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Research Paper

Financial distress pre-warning indicators: a case study on Italian listed companies

Francesco De Luca and Enrica Meschieri

Department of Business Administration, University "G. d'Annunzio" Chieti–Pescara, Viale Pindaro 42, 65127 Pescara, Italy; emails: fdeluca@unich.it; enricameschieri@gmail.com

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ABSTRACT

The reform of the Italian insolvency law in 2005 introduced the troubled debt restructuring (TDR) procedure as a means to restore companies that are in financial distress and avoid potential liquidation. The success of this procedure depends strictly on the timeliness of intervention. Therefore, the availability of a prediction tool appears to be crucial. This paper focuses on the ability of accounting ratios to predict the financial distress status of a firm as defined by the law. Based on a linear discriminant analysis, we formulate the probability of a firm filing for TDR in one year, as well as other quantitative techniques that are intended to monitor financial health. Specifically, we begin with a test of Altman's Z, Z' and Z'' scores for bankruptcy on the listed Italian companies that filed for TDR in the period 2005–12. The test results do not completely satisfy the TDR prediction. We then introduce a new score formula based on seven accounting ratios and specific coefficients. Several confirmative analyses are also conducted to validate the predictive accuracy and the generalization power of our score formula.

Keywords: financial distress prediction; troubled debt restructuring (TDR); accounting ratios; Italian listed companies; predictive effectiveness of credit risk.

Corresponding author: F. De Luca

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1 INTRODUCTION AND RESEARCH QUESTIONS

The spread of the 2007–9 global financial crisis has heavily affected the Italian entrepreneurial environment, and an ever growing number of companies have progressively experienced financial distress. At the same time, the volume of global restructured debt showed a significant growth rate. Remarkably, specific provisions on debt restructuring are not included in the Italian Civil Code and the national accounting standards set by the Organismo Italiano di Contabilità (OIC). Recently, several significant legal innovations have emerged. The Law Decree No. 35 of March 14, 2005 (converted into Law No. 80 on May 14, 2005) and the Legislative Decree No. 5 of January 9, 2006 introduced a new tool to manage company crisis: the Article 182-*bis* restructuring agreements (Di Marzio 2006).

The restructuring agreement is defined within the newly issued Italian accounting standard (OIC 6; see Organismo Italiano di Contabilità 2011) as "an operation whereby the creditor (or group of creditors) grants a concession to the debtor in financial difficulties, such that otherwise it would not have agreed". This new pre-insolvency proceeding, which somewhat resembles the prepackaged plan of Chapter 11 of the US Bankruptcy Code (Altman *et al* 2013),[1] is a hybrid method that occurs partly out-of-court and partly in-court and permits a corporate reorganization. The focus is on the agreements between the debtor and the creditors (Chen *et al* 1995) to provide a "fresh start". This "fresh start" provides the company with new opportunities to operate in the market, including new out-of-court restructuring instruments that prevent the liquidation of the company. In particular, restructuring agreements allow debtors to negotiate new conditions with creditors, including the reduction of residual debt or the rescheduling of the original reimbursement plans. Recently, these instruments have been widely used, especially in negotiations with a group of banks.

The Italian bankruptcy reform appears to closely follow a legislative process similar to that in the United States, even if several differences arise. The main difference is the "cram down" rule. According to this rule, as in US legislation, if a class of creditors votes in favor of the agreement in opposition to one or more classes, the debtor can still seek approval of the restructuring plan based on the process of cram down. In contrast, Article 182-*bis* does not include this provision, and it charges the Italian Court with formal supervision that includes approving the restructuring plan and

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[1] Within the US Bankruptcy Code, Chapter 7 refers to liquidation, whereas Chapter 11 "provides for reorganization, usually involving a corporation or partnership. A Chapter 11 debtor usually proposes a plan of reorganization to keep its business alive and pay creditors over time." (See http://bit.ly/1OlPkqk.)

verifying its compliance with the law. Therefore, the Italian insolvency law appears generally more rigid than US legislation.

Concerning the definition of financial distress, several authors (Altman 1968; Gilson *et al* 1990; Wruck 1990; Gilbert *et al* 1990; John 1993; Johnsen and Melicher 1994; Turetsky and McEwen 2001) have stated that a signal of financial distress is an unexpected decrease in cashflows from continuing operations. This decrease could be followed by a reduction in dividend payments, technical or loan default or troubled debt restructuring (TDR).

We consider TDR to be a warning sign based on liquidity, profitability, leverage, solvency and activity, and firms that face financial distress are eligible to access the TDR procedure in order to avoid potential liquidation. The distinction between TDR and liquidation in the current quantitative models is often aligned to specific modeling requirements and the availability of default and bankruptcy data. Several authors have forecast corporate bankruptcy without distinguishing between liquidation and TDR procedures and have represented them as similar events (Beaver 1966; Ohlson 1980; Zmijewski 1984). Other authors have focused on specifically designed methods to predict financial distress and TDR as a consequence (Gilbert *et al* 1990; John and Vasudevan 1995; Hill 1996; Turetsky and McEwen 2001).

