Evidence from financially distressed firms. *The Journal of Finance, 52*(1), 161-196. https://doi.org/10.1111/j.1540-6261.1997.tb03812.x
71. Gilson, S. C., Hotchkiss, E. S., & Ruback, R. S. (2000). Valuation of bankrupt firms. *The Review of Financial Studies, 13*(1), 43-74. https://doi.org/10.1093/rfs/13.1.43
72. Gilson, S. C., John, K., & Lang, L. H. P. (1990). Troubled debt restructurings: An empirical study of private reorganizations of firms in default. *Journal of Financial Economics, 27*(2), 315-353. https://doi.org/10.1016/0304-405X(90)90059-9
73. Gombola, M. J., Haskins, M. E., Ketz, J. E., & Williams, D. D. (1987). Cash flow in bankruptcy prediction. *Financial Management, 16*(4), 55-65. https://doi.org/10.2307/3666109
74. Grice, J. S., & Dugan, M. T. (2001). The limitations of bankruptcy prediction models: Some cautions for the researcher. *Review of Quantitative Finance and Accounting, 17,* 151-166. https://doi.org/10.1023/A:1017973604789
75. Grice, J. S., & Ingram, R. W. (2001). Tests of the generalizability of Altman's bankruptcy prediction model. *Journal of Business Research, 54*(1), 53-61. https://doi.org/10.1016/S0148-2963(00)00126-0
76. Hambrick, D. C., & D'Aveni, R. A. (1992). Top team deterioration as part of the downward spiral of large corporate bankruptcies. *Management Science, 38*(10), 1445-1466. https://doi.org/10.1287/mnsc.38.10.1445
77. Hedberg, B. L. T., Nystrom, P. C., & Starbuck, W. H. (1976). Camping on seesaws: Prescriptions for a self-designing organization. *Administrative Science Quarterly, 21*(1), 41-65. https://doi.org/10.2307/2391877
78. Himmelberg, C. P., Hubbard, R. G., & Palia, D. (1999). Understanding the determinants of managerial ownership and the link between ownership and performance. *Journal of Financial Economics, 53*(3), 353-384. https://doi.org/10.1016/S0304-405X(99)00025-2
79. Hotchkiss, E. S. (1995). Postbankruptcy performance and management turnover. *The Journal of Finance, 50*(1), 3-21. https://doi.org/10.1111/j.1540-6261.1995.tb05165.x
80. Hotchkiss, E. S., John, K., Thorburn, K. S., & Mooradian, R. (2008). Bankruptcy and the resolution of financial distress. In *Handbook of empirical corporate finance* (Volume 2, pp. 235-287). https://doi.org/10.1016/B978-0-444-53265-7.50006-8
81. Huson, M. R., Malatesta, P. H., & Parrino, R. (2004). Managerial succession and firm performance. *Journal of Financial Economics, 74*(2), 237-275. https://doi.org/10.1016/j.jfineco.2003.08.002
82. Jo, H., Han, I., & Lee, H. (1997). Bankruptcy prediction using case-based reasoning, neural networks, and discriminant analysis. *Expert Systems with Applications, 13*(2), 97-108. https://doi.org/10.1016/S0957-4174(97)00011-0
83. Jones, S., Johnstone, D., & Wilson, R. (2017). Predicting corporate bankruptcy: An evaluation of alternative statistical frameworks. *Journal of Business Finance & Accounting, 44*(1-2), 3-34. https://doi.org/10.1111/jbfa.12218
84. Kahya, E., & Theodossiou, P. (1999). Predicting corporate financial distress: A time-series CUSUM methodology. *Review of Quantitative Finance and Accounting, 13*(4), 323-345. https://doi.org/10.1023/A:1008326706404
85. Kapadia, N. (2011). Tracking down distress risk. *Journal of Financial Economics, 102*(1), 167-182. https://doi.org/10.1016/j.jfineco.2011.05.004
86. Kováčová, M., & Kliestikova, J. (2017). Modelling bankruptcy prediction models in Slovak companies. *SHS Web Conference: Strategic Partnerships in International Trade, 39.* https://doi.org/10.1051/shsconf/20173901013
87. Leland, H. E. (1994). Corporate debt value, bond covenants, and optimal capital structure. *The Journal of Finance, 49*(4), 1213-1252. https://doi.org/10.1111/j.1540-6261.1994.tb02452.x
88. Li, H., & Sun, J. (2008). Ranking-order case-based reasoning for financial distress prediction. *Knowledge-Based Systems, 21*(8), 868-878. https://doi.org/10.1016/j.knosys.2008.03.047
89. Libby, R. (1975). Accounting ratios and the prediction of failure: Some behavioral evidence. *Journal of Accounting Research, 13*(1), 150-161. https://doi.org/10.2307/2490653
90. Libby, R., & Lewis, B. L. (1977). Human information processing research in accounting. The state of the art. *Accounting, Organizations and Society, 2*(3), 245-268. https://doi.org/10.1016/0361-3682(77)90015-0
91. Lin, L., & Piesse, J. (2004). The identification of corporate distress: A conditional probability analysis approach. *Applied Financial Economics, 14,* 73-82. Retrieved from https://www.researchgate.net/publication/313178035_The_identification_of_corporate_distress_in_UK_industrials_a_conditional_probability_analysis_approach
92. Longstaff, F. A., & Schwarts, E. S. (1995). A simple approach to valuing risky fixed and floating rate debt. *The Journal of Finance, 50*(3), 789-819. https://doi.org/10.1111/j.1540-6261.1995.tb04037.x

