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A revision of Altman's Z-Score for SMEs: suggestions from the Italian Bankruptcy Law and pandemic perspectives

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Abstract

As the pandemic urged further investigations on the prediction of firms' financial distress, this study develops and tests an alternative measure to the alert system elaborated by the NCCAAE which combines the benefits of the Z-score's multivariate discriminant model with the background employed to develop the NCCAAE' predictors. Using a sample of 43 viable and 43 non-viable Italian SMEs, we first compare the financial distress predictive accuracy of the NCCAAE's alert system to that of the traditional Z-score over the period 2015-2019. On the basis of the results, we elaborate and compare the revised versions of both approaches which align the traditional Z-score to the current socio-economic conditions and provide an alternative measure to the NCCAAE's alert system which embeds a Z-score calculated using the ratios elaborated by the NCCAAE for the alert system. The analysis of the two baseline approaches showed complementary results as the Z-score overperformed the alert system when predicting the status of non-viable firms whereas the opposite emerged as regards viable firms. The revised version of both approaches pointed out an enhanced predictive accuracy with respect to baseline models. In particular, the complementary role of the Z-score has been integrated into the new alert system as major contribute to its enhancement which pointed it out as the best measure employed. We, therefore, contribute to the literature studying the financial distress prediction developments by elaborating an alternative measure to the alert system developed by the NCCAAE which combines the benefits of the Z-score's multivariate discriminant function with the background employed to develop the NCCAAE' predictors. Our analysis enriches the post-pandemic debate on refined financial distressed prediction methods by pointing out the limits of the alert system as designed by the NCCAAE and suggests an alternative and better performing measure that may be used by third-party bodies to predict financial distress.

Keywords Z-score, Alert System, financial distress prediction, SMEs, NCCAAE.

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Introduction

The outbreak of the COVID-19 pandemic brought financial distress prediction methods under the spotlight for a close scrutiny as traditional predictive frameworks may poorly perform facing the volatile and evolving pandemic and economic scenario.

This question gains in relevance as the pandemic poses a serious threat to the resilience of small and medium-sized enterprises (SMEs) which represent the backbone of the European economy. SMEs are indeed prevalent in those sectors which have been hardest hit by the pandemic such as retail, hospitality, food services, entertainment services, and construction activities (Albaz, Mansour, Rida, & Schubert, 2020).

On the one hand, the decrease in consumer spending has negatively affected SME's profitability whereas, on the other hand, the disruption of the supply chain has caused shortages of the raw materials, goods and parts that are essential for SMEs to produce their goods and services.

In addition, the bank-based financing of SMEs, toghether with the loose monetary policy and regualtory forbearenace further complicate the picture by raising the spectre of zombie firms.

The undermined SMEs' resilience and the pandemic's evolution resume therefore the need for a revison of financial distress prediction methods better suited to navigate the pandemic.

This paper develops and tests an alternative measure to the alert system elaborated by the NCCAAE which combines the benefits of the Z-score's multivariate discriminant model with the background employed to develop the NCCAAE' predictors.

The Legislative Decree n.14 of 01/12/2019 introduced in the Italian national law the new Code of Business Crisis and Insolvency (CBCI) which will enter into force starting from 1st September, 2021. The new Code represents a major overhaul of the Italian Bankruptcy Law as it grounds on a prevention and recovery framework which should prevent a firms to incur into insolvency. In this regard, the main difference with the previous legislative framework consists with an approach designed to preserve the know-how, the expertise and the level of employment related to an ailing firm instead of simply removing it from the economic fabric. This purpose clearly emerges from the introduction of a set of tools aimed to monitor the viability of a firm in order to pre-empt distress conditions and, in such cases, promptly employ recovery measures in order to avoid reaching insolvency conditions. These tools, disciplined by Art.1 of the CBCI, are required to be elaborated every three years, and in accordance with the sectors identified by the Italian national institute of statistics, by the NCCAAE. This set of tools concurs with the logics above descripted to create the structure of the alert system which, accordingly, scrutinizes a firm's viability following a sequential approach that checks for the violation of each tool's threshold following a hierarchy based on their relevance in terms of distress prediction.

The first tool required to be examined is net equity which, if negative or below the minimum legal threshold, represents a reasonable indication of crisis. If positive, instead, the system requires the analysis of another tool, the Debt Service Coverage Ratio (DSCR), namely a measure of dynamic debt repayment. If this tool does not provide an indication of crisis, then the alert system requires the joint consideration of the following five sector ratios: the interest expenses to revenue ratio; the net equity to total debt ratio; the cash-flow to total assets ratio; the current assets to current liabilities ratio; and the pension and tax debts to total assets ratio. The sector ratios provide a reasonable indication of crisis only if all of them violate their specific thresholds conjunctly. In addition, the

CBCI recognizes as crisis indicators two further tools: the reiterated and significative delays in payments and the lack of viability perspectives due to causes different from probable insolvencies.

We, thus, aim to empirically test the financial distress predictive accuracy of the alert system so defined and further compare it to the well-established and widely known Z-score model. In addition, on the basis of the results, we further elaborate and evaluate the revised versions of both approaches, which consist with an alignment of the Z-score to the current socio-economic conditions and an alternative version of the NCCAAE's alert system based on the multivariate discriminant analysis' premises.

We, therefore, contribute to the literature that studies the financial distress prediction developments by contaminating two different approaches to develop a unique predictor.

For the analysis, we use a casual sample of 83 Italian SMEs so distributed: 43 viable firms and 43 non-viable firms. We collected annual firm financial data form the AIDA (Bureau Van Dyke) database over the period 2015-2019.

We, thus, provide an initial analysis of the ex-post application of the alert system designed by the Italian NCCAAE and of the Z-score model to our sample. We break down the analysis by year and tool, or classification output, depending on whether we are considering the alert system or the Z-score, respectively. Further information are provided as regards the timing of the indication of crisis of both approaches. Finally, the confusion matrices of each approach are used to compare the results. Then, we elaborate two multivariate discriminant functions using both the ratios employed to construct the Z-score and the sector ratios developed by the NCCAAE. We, therefore, obtain a modern version of the Z-score and a NCCAE's version of the Z-score. The former is thus compared with its baseline specification by mean of the confusion matrices. Similarly, we compare the NCCAE's version of the Z-score with its previous examined specifications and then we embed it into the alert system framework to obtain the new measure whose financial distress prediction accuracy is finally assessed and compared to its baseline specification.