In this framework, we extend the literature by developing a model to predict financial distress and the consequent TDR request. Therefore, our observations and data collection are focused on the period before the request rather than after its homologation by the court (Beaver 1966; Altman 1968, 2000; Ohlson 1980; Zmijewski 1984).

Basically, this study addresses the following research questions.

(1) Is it possible to estimate the probability that a firm will file for the TDR procedure?

(2) Based on this probability, is it possible to create a simple index that describes the financial equilibrium trend by using historical data?

Thus, the present study specifically contributes to the debate by developing a new model that is able to consider the specific features of TDR procedures in the Italian context.

After testing Altman's scores on a set of Italian listed companies, we conclude that additional ratios could be involved in order to obtain a more powerful decisional tool. Specifically, our contribution is twofold. In the first phase, a descriptive assessment of the distress phenomenon is conducted by using a multivariate discriminant analysis (MDA). Using the accounting ratios, we obtain the scores of a linear boundary for two groups of firms: "distressed" and "nondistressed". These labels depend on whether the TDR procedure has been filed. Then, we estimate a yearly probability that each firm will file for TDR, using Italian data.

Interestingly, the coefficients will be different from those obtained by Altman (1968, 2000) for the same ratios when liquidation is investigated. In fact, Altman's formula has been used to explore the potential for failure. Instead, TDR is a procedure intended to overcome the financial distress of a company in order to regain its health and "going concern" status. In fact, liquidation does not consider the possibility of a firm that continues to operate. With TDR, however, the intention of the Italian legislator is to let a distressed company go down a legally protected path to restore its financial equilibrium. It follows that a financially distressed company presents different features from a company approaching liquidation or failure, whose equilibrium condition is almost certainly compromised.

For this reason, we focused on the specific features that distinguish financial distress and the companies that request (or are eligible for) TDR. Therefore, in the first phase, by beginning with the original formulation of Altman's Z-score, we sought to create a new function to predict the financial distress status, through a more contemporary analysis in a rapidly changing business environment. To this end, we considered two new accounting ratios to be introduced in the score formula because they have a significant ability to represent the financial equilibrium of a company. In fact, these two indicators, ie, the current ratio and the quick ratio, focus on the financial equilibrium of a company in the short term.

As is well known, many companies that experience financial distress still maintain their equilibrium in terms of their revenues-to-costs ratio and market share. In fact, there are cases in which financial equilibrium is corrupted as a consequence of some difficulties in cashing receivables or to incorrect choices in terms of characteristics of funding and/or duration of payables, debts and loans. In such cases, if the company is able to intervene as soon as financial distress is announced, there is a greater probability of success in restoring equilibrium. Therefore, we expect the inclusion of these two ratios to improve the discriminant power of our score formula. Indeed, such ratios are unanimously considered liquidity ratios, and derive directly from the financial aspect of a company's equilibrium.

In the second phase, we introduce a novel trend indicator, called the M-index, to calculate the predictive effectiveness of TDR probabilities. Our results show that the probability of TDR increases when accounting ratios worsen and companies become distressed. Interestingly, we note that, in contrast, the probability trend of nondistressed companies remains constant.

This study should broadly interest researchers, firms, banks and company advisors. It contributes to the previous literature by developing a new model to help financially distressed companies to make prompt decisions in restoring financial equilibrium.

The paper is organized as follows. In Section 2, we discuss a theoretical framework with which to examine firms in financial distress, with a particular focus on TDR in Italy. Section 3 presents our sample, methodology and results. Section 4 offers some concluding remarks.

2 RESOLUTIONS FOR FINANCIAL DISTRESS: THE TROUBLED DEBT RESTRUCTURING PROCEDURE

There are several definitions of the term "financial distress" that have evolved in the literature. Gilson *et al* (1990) and Wruck (1990) state that a company is in financial distress when its cashflow is insufficient to meet its current liabilities, and this is often resolved through a private workout or legal reorganization under Chapter 11 of the US bankruptcy code. John (1993) describes distress events as points in time when a firm's liquid assets are insufficient to meet the currency requirements of its contracts. Gilbert *et al* (1990) and Johnsen and Melicher (1994) compared financial distress with the physical status of a company's health and suggested that there are heterogeneous financial distress characteristics associated with events between corporate health and bankruptcy. Turetsky and McEwen (2001) described financial distress as a series of financial events that reflect various stages of corporate adversity. Common to all these definitions is the unexpected decrease in cashflow from continuing operations signaling the onset of financial distress, where firms may use the TDR procedure.