93. Lummer, S. L., & McConnell, J. J. (1989). Further evidence on the bank lending process and the capital-market response to bank loan agreements. *Journal of Financial Economics, 25*(1), 99-122. https://doi.org/10.1016/0304-405X(89)90098-6
94. Madonna, S., & Cestari, G. (2015). The accuracy of bankruptcy prediction models: A comparative analysis of multivariate discriminant models in the Italian context. *European Scientific Journal, 11*(34), 1-24. Retrieved from https://iris.unica.it/retrieve/handle/11584/190111/363422/Madonna%20%26%20Cestari%20ESJ.pdf
95. McGurr, P. T., & DeVaney, S. A. (1998). Predicting business failure of retail firms: An analysis using mixed industry models. *Journal of Business Research, 43*(3), 169-176. https://doi.org/10.1016/S0148-2963(97)00222-1
96. McKinley, W., Latham, S., & Braun, M. (2014). Organizational decline and innovation: Turnarounds and downward spirals. *Academy of Management Review, 39*(1), 88-110. https://doi.org/10.5465/amr.2011.0356
97. Mooradian, R. M., & Ryan Jr., H. E. (2005). Out-of-court restructurings and the resolution of financial distress: Section 3(a)(9) compared to investment-bank-managed exchange offers. *The Journal of Business, 78*(4), 1593-1624. https://doi.org/10.1086/430870
98. Moyer, R. C. (1977). Forecasting financial failure: A reexamination. *Financial Management, 6*(1), 11-17. https://doi.org/10.2307/3665489
99. Neophytou, E., Charitou, A., & Charalambous, C. (2001). Predicting corporate failure: Empirical evidence for the UK. *European Accounting Review, 13*(3), 465-497. https://doi.org/10.1080/0963818042000216811
100. Ofek, E. (1993). Capital structure and firm response to poor performance: An empirical analysis. *Journal of Financial Economics, 34*(1), 3-30. https://doi.org/10.1016/0304-405X(93)90038-D
101. Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research, 18*(1), 109-131. https://doi.org/10.2307/2490395
102. Ooghe, H., & Balcaen, S. (2006). 35 years of studies on business failure: An overview of the classic statistical methodologies and their related problems. *The British Accounting Review, 38*(1), 63-93. https://doi.org/10.1016/j.bar.2005.09.001
103. Paoloni, M., & Celli, M. (2018). Crisi delle PMI e strumenti di warning. Un test di verifica nel settore manifatturiero. *Management Control, 2,* 85-106. https://doi.org/10.3280/MACO2018-002005
104. Peel, M. J., Peel, D. A., & Pope, P. F. (1986). Predicting corporate failure – Some results for the UK corporate sector. *Omega, 14*(1), 5-12. https://doi.org/10.1016/0305-0483(86)90003-4
105. Peterson, M. A., & Rajan, R. G. (1995). The effect of credit market competition on lending relationships. *The Quarterly Journal of Economics, 110*(2), 407-443. https://doi.org/10.2307/2118445
106. Piesse, J, & Wood, D. (1992). Issues in assessing MDA models of corporate failure: A research note. *The British Accounting Review, 24*(1), 33-42. https://doi.org/10.1016/S0890-8389(05)80065-4
107. Platt, H. D., & Platt, M. B. (1990). Development of a class of stable predictive variables: The case of bankruptcy prediction. *Journal of Business Finance & Accounting, 17*(1), 31-51. https://doi.org/10.1111/j.1468-5957.1990.tb00548.x
108. Pompe, P. P. M., & Feelders, A. J. (1997). Using machine learning, neural networks, and statistics to predict corporate bankruptcy. *Computer-Aided Civil and Infrastructure Engineering, 12*(4), 267-276. https://doi.org/10.1111/0885-9507.00062