The first stage of analysis points out contrasting results. Regarding the sample of non-viable firms, the Z-score has a higher accuracy compared to the alert system as the former has correctly identified the financial distress of 41 out of 43 firms in the year before bankruptcy whereas the latter has correctly identified only 33 out of 43. The Z-score model overperforms the alert system also as regards the rapidity of the intervention as the average time between the first signal of distress and actual bankruptcy is 2 years and 4 months for the Z-score whereas 1 year and 6 months for the alert system. Regarding the sample of viable firms, instead, the alert system overperformed the Z-score as the former inaccurately classified as non-viable an average of 15 out of 43 firms per tool in the five years considered whereas the latter classified as non-viable an annual average of 35 out of 43 firms.

The second stage of the analysis, instead, points out an enhanced financial distress predictive accuracy of both the revised Z-score and alert system. Moreover, the NCCAE's version of the Z-score overperforms both the traditional and updated versions of the Z-score correctly classifying 78 out of 86 firms. Finally, when the NCCAE's version of the Z-score is integrated in the new alert system, the resulting measure emerges as best predictor correctly classifying 80 out of 86 firms.

These results have relevant implications for policymakers, managers, investors and creditors. We indeed provided an alternative measure to the alert system developed by the NCCAAE which, combining the benefits of the Z-score's multivariate discriminant function with the background employed to develop the NCCAAE' sector ratios, overperformed its original version and also the famous Z-score, both in its original and enhanced version. As a result, our analysis points out the limits of the alert system as designed by the NCCAAE and suggests an alternative and better performing measure which may be used also by third-party bodies to predict financial distress alternatively to traditional and widely used methods like the Z-score.

The paper is organized as follows: Section 2 reviews the relevant literature; Section 3 describes the sample selection strategy and the sample; Section 4 presents the methodology employed; Section 5 presents and discusses the results; Section 6 concludes.

2 Literature review

Literature does not provide for a univocal and consistently shared definition of financial distress. The decline of a firm's health is indeed a dynamic ongoing process which develops across different stages ranging from early-stage symptoms to bankruptcy (Sun et al, 2014). The financial distress that an enterprise experiences broadly refers to the difficulties in fulfilling certain obligations which generally are related to liquidity or capital issues (Carminchael, 1972; Foster, 1986; Doumpos & Zopounidis, 1999). If not properly addressed, these difficulties may degenerate into the most severe stage of distress, namely bankruptcy, which literature explores under different perspectives: i) business failure, which refers to the situation when an enterprise is not able to pay the outstanding debt after liquidation; ii) legal bankruptcy, when an enterprise or its creditors requires a court to initiate a bankruptcy proceeding; iii) technical bankruptcy, identifies the situation in which an enterprise cannot fulfill the contract on schedule to repay principal and interest; iv) accounting bankruptcy, when an enterprises' book net assets are negative (Ross et al. 1999). In general, two frameworks are adopted to disentangle the concept of financial distress: the theoretical and the empirical framework. The former considers the intensity of financial distress to identify different degrees of it which range from mere symptoms, such as cash flow difficulties, to the more severe bankruptcy. The empirical framework instead leads scholars focusing on single criteria in order to clearly identify financial difficulty.

The prediction of a firm's financial distress is core in the decision-making process of several actors such as managers, investors and creditors. Moreover, financial distress prediction is crucial in providing an early warning which should trigger the prompt deployment of recovery strategies aimed at preserving the enterprise from failure. As a result, different contributions have been provided by researchers to the development of financial distress prediction methods which can be generally classified in: i) pure single classifier methods; ii) hybrid single classifier methods; iii) ensemble methods; iv) dynamic modeling methods and v) group decision-making methods.

In detail, pure single classifier methods are divided into: i) statistical single classifier methods and ii) artificial intelligence single classifier methods.

Statistical single classifier methods include the single variable analysis, the multivariate discriminant analysis and logit models. The seminal work of Beaver (1966) entitled "Financial Ratios as Predictors of Failure" used the single variable analysis to study the ability of accounting data, i.e. a set of 30 financial ratios, to predict bankruptcy considering a sample of 79 firms over the period 1954-1964. This method allowed to compare the score of a financial ratio of a given firm with that of a benchmark ratio so to discriminate between failed and non-failed firms. Two years later, Altman (1968) employs the multivariate discriminant analysis to predict bankruptcy. Specifically, he developed the Z-score model which is a multivariate linear discriminant function with five financial ratios: working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, market value of equity to total liabilities, and sales to total assets. The purpose of discriminant analysis is indeed that of generating a linear combination of variables which best discriminates between failed and non-failed firms. After gaining importance as reliable measure for predicting bankruptcy, the Z-score developed into more refined versions of the original model. The second version of the Z-score is the Z'-score (Altman, 1983) which simply replaces the market value of equity with its book value in the fourth ratio so to allow for the prediction of bankruptcy also for non-listed firms which cannot rely on market data. Nevertheless, the fifth ratio, namely sales to total assets, might have caused an industry effect if the sample would have included industries different from manufacturing. From this observation takes shape the third version of the Z-score, namely the Z''-score (Altman, 1995), which rules out the ratio of sales to total assets therefore removing the industry effect and allowing for different sectors to be included into the analysis. This model is still in use for predicting bankruptcies both by scholars and practitioners across different sectors and countries (Shaher at al., 2012; Altman et al, 2013; 2017; Chieng, 2013; Malik et al., 2016; Januri et al., 2017; Babatunde et al. 2017; AlAli, 2018; AlManaseer and Al-Oshaibat, 2018). The logit linear probability model employs the logistic function to make the dependent variable of financial distress probability totally continuous so to fit linear regression analysis and overcome the limits of the multivariate discriminant analysis (Ohlson, 1980).

Artificial intelligence single classifier methods include among others: neural networks (Tam, 1991; Tam & Kiang 1992); support vector machines (Wang et al, 2005); evolution algorithms (Varetto, 1998; Shin and Lee, 2002; Kim and Han, 2003); case-based reasoning (Li et al., 2011; Li & Sun, 2008; 2009; 2010; Borrajo et al, 2011); rough set (Dimitras et al., 1999; McKee, 2000); decision tree including RSP, CART and See 5.0 (Frydman et al., 1985; McKee and Greenstein, 2000; Gepp et al., 2010; Li et al., 2010). In general, artificial intelligence methods differ from statistical methods as they are not constrained by statistical assumptions and can fit more complex data sets.