According to the TDR literature, a firm that experiences financial distress can use several methods to overcome it, such as voluntary restructuring of its operations (Donaldson 1990; John *et al* 1992), restructuring under the protection of the bankruptcy court (Weiss 1990) and private restructuring (Gilson *et al* 1990). Brown (1989), Giammarino (1989) and Mooradian (1994) state that firms resolve their financial distress under Chapter 11, despite incurring additional bankruptcy costs. Under Chapter 11, restructuring is preferable to a workout plan when there are a large number of trade creditors (Gilson *et al* 1990). The presence of bank debt is positively associated with the success of a workout plan. Chatterjee *et al* (1996) state that firms filing for Chapter 11 reorganization have more trade credit than those that attempt workout plans. Several authors (Baird 1986; Bebchuk 1988, 2000; White 1989, 1994; Bradley and Rosenzweig 1991; Jensen 1991; Aghion *et al* 1992; Kaiser 1996) contend that Chapter 11 is a debtor-friendly process that grants controlling power to management and fails to liquidate a significant number of economically inefficient firms.

In contrast, Aivazian and Zhou (2012) suggest that Chapter 11 reorganizations tend to boost the operating performances of firms that face temporary profitability problems, and they challenge the contention that Chapter 11 is an inefficient debtor-friendly mechanism. Zhang (2010) states that, with protection from Chapter 11, a firm may emerge as a new entity that fiercely competes with its industry rivals.

One view that most of the above-mentioned works have in common is that companies that decide to access TDR procedures are in financial distress; this certainly represents an adverse situation but is distinct from liquidation or failure. Several authors have developed models to forecast potential business failure in the Chapter 11 framework (see, for example, Beaver 1966; Altman 1968, 2000; Ohlson 1980; Zmijewski 1984), and the definition of default in the quantitative literature is often aligned to specific modeling requirements and the availability of default and bankruptcy data. For example, in Zmijewski (1984), financial distress is considered the act of filing a petition for bankruptcy.

Gilson (1990) defined a firm as financially distressed when it is in default on its debt, bankrupt or privately restructuring its debt to avoid liquidation. Ohlson (1980) classified "failed firms" as companies that must file for bankruptcy, including Chapter 10, Chapter 11 and other bankruptcy proceedings. For both these authors, it seems evident that financial distress and liquidation or failure are considered similar. In the literature, Chapter 11 and liquidation proceedings are considered similar events.

Few authors focus on the methods specifically designed to predict financial distress and the consequent filing for the TDR procedure. John and Vasudevan (1995) create a model to predict when "good" and "medium" quality liquid firms may restructure their debt out of court, when "good" quality illiquid firms may use a prepackaged solution, and when "lower" quality (liquid and illiquid) firms may file for Chapter 11. They show that the choice of restructuring method depends on the quality and liquidity of the firm. Hill (1996) emphasizes that an analysis of the resolution of financially distressed firms demands a dynamic methodology because the movement to and from financial distress is a dynamic process. Previous studies of distressed firms have tended to use ex post sampling techniques that are not representative of the general population of financially troubled firms (Gilbert *et al* 1990). Alternatively, Turetsky and McEwen (2001) group financially troubled firms according to an initial signal, the decrease in operating cashflows, and track them across various distress points. They incorporate the techniques of survival analysis to examine firm longevity. Survival analysis longitudinally tracks firms after a decline in health, via the subsequent occurrence of dividend reduction, default or TDR.

We notice a clearer distinction from a legislative perspective. In US legislation, Chapter 11 is a company reorganization procedure that focuses on the stipulation of an agreement between debtors and creditors to restore the firm after financial distress.

On the other hand, Chapter 7 exclusively concerns liquidation.[2] We note that in Italian insolvency law, this distinction also appears in Article 182-*bis* and Article 216 *et seq.*, respectively. In fact, the TDR designation (Article 182-*bis*) was inspired by the US Bankruptcy Code (namely, Chapter 11).

Several studies have tested the accuracy of Altman's Z-score model and its revised versions Z' and Z'' (Altman 1993, 2000) outside the United States and across different industries (Hayes *et al* 2010; Alareeni and Branson 2013).

Some of these studies have confirmed the Z-score's validity and prediction ability. Other studies have raised doubts over its applicability to other contexts and emphasized the need to update it according to a new time period and different industries (Begley *et al* 1996; Lifschutz and Jacobi 2010). Åstebro and Winter (2012) argue that the outcome of financial distress should be modeled using a multinomial specification that distinguishes between failure, survival as going concern and acquisition, rather than using a binary model. Moreover, De Andrés *et al* (2012) and Tinoco and Wilson (2013) developed risk models for listed companies that try to predict financial distress and bankruptcy by replacing traditional accounting ratios with a combination of accounting data, stock market information and proxies for changes in the macroeconomic environment.

To the best of our knowledge, there are no prior studies on the Italian context except those of Celli (2015) and Altman *et al* (2013).

Celli (2015) assesses the ability of the Z-score model to predict the default of a sample of Italian listed firms up to three years beforehand. He concludes that the Z-score works effectively and performs well in predicting the failures of Italian firms, although with a slightly lower degree of reliability in respect to its application to US and UK companies. Celli considered a simple permanent suspension from quotation, rather than the formal access to a bankruptcy law procedure, as a useful and appropriate proxy for business failure.

Instead, Altman *et al* (2013) focused on adopting Altman's Z-score for Italian companies subject to extraordinary administration. In this case, they expressed concerns regarding the model's consistency with the specific features of the Italian environment (Altman *et al* 2013, p. 135).