109. Rasmussen, R. K. (1997). A new approach to transnational insolvencies. *Michigan Journal of International Law, 19*(1). Retrieved from https://repository.law.umich.edu/mjil/vol19/iss1/1/
110. Reisz, A. S., & Perlich, C. (2007). A market-based framework for bankruptcy prediction. *Journal of Financial Stability, 3*(2), 85-131. https://doi.org/10.1016/j.jfs.2007.02.001
111. Salchenberger, L. M., Cinar, E. M., & Lash, N. A. (1992). Neural networks: A new tool for predicting thrift failures. *Decision Sciences, 23*(4), 899-916. https://doi.org/10.1111/j.1540-5915.1992.tb00425.x
112. Schendel, D. E., & Patton, G. R. (1976). Corporate stagnation and turnaround. *Journal of Economics and Business, 28*(3), 236-241. Retrieved from https://www.econbiz.de/Record/corporate-stagnation-and-turnaround-schendel-dan/10002768322
113. Schivardi, F., Sette, E., & Tabellini, G. (2017). *Credit misallocation during the European financial crisis* (Working Paper No. 1139, Bank of Italy). https://doi.org/10.2139/ssrn.3051189
114. Sheppard, J. P., & Chowdhury, S. D. (2005). Riding the wrong wave: Organizational failure as a failed turnaround. *Long Range Planning, 38*(3), 239-260. https://doi.org/10.1016/j.lrp.2005.03.009
115. Slatter, S., & Lovett, D. (1999). *Corporate recovery: Managing companies in distress.* Washington D.C.: Beard Books.
116. Sun, J., Li, H., Huang, Q.-H., & He, K.-Y. (2014). Predicting financial distress and corporate failure: A review from the state-of-the-art definitions, modeling, sampling, and featuring approaches. *Knowledge-Based Systems, 57,* 41-56. https://doi.org/10.1016/j.knosys.2013.12.006
117. Taffler, R. J. (1977). *Finding those firms in danger* using discriminant analysis and financial ratio data: A comparative UK-based study. (City University Business School Working Paper No. 3).
118. Taffler, R. J. (1984). Empirical models for the monitoring of UK corporations. *Journal of Banking & Finance, 8*(2), 199-227. https://doi.org/10.1016/0378-4266(84)90004-9
119. Taffler, R. J., & Tisshaw, H. (1977). Going, going, gone – Four factors which predict. *Accountancy, 88,* 50-54.
120. Tamari, M. (1964). Financial ratio as a means of forecasting bankruptcy. *Economic Review, 21,* 15-45. Retrived from https://www.econbiz.de/Record/financial-ratios-as-a-means-of-forecasting-bankruptcy-tamari/10002892255
121. Tashjian, E., Lease, R. C., & McConnell, J. J. (1996). An empirical analysis of prepackaged bankruptcies. *Journal of Financial Economics, 40*(1), 135-162. https://doi.org/10.1016/0304-405X(95)00837-5
122. Theodossiou, P. (1991). Alternative models for assessing the financial condition of business in Greece. *Journal of Business Finance & Accounting, 18*(5), 697-920. https://doi.org/10.1111/j.1468-5957.1991.tb00233.x
123. Timmermans, M. (2014). *US corporate bankruptcy predicting models* (Master's thesis, Tilburg University, School of Economics and Management). Retrieved from http://arno.uvt.nl/show.cgi?fid=135794
124. Tinoco, M. H., & Wilson, N. (2013). Financial distress and bankruptcy prediction among listed companies using accounting, market and macroeconomic variables. *International Review of Financial Analysis, 30,* 394-419. https://doi.org/10.1016/j.irfa.2013.02.013
125. Vašíček, B, Žigraiová, D., Hoeberichts, M., Vermeulen, R., Šmídková, K., & de Haan, J. (2017). Leading indicators of financial stress: New evidence. *Journal of Financial Stability, 28,* 240-257. https://doi.org/10.1016/j.jfs.2016.05.005