Hybrid single classifier methods, instead, harness the combined use of different techniques to predict financial distress. The most common forms consist with integrating neural networks, support vector machines and case-based reasoning with other techniques.

Regarding ensemble methods, an ensemble system is able to harness each base classifier's unique information for classification. Classifier ensemble, which is also known as combination of multiple classifiers, has proven performing better as regards financial distress prediction. The seminal work on ensemble has been performed by Bates and Granger (1969) whereas the first application to financial distress prediction is to be attributed to Jo & Han (1996).

Dynamic modeling methods use incremental sample data to update financial distress prediction models as times goes on (Sun & Li, 2011; Sun et al., 2011; 2013) . Depending on whether the sample data that flows in the model is collected from different companies or from different time points of a certain company, the dynamic model is named lateral or longitudinal respectively. These methods focus on the adaptability of financial distress prediction models to internal and external environmental changes for an enterprise.

Group decision-making methods integrate non-financial information and the expertise of key actors related to the firms to support quantitative financial distress prediction methods.

3 Sample selection strategy and description

The sample selection procedure starts with the identification of non-viable firms. From AIDA (Bureau Van Dyke) database, we create this group setting criteria regarding: the legal form, the legal status, the start of the insolvency proceedings, the sector and the availability of balance sheet data for each year of the sample period.

We require the legal form of the firm to be either limited liability company or sole shareholder limited liability company. This criterium matches the characteristics of the Italian socio-economic fabric which mostly consists with small and medium enterprises that adopt the above-mentioned legal forms. We therefore ruled out joint stock companies, sole shareholder joint stock companies and limited joint stock partnerships as well as partnerships and sole proprietorships due to the fact that the former are not representative of the Italian business environment whereas the latter are not required to publish the balance sheet therefore the AIDA database does not provide any data for them.

We require the legal status to be bankrupt and rule out every other status involved with recovery proceedings. The existence of the insolvency proceeding has been checked using the creditor's portal of Fallco platform granted by Zucchetti Group.

We require the insolvency proceeding to be started between 1st January 2020 and 30th November 2020.

In order to allow for the application of the sector ratios elaborated by the NCCAAE, our sector criteria include all the sectors classified in the 2007 Ateco codes but the following ones: letter K "Financial and Insurance activities", letter L "Real estate activities", letter O "Public administration and defense, compulsory social insurance", letter T "Activities of households as employers of domestic personnel, production of undifferentiated goods and services for own use of households", letter U "Activities of extraterritorial organizations and bodies".

Finally, we require data availability for each year of the time period, namely 2015 to 2019.

This procedure resulted in 527 Italian firms. Then, we manually refined the sample ruling out those firms which does not have the financial data necessary to calculate the parameters of both the Z-score and the alert system. At the end of this procedure the sample counted 322 firms. Then, we have organized firms in descending order according to the total assets as per 2019 accounting value. Thus, we selected the first 43 firms to constitute our sample of non-viable firms.

In order to create the sample of viable firms, we select for each non-viable firm a viable peer comparable in terms of size (i.e. total assets as per 2019 accounting value) and Ateco sector. Regarding the other criteria, the legal form and the availability of balance sheet data follow those set out for the sample of non-viable firms but the legal status in this case is active.

Table 1 shows the sector distribution of our sample according to the ISTAT's 2007 Ateco codes. Our sample results characterized by wide sector heterogeneity as it consists with 22 different sectors. The most prevalent sectors are: i) "manufacture of products in metal" (13,95%); ii) "wholesale trade" (11,63%); and, at the same level, iii) "specialized construction works", "furniture manufacturing" and "restaurant business" (6,98%).

<< Please, insert here Table 1>>

4 Methodology

The analysis develops along two stages: the former compares the application of the NCCAAE's alert system and the Altman's Z-score to our sample whereas the latter consists in the elaboration of two alternative and refined measures whose financial distress predictive accuracy is assessed to draw conclusions on the most accurate financial distress predictor.

The first stage consists in two steps which describe the implementation and presentation of the results of the NCCAAE's alert system and the Z-score model, respectively.

The first step consists in applying the alert system, as developed by the NCCAAE, to our sample of firms. Of the set of tools elaborated by the NCCAAE, we ruled out the DSCR because of its previsional nature which impedes its calculation using balance sheet data. Therefore, the tools examined by this analysis consist only with the net equity and the five sector ratios. In addition, it is worth to notice that we calculate the pension and tax debts to total assets ratio net of debts already expired in previous business years and not reported in the following balance sheets due to the unavailability of values. We, therefore, strictly follow the approach as designed by the NCCAAE applying to the firms of our sample the net equity tool first, and in case of positive value, further checking for the joint violation of the sector ratios. The objective of the analysis is to evaluate the financial distress predictive accuracy of the alert system by controlling the number of firms correctly classified after its implementation. As we know the legal status a priori, it is indeed possible to observe the wrong indications of crisis in both sub-samples of viable and non-viable firms. Such wrong indications emerge as Type I and Type II errors namely the case of judging a firm insolvent when it is viable and the opposite, respectively. As a result, our evaluation of the alert system would be higher the less errors the system produces. Results are thus presented distinguishing between viable and non-viable firms and considering each year of the time-period and each tool of the alert system. Results about the timing of the indication of crisis conclude the reporting.

The second step consists in applying the Z-score to our sample of firms. In particular, we apply the Z'-score (Altman, 1983) to firms belonging to the manufacturing sector, namely those firms conducting an activity listed in the Section C of the 2007 Ateco codes, and the Z''-score (Altman, 1995) to the remaining firms.

As introduced in the literature review section, the Z'-score is a is a multivariate linear discriminant function of five financial ratios so defined:

$$Z' = 0{,}717X1 + 0{,}847X2 + 3{,}107X3 + 0{,}420X4 + 0{,}998X5$$

Where: X1 is the ratio of working capital to total assets, X2 is the ratio of retained earnings to total assets, X3 is the ratio of earnings before interest and taxes to total assets, X4 is the ratio of book value of equity to total liabilities, and X5 is the ratio of sales to total assets. According to Z'-score, a firm is considered viable for values greater than 2.99 whereas the same firm is considered non-viable for values lower than 1.23. The intermediate values between these two extremes represent the so called "grey area" which signal uncertainty regarding the viability of the firm. With respect to the original formulation of the Z-score, this version replaces the ratio of market value of equity to total liabilities with the ratio of book value of equity to total liabilities so to fit also those manufacturing firms, on which the original Z-score has been designed, that are not listed.