Unlike Celli (2015), and considering the concerns of Altman *et al* (2013), our paper shows that applying Altman's Z-score model to our main and control samples of Italian companies gives results that are not entirely accurate. This inaccuracy mainly emerges because the conditions of financial distress of the companies that file for (or are eligible to file for) the TDR procedure are different from those of companies that are approaching liquidation or failure. The Italian entrepreneurial context specifically

[2] Chapter 7 of the Bankruptcy Code provides for "liquidation – the sale of a debtor's nonexempt property and the distribution of the proceeds to creditors" (see http://bit.ly/1GBfXot).

highlights the prevalent restriction of the ownership of companies and the relevant role of banks in financing companies.

3 DATA AND EMPIRICAL ANALYSIS

3.1 Sample description

Our data, coming from the Analisi Informatizzata delle Aziende Italiane–Bureau Van Dijk database, consists of a panel of fifty companies whose financial reports are made under the International Financial Reporting Standards.

These companies have been labeled "distressed" (or "nondistressed") if they have filed for Article 182-*bis* restructuring agreements (or not). The group of "distressed" firms contains all twenty of the listed Italian companies that filed for the TDR procedure from right after the reform (in 2005) up to 2012. The control group comprises thirty companies of similar size and industry type to the distressed companies. Although the control/case ratio of the sample sizes is traditionally taken as equal to 1, we have set it to be 1.5 because the recent literature suggests increasing it improves its convenience.

Although the reform was effective from 2005, we collected financial data from 2003 to 2012 to observe the trend of companies' ratios before and after the reform.

We computed several accounting ratios for 2003–12. These are denoted by X_i, $i = 1, \dots, 7$:

- X_1 denotes a measure of the net liquid assets of the firm, which is calculated as working capital/total assets;
- X_2 represents profitability through retained earnings/total assets;
- X_3 measures leverage and indicates earnings before interest and taxes (EBIT)/total assets;
- X_4 shows the solvency of a firm that involves the market value of equity/book value of total liabilities;
- X_5 represents a standard financial ratio that shows sales/total assets;
- X_6 is the current ratio between current assets (cash, cash equivalents, short-term receivables and inventory) and short-term liabilities (payables);
- X_7 is the quick ratio between total liquidity (cash, cash equivalents and short-term receivables) and short-term liabilities (payables).

The longitudinal nature of our approach is motivated by the fact that filing for the TDR procedure is viewed not as a single instantaneous occurrence but an ongoing

TABLE 1 Industry classification for the sample.

Industry type	Number of firms	Distressed (group 1)	Nondistressed (group 2)
Consumer goods	11	7	4
Consumer service	9	4	5
Finance	7	4	3
Health and food	7	0	7
Manufacturing	5	1	4
Oil and natural gas	4	1	3
Technology	7	3	4
Total	50	20	30

The "distressed" group comprises the firms that filed for TDR in 2005–12. The "nondistressed" group comprises the firms selected by following a stratified sampling scheme (by size and industry), and they are matched with the distressed firms in the same observation period for every industry.

process, which evolves over a considerable period of time. We assume, moreover, that this process provides signals that allow the forecasting of future financial TDR filings.

Table 1 summarizes the data by industry classification. Although the macro-industry "health and food" shows no distressed firms, we include this sector in order to consider all the macro-industries on the Milan Stock Exchange, which are subject to the same TDR law (banks and insurance companies are excluded because they are subject to different restructuring and bankruptcy laws).

3.2 Altman's Z-scores of the Italian sample: main results

By adopting Altman's Z-score and its revised models (Z' and Z'') for the above-described Italian sample, we obtain the following results. As represented in Table 2, more than 50% of the control sample companies were classified between the distress zone and the gray zone during the observation period. In the distressed group, the companies always seemed to belong to the distress zone during the observation period, with a significant percentage between 75% and 90%.

Then, we test the Z'-score for both groups. As shown in Table 3, on average, only 5.3% of "healthy" firms belong to the safe zone, and this emphasizes that most of these firms are classified between the gray and the distress zones. On the contrary, the distressed sample demonstrates the same state of health (distressed) from the first to the last year of observation. Therefore, the findings from the Z'-score do not seem to reflect the natural evolution of the health status of the companies.

The Z''-score should better fit the Italian entrepreneurial context because it is characterized by a stronger relationship between companies and banks. Table 4 shows that, on average, 97% of the distressed companies are classified as being in the distress

TABLE 2 Results of the Z-score for the two groups of Italian listed firms.

	Distressed sample			Nondistressed sample		
	Insolvency area	Gray area	Low-risk area	Insolvency area	Gray area	Low-risk area
2012	90	10	0	50	37	13
2011	90	10	0	50	33	17
2010	90	10	0	50	43	13
2009	100	0	0	57	30	13
2008	95	5	0	53	37	10
2007	100	0	0	47	47	7
2006	90	5	5	50	50	0
2005	75	25	0	53	37	10
2004	75	15	10	43	47	10
2003	75	15	10	50	37	13

All values given in percent. Insolvency area: $Z < 1.81$. Gray area: $1.81 < Z < 2.99$. Low-risk area: $Z > 2.99$.