126. Ward, T. J. (1994). An empirical study of the incremental predictive ability of Beaver's naive operating flow measure using four state ordinal models of financial distress. *Journal of Business Finance & Accounting, 21*(4), 547-561. https://doi.org/10.1111/j.1468-5957.1994.tb00335.x
127. Warner, J. B. (1977). Bankruptcy costs: Some evidence. *The Journal of Finance, 32*(2), 337-347. https://doi.org/10.2307/2326766
128. Westgaard, S., & van der Wijst, N. (2001). Default probabilities in a corporate bank portfolio: A logistic model approach. *European Journal of Operational Research, 135*(2), 338-349. https://doi.org/10.1016/S0377-2217(01)00045-5
129. Wilcox, J. W. (1976). The gambler's ruin approach to business risk. *Sloan Management Review, 12*(1), 33-46.
130. Winn, J. (1993). Performance measures for corporate decline and turnaround. *Journal of General Management, 19*(2), 48-63. https://doi.org/10.1177/030630709301900204
131. Wruck, K. H. (1990). Financial distress, reorganization, and organizational efficiency. *Journal of Financial Economics, 27*(2), 419-444. https://doi.org/10.1016/0304-405X(90)90063-6
132. Wu, Y., Gaunt, C., & Gray, S. (2010). A comparison of alternative bankruptcy prediction models. *Journal of Contemporary Accounting & Economics, 6*(1), 34-45. https://doi.org/10.1016/j.jcae.2010.04.002
133. Yang, Z. R., Platt, M. B., & Platt, H. D. (1999). Probabilistic neural networks in bankruptcy prediction. *Journal of Business Research, 44*(2), 67-74. https://doi.org/10.1016/S0148-2963(97)00242-7
134. Zhu, L., Qiu, D., Ergu, D., Ying, C., & Liu, K. (2019). A study on predicting loan default based on the random forest algorithm. *Procedia Computer Science, 162,* 503-513. https://doi.org/10.1016/j.procs.2019.12.017
135. Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial, distress prediction models. *Journal of Accounting Research, 22,* 59-82. https://doi.org/10.2307/2490859