In a similar vein, the Z''-score further refine the model ruling out the variable X5 which regards the ratio of sales to total assets because of its sensitivity to the firm-specific sector. As a result, the model address possible concerns stemming from the sectorial bias. The refined model is a follows:

$$Z'' = 3{,}25 + 6{,}56X1 + 3{,}26X2 + 6{,}72X3 + 1{,}05X4$$

Where the variables X1, X2, X3 and X4 resembles those of the Z'-score. In addition, as can be noted, this formulation differs from the previous one as regards the weights assigned to each variable, which maximize the medium values of Z among viable and non-viable firms and minimize the within-group variability, and the presence of a constant of 3.25 in order to standardize the Z''-score for values equal or lower than 0. Regarding its specific thresholds, a firm is considered viable for values greater than 6.25 whereas the same firm is considered non-viable for values lower than 4.75. The "grey area" consists, in this case, of those values ranging from 4.75 to 6.25. As a result, we test the financial distress predictive accuracy of the Z-score and present the results coherently with those of the NCCAAs alert system so to provide a consistent framework for the comparison between the two measures.

Finally, the confusion matrices of each approach are used to compare the results.

The second stage consists in two steps which describe the elaboration, application and presentation of the results of the refined version of the Z-score and the NCCAAE's alert system, respectively.

The first step consists in elaborating a new version of the Z-score, which we call Z*-score, aligned with the current socio-economic situation. To this purpose, we use DTREG, a software of predictive modelling to calculate the new coefficients for our model and the cut-off points which enables the classification of firms between viable, non-viable and uncertain (i.e. belonging to the grey-area). The software requires the definition of a dependent variable, which in our case is binary and assumes value 1 if the firm is non-viable and 0 otherwise, and a set of independent variables which we retrieve from the Z''-score. The values of the variables refer to the 2018 business year. The software provides, thus, information regarding the accuracy of the model so defined bringing out the Type I and Type II errors and the coefficients to weigh each variable. The resulting Z*-score model is as follows:

$$Z\text{*-score} = -0{,}108X1 + 3{,}291X2 + 6{,}987X3 - 0{,}142X4$$

Where: X1 is the ratio of working capital to total assets, X2 is the ratio of retained earnings to total assets, X3 is the ratio of earnings before interest and taxes to total assets, X4 is the ratio of book value of equity to total liabilities. Then, we calculate the new Z*-scores using 2018 accounting data and relate each error to its relative score. The grey area is therefore the interval delimited by the lowest score associated with type I errors and the highest score associated with type II errors. According to the new thresholds, a firms is considered viable for values greater than 0.286 whereas the same firm is considered non-viable for values lower than 0.227. Thus, so defined, we use the new model to calculate the Z*-scores using 2019 accounting data, and present the results in form of distribution of firms according to their classification as viable, non-viable and uncertain. Finally, we use the confusion matrices to compare the financial distress predictive accuracy of the new Z*-score to that of the classic Z-scores employed in the first stage.

The second step consist in elaborating a different version of the NCCAAE's alert system with the purpose of combining the NCCAAE's expertise underlying the choice of the predictors with the simplicity, immediacy and synthesis of the Z-score model. Similarly to the approach deployed in the first step, we use the DTREG software to identify the cut-off points and the coefficients for the new Z-score model which we call Z**-score. The software requires as input a dependent variable, which we model as binary variable assuming value 1 if the firm is non-viable and 0 otherwise, and a set of independent variables, which we retrieve from the five sector ratios elaborated by the NCCAAE. The values of the variables refer to the 2018 business year. The software provides, thus, information regarding the accuracy of the model so defined bringing out the Type I and Type II errors and the coefficients to weigh each variable. The resulting Z**-score model is as follows:

$$Z\text{**-score} = 1{,}72 + 0{,}013709X1 + 0{,}002998X2 - 0{,}000036X3 + 0{,}041849X4 - 0{,}045367X5$$

Where: X1 is the interest expenses to revenue ratio; X2 is the net equity to total debt ratio; X3 is the cash-flow to total assets ratio; X4 is the current assets to current liabilities ratio; and X5 is the pension and tax debts to total assets ratio. Then, we calculate the new Z**-scores using 2018 accounting data and relate each error to its relative score. The grey area is therefore the interval delimited by the lowest score associated with type I errors and the highest score associated with type II errors. According to the new thresholds, a firms is considered viable for values greater than 1.476 whereas the same firm is considered non-viable for values lower than 1.146. Thus, so defined, we use the new model to calculate the Z**-scores using 2019 accounting data. We present the results in the form of distribution of firms according to their classification as viable, non-viable and uncertain. In addition, we provide the confusion matrix with respect to the other previous specifications of the Z-score examined. We, therefore, design the new alert system which requires the joint interpretation of two measures: the net equity value and the Z**-score. Thus, we develop an interpretative framework that attributes to each combination of both measures' values an alert level which permits us to consider them jointly and assess the predictive accuracy of the new alert system. Therefore, we provide the results of the new alert system according to the interpretative framework and along its confusion matrix with respect to that of its baseline model.

5 Results

As regards the first step of the first stage of our analysis, we present the results of the application of the NCCAAE's alert system to our sample of firms.

Table 2 reports, for each tool and each year of analysis, the number of non-viable firms for which the specific tool has violated (in red) or not (in green) its relative thresholds. Regarding the net equity, the tool performs good in 2019 indicating as non-viable 33 out of 43 firms in 2019. However, the tool gradually loses its predictive power as time distances from the start of the insolvency proceedings till identifying only one non-viable firm in 2015. Regarding sector ratios, results point out the good performance of the cash-flow to total assets ratio and the pension and tax debts to total assets ratio. In addition, it is worth to notice that, focusing on the results of the net equity to total debt ratio, firms do not suffer from structural issues as signaled firms are always lower than non-signaled firms.