TABLE 3 Results of the Z'-score for the two groups of Italian listed firms.

	Distressed sample			Nondistressed sample		
	Insolvency area	Gray area	Low-risk area	Insolvency area	Gray area	Low-risk area
2012	80	10	10	37	53	10
2011	85	10	5	33	57	10
2010	80	20	0	33	60	7
2009	90	10	0	37	60	3
2008	90	10	0	30	67	3
2007	70	30	0	30	67	3
2006	70	30	0	27	73	0
2005	55	45	0	40	53	7
2004	45	50	5	27	67	7
2003	45	50	5	30	67	3

All values given in percent. Insolvency area: $Z < 1.23$. Gray area: $1.23 < Z < 2.90$. Low-risk area: $Z > 2.90$.

zone from 2003 onward, and it follows that these companies were constantly distressed during the entire observation period. In contrast, more than 80% of the control sample belongs in the distressed area. Therefore, the Z''-score does not appear to be useful to describe the health trend of Italian companies from 2003 to 2012.

TABLE 4 Results of the Z''-score for the two groups of Italian listed firms.

	Distressed sample			Nondistressed sample		
	Insolvency area	Gray area	Low-risk area	Insolvency area	Gray area	Low-risk area
2012	95	0	5	83	10	7
2011	95	5	0	83	13	3
2010	100	0	0	83	7	10
2009	100	0	0	80	13	7
2008	100	0	0	80	17	7
2007	100	0	0	90	7	3
2006	95	0	5	80	20	0
2005	95	0	5	83	17	0
2004	95	0	5	77	23	0
2003	95	0	5	77	17	7

All values given in percent. Insolvency area: $Z < 1.75$. Gray area: $4.50 < Z < 5.65$. Low-risk area: $5.83 < Z < 8.15$.

We emphasize that the results for both the listed Italian companies that filed for the TDR procedure beginning in 2006 and those for the control sample companies are not consistent with their real conditions. In fact, most companies in the distressed group are classified in the insolvency area from 2003 (75% of the sample), and this is inconsistent with the fact that they did not file for bankruptcy until 2012. At the same time, nearly all companies do not belong in the healthy area. In the control sample, the companies are divided between the three areas in a way that does not appear to be very intuitive.

3.3 Methodology

Our statistical analysis is divided into two steps. In the first step, we derive two discriminant functions through multivariate linear discriminant analysis: the first function is based on the five original accounting ratios ($X_1, \dots, X_5$) adopted by Altman (1968, 1993); the second function is based on the five original accounting ratios plus the current ratio (X_6) and the quick ratio (X_7).

In the second step, we use the scores of the linear discriminant analysis to estimate the yearly degree of confidence of the likelihood of each firm resorting to Article 182-*bis* restructuring agreements in the following year. This assessment method appears to be fairly novel in the field of financial distress.

A confirmative analysis is included to assess the predictive accuracy of our likelihood measurement. To this end, we introduce a simple measure, called the M-index, which is calculated for each distressed firm. This measure is obtained based on the estimated TDR probabilities calculated right before the TDR request. This index should signal the likelihood of financial conditions worsening, and it could also be considered a predictive tool for the TDR request procedure.

3.4 Linear discriminant analysis

Accounting ratios have been widely adopted as a method of determining the relative strength and performance of companies for financial statement analysis. Ratio analysis helps to identify trends over time for a company and to compare two or more companies at a single point in time. Ratios usually focus on three key aspects of a business: liquidity, profitability and solvency. The reliability of this type of analysis lies in the reliability of the reported accounting numbers. Therefore, if fraudulent policies are adopted in financial reporting, the accounting ratios are misleading. Nevertheless, we assume that the financial reports of the listed Italian companies that are included in the present observation are reliable, because they have been reviewed by auditing firms and by the Commissione Nazionale per le Società e la Borsa (the authority that regulates the Italian financial market).

To conduct a discriminant analysis, we first use the five financial ratios suggested by Altman (1968, 1993), which are specific to liquidation/failure studies. Then, we run the discriminant analysis by adding to these the current ratio (X_6) and the quick ratio (X_7) with the aim of increasing the detecting power of our score formula in terms of the financial equilibrium of the company. In fact, the general equilibrium of a company is based on an unstable combination of economic equilibrium (based on profitability) and financial equilibrium (based on liquidity and solvency). X_6 and X_7 are typically considered to be liquidity ratios because they measure the ability of a company to repay short-term debts and meet unexpected cash needs. Provided that a deterioration in this ability eventually influences the profitability of the company, a sudden intervention could often prevent the deterioration in economic equilibrium. The TDR procedure is fit for this purpose because it could be helpful to restore the financial equilibrium when the company is still viable and sound from a profitability point of view. For these reasons, we assume that these variables play a key role in explaining financial distress. In our specific case, these ratios should have a high discriminant power for the prediction of filing for Article 182-*bis* restructuring agreements. In our study, the companies that filed for TDR are labeled "distressed", whereas the control sample companies are labeled "nondistressed".