APPENDIX

Table 1. Industries represented in the sample by company status

	ATECO 2007 (Nace Rev. 2)	***701000***	***241000***	***255000***	***282500***	***283000***	***412000***	***500000***	***522209***	***681000***
Firms in financial distress that succeeded in restructuring		4.3%	2.9%	2.9%	2.9%	2.9%	2.9%	2.9%	2.9%	2.9%
Firms in a financially sound position		4.2%	4.2%	2.8%	2.8%	2.8%	2.8%	0.0%	5.6%	2.8%
Firms which have failed		1.3%	1.3%	1.3%	1.3%	0.0%	31.6%	0.0%	0.0%	13.2%
	ATECO 2007 (Nace Rev. 2)	***932100***	***011900***	***012100***	***103900***	***107300***	***130000***	***132000***	***143900***	***151209***
Firms in financial distress that succeeded in restructuring		2.9%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%
Firms in a financially sound position		2.8%	0.0%	1.4%	1.4%	1.4%	0.0%	2.8%	1.4%	1.4%
Firms which have failed		0.0%	0.0%	1.3%	0.0%	0.0%	0.0%	1.3%	0.0%	0.0%
	ATECO 2007 (Nace Rev. 2)	***162940***	***201000***	***205920***	***231000***	***231200***	***240000***	***251100***	***252100***	***256100***
Firms in financial distress that succeeded in restructuring		1.4%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%
Firms in a financially sound position		1.4%	0.0%	1.4%	1.4%	1.4%	0.0%	1.4%	1.4%	1.4%
Firms which have failed		0.0%	0.0%	0.0%	0.0%	1.3%	0.0%	6.6%	0.0%	1.3%
	ATECO 2007 (Nace Rev. 2)	***257200***	***257312***	***259000***	***259919***	***271100***	***279009***	***282000***	***282202***	***282992***
Firms in financial distress that succeeded in restructuring		1.4%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%
Firms in a financially sound position		1.4%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%
Firms which have failed		0.0%	0.0%	0.0%	0.0%	0.0%	2.6%	0.0%	0.0%	0.0%
	ATECO 2007 (Nace Rev. 2)	***284000***	***284909***	***289300***	***289900***	***301100***	***310000***	***310910***	***310990***	***351100***
Firms in financial distress that succeeded in restructuring		1.4%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%
Firms in a financially sound position		2.8%	1.4%	1.4%	1.4%	1.4%	2.8%	1.4%	1.4%	1.4%
Firms which have failed		1.3%	1.3%	0.0%	0.0%	1.3%	2.6%	0.0%	0.0%	1.3%
	ATECO 2007 (Nace Rev. 2)	***422100***	***463920***	***466100***	***467720***	***472100***	***476410***	***477100***	***477820***	***551000***
Firms in financial distress that succeeded in restructuring		1.4%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%
Firms in a financially sound position		1.4%	1.4%	0.0%	1.4%	1.4%	1.4%	1.4%	1.4%	1.4%
Firms which have failed		0.0%	1.3%	0.0%	0.0%	0.0%	0.0%	2.6%	1.3%	3.9%
	ATECO 2007 (Nace Rev. 2)	***610000***	***620100***	***649920***	***791100***	***861010***				
Firms in financial distress that succeeded in restructuring		1.4%	1.4%	1.4%	1.4%	1.4%				
Firms in a financially sound position		1.4%	1.4%	1.4%	1.4%	1.4%				
Firms which have failed		0.0%	3.9%	0.0%	1.3%	0.0%				

Table 2. Descriptive statistics by company status

	Average term of office									
	Director	***CEO***	***Sole director***	***Board members***	***Managing directors***	***General manager***	***Liquidators***	***BoD president***	***Sole shareholder***	
Firms in financially sound position	5.37	6.79	9.70	10.52	7.19	5.61	n.d.	10.37	7.90	
Firms in financial distress that succeeded in restructuring	4.76	5.69	4.93	7.72	5.37	5.68	2.00	8.60	5.79	
Firms which have failed	7.75	5.95	10.32	7.31	6.07	n.d.	1.83	7.54	9.19	
	Total change of role									
	Director	***CEO***	***Sole director***	***Board members***	***Managing directors***	***General manager***	***Liquidators***	***BoD president***	***Sole shareholder***	***Change in majority shareholding***
Firms in financially sound position	4.75	2.43	1.23	6.70	2.42	1.33	n.d.	1.80	1.16	1.13
Firms in financial distress that succeeded in restructuring	2.60	2.62	1.53	10.88	2.49	1.25	1.00	1.81	1.32	1.08
Firms which have failed	2,67	1.88	1.78	4.42	2.13	n.d.	1.67	1.62	1.29	1.01
	Z-Score									
	2007	***2008***	***2009***	***2010***	***2011***	***2012***	***2013***	***2014***	***2015***	***2016***
Firms in financially sound position	2.45	2.71	2.44	2.41	2.48	2.61	2.64	2.80	2.89	2.82
Firms in financial distress that succeeded in restructuring	1.42	1.16	1.04	1.27	1.19	0.98	0.87	1.09	1.31	1.51
Firms which have failed	1.47	1.57	1.35	1.55	1.50	1.21	1.24	0.53	1.32	1.92
	Z-Score"									
	2007	***2008***	***2009***	***2010***	***2011***	***2012***	***2013***	***2014***	***2015***	***2016***
Firms in financially sound position	6.18	6.51	6.14	6.07	6.06	6.18	6.45	6.78	6.86	6.87
Firms in financial distress that succeeded in restructuring	4.03	3.48	3.30	3.78	3.64	3.09	2.73	3.24	3.81	4.37
Firms which have failed	4.90	5.12	4.74	5.03	4.81	4.40	4.21	2.79	5.01	6.03

Table 3. Average values of ROS and D/E by year and type of status of the companies