<< Please, insert here Table 2>>

Table 3 reports for each tool and each year of analysis, the number of viable firms for which the specific tool has violated (in red) or not (in green) its relative thresholds. The net equity tool only indicates two firms from 2015 to 2016 and one firm from 2017 to 2019 which provide and indication of crisis. Regarding the sector ratios, the cash-flow to total assets ratio and the pension and tax debts to total assets ratio poorly performed as well as the current assets to current liabilities ratio.

<< Please, insert here Table 3>>

Finally, table 4 reports, per each year, the number of viable and non-viable firms which have provided an indication of crisis according to the alert system. As can be noted, the 38,37% of the entire sample have provided an indication of crisis the year before the start of the insolvency proceedings. On the other hand, only one firm has provided an indication of crisis in the 5th year before bankruptcy. As a result, the accuracy of the model decreases the higher the time period analyzed.

<< Please, insert here Table 4>>

As regards the second step of the first stage of our analysis, we present the results of the application of the Z-score to our sample of firms. The logic behind the presentation of the results resembles that used in the first step to ease the comparison.

Table 5 reports, for each year, the number of viable and non-viable firms distributed according to the Z-score thresholds which divide firms in viable, non-viable and uncertain. In 2019, Z-scores identify as non-viable 57 out of 86 firms, almost the 66,28% of the entire sample. As opposite, Z-scores identify as viable only 9 firms which all belong to the viable sample. The number of non-viable firms correctly classified has a fluctuating trend until 2017 and then steadily increase whereas, as expected, the number of non-viable firms wrongly classified as viable decreases. Regarding viable firms, it is interesting to notice that, despite the higher presence among non-viable and uncertain classifications, their number does not change substantially across time, especially as regards viable firms signaled as non-viable which maintain an almost constant trend throughout time. A possible explanation stems from the fact that 9 out of 20 of the viable firms signaled as non-viable in 2015 have been established in 2013. Due to their recent constitution, the losses, which emerge from the initial material costs beared to start the business, do not permit to retain earnings therefore their net equity value results low and so the Z-score values which provide an indication of crisis.

<< Please, insert here Table 5>>

Table 6 reports, for each year, the number of non-viable firms which have a constant status of non-viable according to the Z-score category in the following years. The trend is stable from 2015 to 2017 and then sharply increases from 2017 to 2019 suggesting that crisis stems from the perpetuated overlook of a negative physiological situation.

<< Please, insert here Table 6>>

The analysis conducted over the financial distress predictive accuracy of the alert system and the Z-score are now compared to draw conclusions about the pros and cons of each approach.

Table 7 provides a summary of the financial distress predictive accuracy of the two approaches. In detail, the table reports, per each year, the number and relative percentage of the viable and non-viable firms signaled by the alert system and the Z-score model.

The Z-score model outperformed the alert system as regards the financial distress predictive accuracy of the non-viable firms along all the period considered. In this regard, the distance between the two performance is greater in the period 2015-2017 but shrinks approaching the start of the insolvency proceedings which suggests that the net equity tool of the alert system may be good predictor in the short terms but loses efficacy for longer time periods.

However, it is interesting to notice the steady and high number of viable firms classified as non-viable due to their poor Z-score. Thus, we decided to delve into the drivers of such low Z-scores. The scrutiny of the balance sheets of these firms brough out the negative values of working capital, or irrelevant with respect to the total assets, which highlight a severe financial disequilibrium because of firms may not be able to fulfill obligations due to a lack of liquid assets. Another driver is represented by the operating income, measured as difference between income and production costs. It results, indeed, that the income is mostly absorbed by the costs related to the personnel and the purchase of raw materials. Finally, also the ratio of net equity to total debts concurs to lower the Z-score as net equity values are way lower than total debt values signaling a situation of undercapitalization.

<< Please, insert here Table 7>>

With the purpose of providing a more detailed comparison, table 8 reports, for each year and tool of the alert system, the summary statistics relative to viable and non-viable firms. The values of each statistic measure significantly differ between viable and non-viable firms suggesting a good accuracy of the alert system in discerning between viable and non-viable firms. Moreover, the accuracy increases as approaching the start of the insolvency proceedings as the average and median values of each tool keep exceeding the NCCAAE's thresholds for non-viable firms and instead remain below the thresholds for viable firms.

<< Please, insert here Table 8>>

In a similar vein, table 9 reports, for each year, the summary statistics of the Z-score relative to viable and non-viable firms. Also in this case, the average and median values of the Z-score decrease, with respect to non-viable firms, as approaching the start of the insolvency proceedings therefore suggesting the higher accuracy of the model in predicting financial distress the closer the point of no return. Regarding viable firms, the average and median values relative to the Z-score are higher but we cannot draw solid conclusions because of the employment of two different versions of the Z-score which have different thresholds.

<< Please, insert here Table 9>>

Finally, table 10 shows the 2019 confusion matrices of the alert system and the Z-score model. The table reports the combination between the effective and the predicted status of viable and non-viable firms so to highlight the type I and type II errors which allow for the comparison between the financial distress predictive accuracy of each approach. The Z-score model outperformed the alert system as regards the financial distress predictive accuracy of non-viable firms with a result of 41 out of 43 compared to the 33 out of 43 of the latter (10 type II errors). It is worth to specify that the alert systems indication of crisis stem all from the violation of the net equity tool as the joint violation of all sector ratios is instead a rare case. However, the alert system overperformed the Z-score model as regards the financial distress predictive accuracy of the sample of viable firms. The alert system, indeed, correctly classifies 42 out of 43 viable firms whereas the Z-score model correctly classifies only 9 firms causing therefore 34 type I errors.

<< Please, insert here Table 10>>

Overall, the alert system correctly classifies 75 out of 86 firms therefore outperforming in general terms the Z-score model which correctly classifies only 50 out of 86 firms.

Due to the lack of consistency in the performance of both approaches, we proceed with the second stage of this analysis which consists with presenting the results of the application of the refined version of both the Z-score and the alert system to our sample of firms.

We start presenting the results of the implementation of the Z*-score. Table 11 reports, for year 2019, the number of viable and non-viable firms distributed according to the Z*-score thresholds which divide firms in viable, non-viable and uncertain. From the results, it clearly emerges that the Z*-score outperformed its traditional version wrongly classifying only 11 out of 86 firms against the 36 out of 86 of the latter. A detailed comparison between the Z*-score and its traditional version, employed in the first stage of the analysis, is provided by table 12 which shows the confusion matrix of the two approaches. The Z*-score correctly classifies 75 over 86 firms therefore equaling the performance of the baseline alert system. However, it is worth to recommend the use of the Z*-score only to limited companies as its employment for partnerships could bias the results regarding the firm predicted status due to their different economic and patrimonial structure.