The number of misclassified observations is reported in Table 5(a) for the five original accounting ratios and in Table 5(b) for the score with the two additional ratios.

We note a reasonable discriminant power in both analyses, but, as expected, this performs better if we consider the seven accounting ratios (Table 5(b)), especially in recent years. This result confirms that the "distressed" labels mainly assume significance with the imminence of a request for TDR. Moreover, the errors reduce over the years, because when data of a restructured firm dates back sufficiently far from the TDR recourse, the "distressed" status makes little sense and generates a widely biased boundary.

In order to check for the absence of overfitting, we used tenfold cross-validation. This scheme requires, at each of ten steps, the prediction of 10% of data by using the remaining 90%. This has been done for each year, and Table 6 shows the average error rates for the ten predictions. It can be seen that the prediction error rates are quite similar to the misclassification rates over time, as shown in Table 5(b). By contrast, overfitting would have typically showed high performance in some years and poor performance in other years.

3.5 Developing a TDR probability model: S_{it} score

In the second step of our statistical analysis, we assess the probability of financially distressed companies filing for TDR as a way to avoid failure. This is estimated via the explanatory variables. The research closest to our approach is by Shumway (2001), who also calculates the probability of a business failure event by using a logistic regression model. In addition, this approach relates to the previous literature pioneered by Beaver (1966) and Altman (1968, 1993, 2000), who introduced several models as measures of bankruptcy risk. The well-known studies by these authors investigate the ability of financial ratios to predict corporate financial distress. Beaver's (1966) study notes that financial ratios can predict the likelihood of bankruptcy. In particular, he confirmed that these financial ratios can provide significant information and warning about the financial conditions of firms before their liquidation. Subsequently, Altman (1968) developed a model that included a set of financial ratios that were analyzed through MDA to demonstrate the relation between the financial ratios in previous years and at the time of the subsequent bankruptcy.

Our formula for the TDR probability associated to the ith firm at time t is as follows:

$$\hat{P}_{it} = \frac{\mathrm{e}^{S_{it-1}}}{1 + \mathrm{e}^{S_{it-1}}}, \tag{3.1}$$

where e indicates the Euler number, and S_{it} is a score associated with the ith firm at time t, which is given by the following formula:

$$\begin{aligned} S_{it} = 0.003X_{1it} + 0.267X_{2it} + 0.663X_{3it} + 0.431X_{4it} \\ + 0.533X_{5it} + 0.147X_{6it} + 0.092X_{7it}, \end{aligned} \tag{3.2}$$

where X_{jit} is the jth variable associated with the ith firm at time t.

TABLE 5 Multivariate discriminant analysis with (a) five accounting ratios and (b) seven accounting ratios.

(a) $X_1, \ldots, X_5$

	Distressed firms		Nondistressed firms		Total
2003	8	(40%)	6	(20%)	12
2004	7	(35%)	5	(16%)	12
2005	7	(35%)	8	(26%)	15
2006	3	(15%)	10	(33%)	13
2007	3	(15%)	6	(20%)	9
2008	1	(3%)	6	(20%)	7
2009	2	(10%)	1	(3%)	5
2010	3	(15%)	7	(23%)	10
2011	3	(15%)	5	(16%)	8
2012	7	(35%)	5	(16%)	12

(b) $X_1, \ldots, X_7$

	Distressed firms		Nondistressed firms		Total
2003	6	(32%)	4	(14%)	10
2004	7	(37%)	6	(20%)	13
2005	6	(32%)	9	(30%)	15
2006	3	(15%)	10	(34%)	13
2007	3	(15%)	5	(16%)	8
2008	2	(10%)	7	(23%)	9
2009	1	(5%)	2	(6%)	3
2010	2	(10%)	3	(10%)	5
2011	3	(15%)	6	(20%)	9
2012	7	(37%)	2	(6%)	8

Part (a) shows the number of misclassified firms of the linear discriminant analysis from 2003–12 for the distressed and nondistressed groups based on the five original accounting ratios (Altman 1968, 1993). Part (b) shows the number of misclassified firms of the linear discriminant analysis from 2003–12 for the distressed and nondistressed groups based on the seven accounting ratios. The figures between parentheses represent percentages of error.

The value of $\hat{P}_{it}$ is always between 0 and 1 and quantifies the opportunity for a firm to file for TDR. As can clearly be seen from the above formula, given that S_{it} is inversely proportional to the firm's health status, this probability increases with the tendency to file for TDR.

TABLE 6 Averages of prediction error rates using tenfold cross-validation.

	Error (%)
2003	26
2004	24
2005	34
2006	24
2007	18
2008	22
2009	14
2010	16
2011	16
2012	14

This table shows the results of a tenfold cross-validation in the form of the average error rates over the ten predictions.