	ROS (%)									
	2016	***2015***	***2014***	***2013***	***2012***	***2011***	***2010***	***2009***	***2008***	***2007***
Firms in financial distress that succeeded in restructuring	5.11	4.76	1.23	-1.68	-2.55	-0.43	0.34	-1.93	3.32	4.72
Firms in financially sound position	8.30	8.05	8.03	7.58	6.39	7.95	5.97	4.13	7.15	7.61
Firms which have failed	-2.08	-4.82	-4.15	-3.09	-2.70	-3.18	-2.52	-1.23	0.80	2.19
	D/E (%)									
	2016	***2015***	***2014***	***2013***	***2012***	***2011***	***2010***	***2009***	***2008***	***2007***
Firms in financial distress that succeeded in restructuring	10.18	8.22	14.01	9.61	5.90	3.10	2.72	2.96	3.87	3.79
Firms in financially sound position	2.99	1.28	2.01	1.18	0.94	1.06	0.96	1.44	1.03	1.37
Firms which have failed	6.89	2.44	31.83	-3.26	4.28	-0.85	41.40	7.20	-2.20	5.17

Table 4. Variables definition

Variables	*Definition*
Z'-Score (2007-2011)	The average score in the period before the crisis (2007-2011).
Z'-Score (2012-2014)	The average score in the period during the crisis (2012-2014).
Z'-Score (2015-2016)	The average score in the period after the crisis (2015-2016).
Z''-Score (2007-2011)	The average revised version of the score in the period before the crisis (2007-2011).
Z''-Score (2012-2014)	The average revised version of the score in the period during the crisis (2012-2014).
Z''-Score (2015-2016)	The average revised version of the score in the period after the crisis (2015-2016).

Table 5. Control variables definition

Control variables[2]	*Definition*
Number of board members (2007-2011)	Number of people who took the role of a member of the board of directors in the period prior to the crisis (2007-2011).
Number of CEO (2015-2018)	Number of people who took the role of CEO Chief Executive Officer in the period following the crisis (2015-2018).
Number of sole directors (2007-2011)	Number of people who took the role of sole director in the period prior to the crisis (2007-2011).
Number of sole directors (2015-2018)	Number of people who took the role of sole director in the period following the crisis (2015-2018).
Number of liquidators (2015-2018)	Number of people who took the role of judicial liquidator in the period following the crisis (2015-2018).
President of BoD (2015-2018)	Number of people who took the role of President of the board of directors in the period following the crisis (2015-2018).
Sole director average term of office	Average duration of the role of sole director.
Board of directors average term of office	Average duration of the role of board member.

Table 6. Correlations: Summary of results

Variable	*Variable*	*Number of observations (No.)*	*Positive or negative relationship*
Company status	No. of board members (2007-2011)	220	-
Company status	No. of CEO (2015-2018)	220	-
Company status	No. of sole directors (2007-2011)	220	+
Company status	No. of sole directors (2015-2018)	220	+
Company status	No. of liquidators (2015-2018)	220	+
Company status	President of BoD (2015-2018)	220	-
Company status	Sole directors average term of office	220	+
Company status	Board of directors average term of office	220	+
Company status	Z'-Score (2007-2011)	220	-
Company status	Z'-Score (2012-2014)	220	-
Company status	Z'-Score (2015-2016)	220	-
Company status	Z''-Score (2007-2011)	220	-
Company status	Z''-Score (2012-2014)	220	-
Company status	Z''-Score (2015-2016)	220	-

Table 7. Regression results: Model 1 (No. 220)

Model	*R*	*R-square*	*R-square adjusted*	*Standard error*
1	.561(a)	.315	.289	.39664

Model		*Non-standard ratios*		*Standard ratios*	*T*	*Sign.*
		Beta	*Standard error*	*Beta*		
1	(Steady)	.832	.080		10.466	.000
	Sole directors (2007-2011)	.092	.052	.108	1.768	.079
	Liquidators (2015-2018)	.112	.061	.110	1.829	.069
	President of BoD (2015-2018)	-.107	.043	-.150	-2.472	.014
	Z'-Score (2007-2011)	.060	.032	.157	1.855	.065
	Z'-Score (2012-2014)	-.158	.033	-.450	-4.855	.000
	Z'-Score (2015-2016)	-.032	.018	-.127	-1.786	.075
	BoD average term of office	.015	.005	.174	2.900	.004

Note: (a) dependent variable: status.