<< Please, insert here Table 11>>

<< Please, insert here Table 12>>

Finally, we present the results of the application of the Z**-score and the overall new alert system to our sample of firms. The logic underlying the functioning of the new alert system entails the joint interpretation of two variables: the net equity value and the Z**-score. With the purpose of providing a synthetic description of the new alert system, table 13 reports, for each combination resulting for the joint read of the two variables, a specific alert level with a brief description of the associated firm' status. Table 14 reports, for year 2019, the number of viable and non-viable firms distributed according to the Z**-score thresholds which divide firms in viable, non-viable and uncertain. From the results, it emerges that the Z**-score correctly predicts the financial distress of 78 out of 86 firms, namely the 90.69% of the entire sample. Thus, the Z**-score already overperforms all the specifications employed so far, as presented in table 15. We then present the results of the new alert system which jointly considers the net equity value and the Z**-score. Table 16 reports, for each level of alert identified by the joint read of the net equity value and the Z**-score, the number of viable and non-viable firms identified by the new alert system. The results point out the new alert system as the best financial distress predictor as it correctly identifies as non-viable 41 out of 43 firms and as viable 39 out of 43 (namely the sum of the firms included in the low and medium/low alert levels). Thus, the new alert system outperformed the original version correctly classifying 80 out of 86 firms against the 75 out of 86 firms of the latter as presented by the confusion matrices of the two approaches in table 17.

<< Please, insert here Table 13>>

<< Please, insert here Table 14>>

<< Please, insert here Table 15>>

<< Please, insert here Table 16>>

<< Please, insert here Table 17>>

6 Conclusions

The study develops an alternative measure to the alert system elaborated by the NCCAAE which combines the benefits of the Z-score's multivariate discriminant model with the background employed to develop the NCCAAE' predictors.

The study consists of an initial comparison exercise between the financial distress predictive accuracy of the NCCAAE's alert system with respect to that of the traditional Z-score over the period 2015-2019. The emerging results are then used to refine and reassess both measures as the traditional Z-score is aligned to the current socio-economic conditions whereas the alert system is integrated with a Z-score calculated using its predictors as inputs.

Initially, our analysis highlights the limits of the alert system as designed by the NCCAAE.

First of all, it should be noted that the notion of crisis used by the alert system is that indicated in the new Code of Business Crisis and Insolvency, it's to say "the inadequacy of current liquid funds and prospective cash flows to regularly meet existing and expected obligations over a period of six months. Such a short time horizon was probably chosen to increase the reliability of the system of indicators. Furthermore, the NCCAAE itself specified that the model has been set up in such a way as to minimize the number of "false positives", that is, those companies whose insolvency is expected but that in reality they will not incur in the time span examined and admit the possibility of a greater number of "false negatives", or companies whose crisis is not diagnosed but will become insolvent.

The disclaimers listed above are indicative of the NCCAAE awareness that the alert measures can have significant repercussions on a large number of companies and so that the alert thresholds have to lead to pointing out only those companies that appear to be very close to insolvency. It seems almost superfluous to say that an alert signal is useful only when it actually manages to identify the first hints of a business crisis.

From this point of view, our empirical results were not surprising as we found some problems in the alert system in predicting the financial distress of non-viable firms.

In detail, the alert system detected only 33 out of 43 non-viable firms, therefore committing 10 type II errors. The Z-score, instead, showed a better accuracy predicting the financial distress of 41 out of 43 non-viable firms. As regards viable firms, the alert system outperformed the Z-score model by correctly predicting the viable status of 42 against 9 firms. Regarding timing, the Z-score has an average of two years and four months between the first signal and the effective bankruptcy of a firm against the one year and six months of the alert system.

The abovementioned considerations clarify the logical and practical limits of the NCCAAE's alert system.

We, therefore, developed the enhanced version of both approaches which consists of aligning the traditional Z-score to the current socio-economic situation and compensate the limits of the alert system with the complementarities expressed by the Z-score. The revised Z-score outperformed its traditional version fixing its poor financial distress predictive accuracy as regards viable firms. However, the Z-score employed as part of the renewed alert system already overperformed the revised version as regards the financial distress predictive accuracy of both non-viable (40 out of 43 against 39 out of 43) and viable firms (38 out of 43 against 36 out of 43). In addition, when integrated into the alert system framework, it permits the resulting new alert system to significantly improve its performance. In detail, the new alert system improves the financial distress predictive accuracy of non-viable firms with respect to its baseline version (41 out of 43 against 33 out of 43) while slightly decreased its accuracy as regards viable firms (39 out of 43 against 42 out of 43). Overall, the new alert system emerges as best measure employed in this study by correctly classifying 80 out of 86 firms.

In conclusion, our finding may have important policy implications since it points out the limits of the alert system as designed by the NCCAAE and suggests an alternative and better performing measure which may be used by third-party bodies to predict financial distress.

The range of these implications is significant given the hampered resilience of SMEs, which play a crucail role played for the European ecomony, in particular that of Italy, and the uncertain future caused by the pandemic.

Traditional predictive frameworks, indeed, may prove inadequate to address the upcoming and volatile economic scenario and need, therefore, a new design able to capture the peculiarities of the pandemic implications for SMEs' resilience.

Loose regulatory and policy action further complicate the picture by raising the spectre of zombie firms and laying down the conditions for government funding to be vabished in the "wrong hands".

A suitable predictive framework is therefore of utter importance and our study contributes in this vein by developing a financial distress prediction method that may help navigating the new scenario posed by the pandemic.

Much more work has however to be done; it's clear, in fact, that every backward-looking test completely loses its meaning considering the new pandemic economic scenario that companies will have to face.