The numerical coefficients in the above formula have been obtained from a linear discriminant analysis, where the ratios used for each firm are as follows:

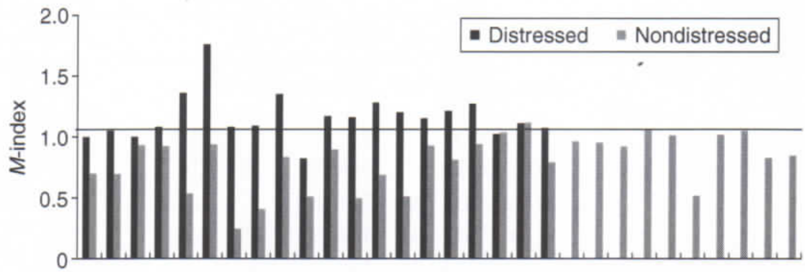
(a) for distressed firms, the ratios belong to the year when the TDR was filed;

(b) for nondistressed firms, the ratios are the best ratios over the entire observation period.

This approach allows an efficient estimation of the S_{it} score for both the high discriminant potential of the ratios chosen in this manner and the reduction in temporal correlation because the data from different years are compared. A fundamental assumption for our multivariate estimation is the independence of sample observations, which has rarely been considered seriously in prior studies.

Comparing the S_{it} score formula with the Z-score (Altman 1968, 1993, 2000), it appears that the same ratios can exert different influences on the formula because of the different coefficients. This effect may be explained by noting that financial distress and liquidation/failure are different phenomenons, because these ratios may affect a company's choice to access TDR procedures without necessarily resulting in liquidation. Moreover, the Z-score formula comes from data collected over a one-year interval that is focused only on manufacturing companies, whereas S_{it} is obtained from a multi-year and multi-industry analysis of listed Italian companies. Further, the S_{it} score is calculated to be included in the determination of $\hat{P}_{it}$, which represents the assessment of the probability of TDR for a company. On the contrary, the Z-score formula was developed to determine a cut-off value.

FIGURE 1 M-index.



Predictive effectiveness of the TDR probabilities for both the distressed and nondistressed groups.

3.6 The effectiveness of TDR probabilities

In this section, we analyze the predictive accuracy of the TDR probabilities that were introduced in the previous section. Assuming that the TDR request is beneficial in overcoming a temporary state of crisis, the analysis of the time series $\hat{P}_{it}$, $t = 2003, \dots, 2012$, should satisfy the following two hypotheses.

(H1) For "distressed" companies, the associated probability should increase until the year of TDR application and then become stationary or even decrease.

(H2) For "nondistressed" companies, the time series should appear stationary and follow a nearly constant trend over the years.

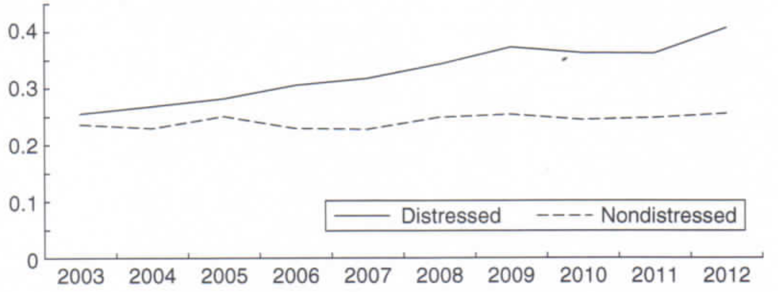
We investigate these hypotheses below.

First, we introduce an indicator, the M-index, which is intended to determine whether, for a distressed firm, a relative increment in TDR probability is expected to occur in the proximity of the request for TDR. This indicator is given by the following expression:

$$M_i = \frac{\max(\hat{P}_{i,t_0}, \hat{P}_{i,t_0-1}, \hat{P}_{i,t_0-2})}{\sum_{t=t_{\min}}^{t_{\max}} \hat{P}_{i,t}/T}. \tag{3.3}$$

The above index, which is calculated for the ith distressed firm, is constructed from a ratio whose denominator is the average of the TDR probabilities over the observational period. The numerator is calculated as the maximum probability associated with the two years before the restructuring agreements and the year when TDR was effectively approved in court (the latter is denoted by t_0). The symbols $t_{\min}$ and $t_{\max}$ represent the first and last observation years in the analysis. Clearly, the more the probabilities increase before a TDR request, the more likely it is that the indicator is greater than 1. Moreover, we selected the years of the best performing ratios for the control sample

FIGURE 2 The probabilities of TDR.



Trends in the average TDR probabilities for both the distressed and nondistressed groups from 2003 to 2012.

companies, given that these companies did not file for TDR during the observation period. For these years, we calculated the respective probabilities in order to obtain the M-index for the control sample companies. Therefore, the black bars in Figure 1 show the values of the M-index of the distressed sample (the period considered for calculating the denominator is from 2003 to 2012). This result clearly confirms the strong predictive potential of TDR probabilities in our case because for the distressed firms this indicator is greater than 1 as the probabilities increase before the TDR request. The gray bars represent the values of the M-index of the control sample companies. On average, the gray bars are almost always below 1.