[2] Please note that we report only the definitions of the control variables that show a significant correlation with the dummy variable and that are therefore subsequently used in the regression.

Table 8. Regression results: Model 2 (N = 220)

Model	*R*	*R-square*	*R-square adjusted*	*Standard error*
2	.491(a)	.241	.213	.41728

Model		*Non-standard ratios*		*Standard ratios*	*T*	*Sign.*
		Beta	*Standard error*	*Beta*		
2	(Steady)	.921	.088		10.488	.000
	Sole directors (2007-2011)	.115	.054	.136	2.114	.036
	Liquidators (2015-2018)	.101	.064	.099	1.575	.117
	President of BoD (2015-2018)	-.158	.044	-.223	-3.570	.000
	Z''-Score (2007-2011)	-.061	.029	.114	1.111	.037
	Z''-Score (2012-2014)	.016	.006	-.356	-3.395	.005
	Z''-Score (2015-2016)	.020	.018	-.109	-1.541	.268
	BoD average term of office	-.012	.008	.179	2.831	.125

Note: (a) dependent variable: status.

Table 9. Regression results: Z'-Score for healthy and restructured companies (N = 144)

Model		*Non-standard ratios*		*Standard ratios*	*T*	*Sign.*
		Beta	*Standard error*	*Beta*		
1	(Steady)	.646	.109		5.949	.000
	Sole directors (2007-2011)	.080	.102	.061	.784	.435
	Liquidators (2015-2018)	.084	.467	.014	.180	.857
	President of BoD (2015-2018)	.038	.061	.046	.619	.537
	Z'-Score (2007-2011)	.018	.047	.046	.388	.698
	Z'-Score (2012-2014)	-.157	.047	-.433	-3.321	.001
	Z'-Score (2015-2016)	-.014	.022	-.058	-.623	.534
	BoD average term of office	.017	.007	.210	2.518	.013

Table 10. Regression results: Z''-Score for healthy and restructured companies (N = 144)

Model		*Non-standard ratios*		*Standard ratios*	*T*	*Sign.*
		Beta	*Standard error*	*Beta*		
1	(Steady)	.667	.112		5.983	.000
	Sole directors (2007-2011)	.069	.107	.053	.648	.518
	Liquidators (2015-2018)	.132	.467	.022	.282	.779
	President of BoD (2015-2018)	.039	.062	.048	.638	.525
	Z''-Score (2007-2011)	.030	.024	.176	1.275	.205
	Z''-Score (2012-2014)	-.083	.023	-.515	-3.569	.000
	Z''-Score (2015-2016)	-.007	.009	-.069	-.749	.455
	BoD average term of office	.017	.007	.208	2.469	.015

Table 11. Regression results: Z'- Score for the control sample

Model		*Non-standard ratios*		*Standard ratios*	*T*	*Sign.*
		Beta	*Standard error*	*Beta*		
1	(Steady)	.578	.121		4.794	.000
	Sole directors (2007-2011)	.082	.108	.067	.754	.452
	Liquidators (2015-2018)	.032	.472	.006	.068	.946
	President of BoD (2015-2018)	.042	.066	.054	.628	.532
	Z'-Score (2007-2011)	.045	.054	.117	.836	.405
	Z'-Score (2012-2014)	-.181	.056	-.475	-3.230	.002
	Z'-Score (2015-2016)	-.014	.023	-.061	-.608	.545
	BoD average term of office	.020	.007	.252	2.668	.009

Table 12. Regression results: Z''-Score for the control sample

Model		*Non-standard ratios*		*Standard ratios*	*T*	*Sign.*
		Beta	*Standard error*	*Beta*		
1	(Steady)	.636	.124		5.112	.000
	Sole directors (2007-2011)	.047	.113	.039	.416	.678
	Liquidators (2015-2018)	.150	.467	.028	.322	.748
	President of BoD (2015-2018)	.055	.066	.072	.836	.405
	Z''-Score (2007-2011)	.040	.025	.234	1.590	.115
	Z''-Score (2012-2014)	-.099	.026	-.571	-3.750	.000
	Z''-Score (2015-2016)	-.006	.009	-.059	-.601	.549
	BoD average term of office	.017	.007	.220	2.296	.024