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Table 1: Sample's firms according to their relative 2007 Ateco code

2007 Ateco codes	No. of firms	No. of firms (%)
Food industries	2	2.33%
Textile industries	4	4.65%
Manufacture of other non-metallic mineral products	2	2.33%
Metallurgy	2	2.33%
Manufacture of products in metal	12	13.95%
Manufacture of electrical equipment	2	2.33%
Manufacture of nca machinery and equipment	2	2.33%
Furniture manufacturing	6	6.98%
Other manufacturing industries	2	2.33%
Construction of buildings	4	4.65%
Specialized construction works	6	6.98%
Wholesale and retail trade and repair of motor vehicles and motorcycles	4	4.65%
Wholesale trade	10	11.63%
Retail trade	4	4.65%
Land transport and pipeline transport	4	4.65%
Restaurant business	6	6.98%
Software production, software production, IT consulting and related activities	2	2.33%
Business management and management consulting activities	2	2.33%
Activities of architectural and engineering firms; technical testing and analysis	4	4.65%
Advertising and market research	2	2.33%
Creative, artistic and entertainment activities	2	2.33%
Repair of computers of goods for personal and home use	2	2.33%
Total	86	100.00%

Table 2: Non-viable firms according to the compliance or violation of NCCAAE tools' thresholds - Detail per years

Years	Negative value of net equity		The interest expenses to revenue ratio		The net equity to total debt ratio		The current assets to current liabilities ratio		The cash-flow to total assets ratio		The pension and tax debts to total assets ratio	
2019	33	10	5	5	3	7	6	4	9	1	9	1
2018	11	32	16	16	14	18	12	20	27	5	24	8
2017	6	37	14	23	5	30	10	25	24	11	22	13
2016	2	41	16	25	7	34	10	41	25	16	24	17
2015	1	42	19	23	8	34	11	31	27	15	23	19

Table 3: Viable firms according to the compliance or violation of NCCAAE tools' thresholds - Detail per years

Years	Negative value of net equity		The interest expenses to revenue ratio		The net equity to total debt ratio		The current assets to current liabilities ratio		The cash-flow to total assets ratio		The pension and tax debts to total assets ratio	
2019	1	42	6	36	5	37	9	33	13	29	7	35
2018	1	42	2	40	2	40	8	34	8	34	6	36
2017	1	42	5	37	2	40	6	36	8	34	5	37
2016	2	41	6	35	5	36	9	32	9	32	10	31
2015	2	41	8	33	8	33	11	30	13	28	12	29

Table 4: Non-viable firms signaled by the alert system - Detail per time series

Time	t_{-1}	t_{-1} (%)	t_{-2}	t_{-2} (%)	t_{-3}	t_{-3} (%)	t_{-4}	t_{-4} (%)	t_{-5}	t_{-5} (%)
No. of non-viable firms	33	38.37%	15	17.44%	4	4.65%	2	2.33%	1	1.16%
Average (years)	1.60									

Table 5: Sample's firms according to the Z-score classification

		Non-viable	Uncertain	Viable	Total
2019	Non-viable firms	41	2	0	43
	Viable firms	16	18	9	43
	Total	57	20	9	86
2018	Non-viable firms	34	7	2	43
	Viable firms	16	18	9	43
	Total	50	25	11	86
2017	Non-viable firms	27	12	4	43
	Viable firms	18	17	8	43
	Total	45	29	12	86
2016	Non-viable firms	28	10	5	43
	Viable firms	18	17	8	43
	Total	46	27	13	86
2015	Non-viable firms	26	13	4	43
	Viable firms	20	17	6	43
	Total	46	30	10	86

Table 6: Non-viable firms signaled by the Z-score - Detail per time series

Time	t_{-1}	t_{-1} (%)	t_{-2}	t_{-2} (%)	t_{-3}	t_{-3} (%)	t_{-4}	t_{-4} (%)	t_{-5}	t_{-5} (%)
No. of non-viable firms	41	47.67%	25	29.07%	14	16.28%	13	15.12%	12	13.95%
Average (years)	2.33									

Table 7: Sample's firms as classified by the alert system and the Z-score model

Year	Firms signaled by the alert system		Percentage of firms signaled by the alert system (*)		Firms signaled by the Z-score		Percentage of firms signaled by the Z-score (*)	
	Non-viable	Viable	Non-viable	Viable	Non-viable	Viable	Non-viable	Viable
2019	33	1	38.37%	1.16%	41	16	47.67%	18.60%
2018	15	1	17.44%	1.16%	34	16	39.53%	18.60%
2017	6	1	6.98%	1.16%	27	18	31.40%	20.93%
2016	2	2	2.33%	2.33%	28	18	32.56%	20.93%
2015	2	2	2.33%	2.33%	26	20	30.23%	23.26%

(*) The percentage is given by the ratio of the annual number of signaled firms to the total number of firms.

Table 8: Summary statistics of the alert system

		Net equity value		The interest expenses to revenue ratio		The net equity to total debt ratio		The current assets to current liabilities ratio		The cash-flow to total assets ratio		The pension and tax debts to total assets ratio	
		Non-viable firms	Viable firms	Non-viable firms	Viable firms	Non-viable firms	Viable firms	Non-viable firms	Viable firms	Non-viable firms	Viable firms	Non-viable firms	Viable firms
	Mean	-1,610,824	1,443,151	4.58	1.19	-24.02	74.05	63.75	167.62	-35.67	2.32	34.48	4.45
	Median	-560,359	461,769	2.69	0.35	-25.29	26.64	64.66	121.56	-32.29	2.86	25.26	2.28
	Std. Dev.	n.d.	3,257,436	5.20	2.05	32.02	97.34	33.38	129.17	28.21	7.76	28.85	6.87
	Minimum	-11,491,159	-41,568	0.22	0.00	-88.29	1.64	3.26	38.16	-109.33	-17.79	0.46	0.01
2019	Maximum	6,991,962	19,222,520	22.83	11.96	49.43	404.26	151.52	563.43	4.31	22.09	115.05	34.52
	Mean	121,280	1,276,058	3.75	1.05	22.69	72.51	108.30	385.25	-7.61	4.63	17.91	4.41
	Median	116,225	407,143	1.96	0.42	12.90	29.85	114.23	127.28	-3.28	3.09	13.11	2.00
2018	Std. Dev.	n.d.	n.d	6.99	1.47	26.92	116.95	45.87	1519.62	14.65	6.97	15.79	7.03

	Minimum	-5,815,932	638	0.26	0.00	0.19	0.74	27.25	26.00	-77.62	-11.12	0.41	0.00
	Maximum	8,794,774	15,543,834	40.67	7.22	93.85	634.17	245.12	9976.03	3.22	20.22	63.80	36.73
	Mean	707,137	1,115,143	2.44	1.15	26.45	64.11	112.21	365.29	-2.29	5.45	11.82	3.59
	Median	464,809	362,608	2.06	0.49	18.70	26.41	108.54	118.64	-0.72	4.41	9.08	1.46
	Std. Dev.	n.d.	n.d	2.04	1.86	26.47	119.25	41.19	1429.50	7.18	7.21	9.86	6.84
	Minimum	-1,873,322	8,737	0.17	0.00	-1.21	1.34	12.49	24.68	-38.01	-11.98	0.18	0.01
2017	Maximum	3,453,948	14,052,352	9.44	10.86	112.40	730.45	235.72	9374.26	6.17	23.39	39.07	35.17
	Mean	816,068	963,634	3.19	1.26	25.89	57.51	112.72	295.57	-1.69	4.47	11.68	3.46
	Median	482,598	285,417	2.03	0.81	17.26	23.21	109.22	115.14	0.04	3.19	7.49	1.57
	Std. Dev.	n.d.	n.d.	3.03	1.52	27.04	96.92	37.69	677.76	5.51	7.51	11.31	5.30
	Minimum	-269,324	-92,842	0.23	0.00	0.57	1.41	14.91	24.03	-17.48	-13.26	0.40	0.00
2016	Maximum	3,641,091	10,639,041	13.71	6.91	119.07	582.31	194.26	3815.76	5.56	24.55	57.66	28.34
	Mean	803,355	765,938	3.37	1.43	25.75	52.30	110.04	172.64	-0.93	4.37	9.79	6.36
2015	Median	470,590	216,615	2.49	0.79	14.95	23.13	106.17	118.32	0.10	2.28	7.73	2.22
	Std. Dev.	n.d.	n.d.	4.23	1.77	32.29	92.01	36.94	168.49	5.17	8.76	10.00	10.86

Minimum	-255,308	36	0.24	0.00	0.64	1.52	17.92	14.39	-18.69	-10.13	0.09	0.00
Maximum	4,778,372	7,991,233	26.35	8.00	164.42	563.63	205.07	849.91	7.24	39.68	55.46	46.11

Table 9: Summary statistics of the Z-score

Year	Firm status	Mean	Median	Std. Dev	Minimum	Maximum
2019	Non-viable firms	-1,73	-1,52	4,00	-14,32	5,76
	Viable firms	4,04	3,48	2,81	0,69	10,84
2018	Non-viable firms	1,74	1,13	2,73	-3,99	8,78
	Viable firms	3,88	2,99	2,81	-0,29	10,75
2017	Non-viable firms	2,64	1,83	2,33	-1,17	8,52
	Viable firms	3,85	3,56	2,66	-0,69	12,28
2016	Non-viable firms	2,90	2,19	2,18	-0,30	7,83
	Viable firms	3,77	3,24	2,97	-2,65	11,74
2015	Non-viable firms	2,92	2,83	2,20	-0,58	8,69
	Viable firms	4,13	3,05	4,15	-0,37	24,21

Table 10: Confusion matrixes of the alert system and the Z-score model

		Alert system's predicted status	
		Non-viable	Viable
Actual status	Non-viable firms	33	10
	Viable firms	1	42

		Z-score's predicted status	
		Non-viable	Viable
Actual status	Non-viable firms	41	2
	Viable firms	34	9

Table 11: Sample's firms as classified by the Z*-score

Year	Firm Status	Non-viable	Uncertain	Viable	Total
2019	Non-viable firms	39	0	4	43
	Viable firms	5	2	36	43
Total		44	2	40	86

Table 12: Confusion matrices comparing the Z*-score to the Z-score

		Z*-score's predicted status	
		Non-viable	Viable
Actual status	Non-viable firms	39	4
	Viable firms	7	36

		Z-score's predicted status	
		Non-viable	Viable
Actual status	Non-viable firms	41	2
	Viable firms	34	9

Table 13: Z**-scores' alert levels and description

Net equity tool	Z**-Score	Level of alert	Description
Negative, namely below the minimum legal threshold	Non-viable	High	Certain crisis status due to severe losses and serious liqidity and structural difficulties.
Negative, namely below the minimum legal threshold	Uncertain	Medium-High	High probability of insolvency due to high leverage and/or temporary liquidity difficulties which jeopardize the fulfilment of financial obligations
Negative, namely below the minimum legal threshold	Viable	Medium	Significant probability of insolvency due to structural and assets disequilibria
Positive	Non-viable	Medium	Moderated probability of insolvency due to financial and economic fragilities
Positive	Uncertain	Medium/Low	Low probability of insolvency given the great assets equilibrium

Positive	Viabl e	Low	Very low probability of insolvency given the solid assets and economic equilibria and the ability of timely fulfiling financial obligations

Table 14: Sample's firms as classified by the Z**-score

Year	Firm Status	Non-viable	Uncertain	Viable	Total
2019	Non-viable firms	40	2	1	43
	Viable firms	3	2	38	43
Total		43	4	39	86

Table 15: Confusion matrices comparing all the specifications of the Z-score

		Z*-score's predicted status	
		Non-viable	Viable
Actual status	Non-viable firms	39	4
	Viable firms	7	36

		Z-score's predicted status	
		Non-viable	Viable
Actual status	Non-viable firms	41	2
	Viable firms	34	9

		Z**-score's predicted status	
		Non-viable	Viable
Actual status	Non-viable firms	40	3
	Viable firms	5	38

Table 16: Sample's frims as classified by the new alert system – Year 2019

Net Equity Index Value	Z**-Score	Alert level	No. Of Non-viable firms	No. Of Viable firms
Negative, namely below the minimum legal threshold	Non-viable	High	32	0
Negative, namely below the minimum legal threshold	Uncertain	Medium/High	1	0
Negative, namely below the minimum legal threshold	Viable	Medium	0	1
Positive	Non-viable	Medium	8	3
Positive	Uncertain	Medium/Low	1	2
Positive	Viable	Low	1	37
Total			43	43

Table 17: Confusion matrixes of the specifications of the alert system

		New Alert System's predicted status	
		Non-viable	Viable
Actual status	Non-viable firms	41	2
	Viable firms	4	39

		Alert system's predicted status	
		Non-viable	Viable
Actual status	Non-viable firms	33	10
	Viable firms	1	42