Although the M-index is a validation tool that focuses on a single firm, a general view could be gained by calculating the trends of the average of the TDR probabilities for the two groups of firms for every year.

In Figure 2, we represent the two trends. In particular, the solid line indicates the trend of the distressed firms. For a simpler comparison between the two groups, we have not used standardized values.

We note that the trend of the distressed firms increases with increasing proximity to the critical period. Interestingly, we have sixteen TDR requests in the last three years (from a total of twenty cases), which is when the trend approached its maximum. In contrast, the dashed line represents the average of the probabilities of nondistressed firms to file for TDR. In this case, we have a nearly constant trend, which provides no cause for concern.

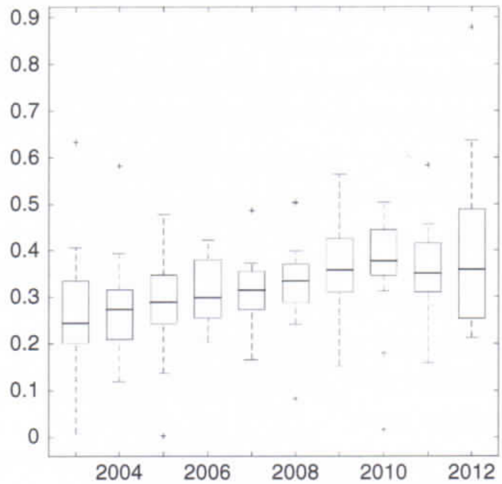
Table 7 shows that the values of the averages of the case and control groups differ significantly for each year from 2006 onward at the usual smallest levels of confidence. This shows that it is possible to generalize our result to the potential population of firms with the same features as those of the distressed sample.

TABLE 7 Comparison between TDR probability series.

	p-value
2003	0.3113145
2004	0.100861
2005	0.1034408
2006	0.0003056672
2007	0.0005674411
2008	0.002576639
2009	0.0001212181
2010	0.0002130407
2011	0.00003964437
2012	0.001247192

p-values related to two sample t-tests comparing average TDR probabilities of distressed and control firms between 2003 and 2012.

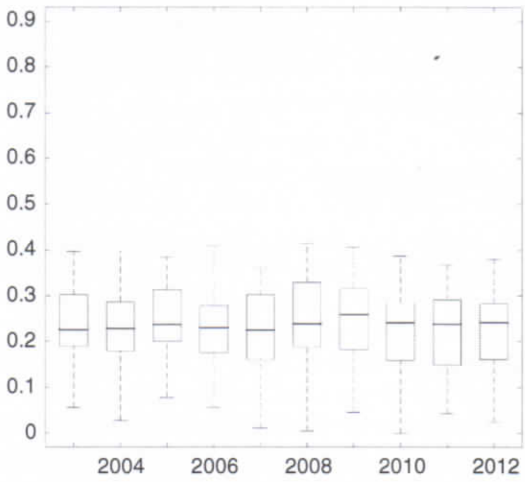
FIGURE 3 Sequence of distributions of TDR probabilities, distressed firms.



95% box plots of the $\hat{P}_{it}$ values for the distressed companies between 2003 and 2012.

In order to show the model accuracy at the firm level, in Figure 3 we represent the $\hat{P}_{i,t}$ data using box plots. With regard to the distressed companies (Figure 3), the increasing trend in the medians and the decently concentrated distributions (except for 2012), along with a moderate number of outliers, show that our analysis is relatively robust to the presence of false positives. The correspondence between the medians for

FIGURE 4 Box plot of the probabilities of TDR for control sample companies.



95% box plots of the $\hat{P}_{it}$ values for the control sample companies between 2003 and 2012.

2011 and 2012 suggests stationarity, as some companies that previously filed for TDR start to restore financial equilibrium and therefore have slightly decreased their $\hat{P}_{it}$. However, for our control sample companies (Figure 4), the trend of medians appears to be stationary, which confirms the robustness of the model at the firm level.

4 SUMMARY AND CONCLUSIONS

In this paper, we describe the ability of accounting ratios to forecast the probability of a financially distressed firm filing for TDR. To this end, we constructed a financial "prewarning" model to predict the financial distress of listed companies. In this context, we collected the financial data from 2003 to 2012 for all twenty listed Italian companies that filed for Article 182-*bis* restructuring agreements and for a control group of thirty other companies listed on the Milan Stock Exchange. Our data set is a panel covering a period of nine years and is not considered small.

Using the MDA, we created a simple and efficient discriminant function. Once assured that the seven ratios we adopted are informative regarding financial distress, we defined the probability of a TDR filing. Based on this probability, we also introduced a user-friendly indicator, the M-index, which can describe the financial equilibrium trend using historical data.

As a result of our findings, we suggest the application of this model to predict the financial distress of firms across different industries.

This study provides tools that could be useful not only to companies undergoing reorganization but also to banks, creditors and investors, which can evaluate the opportunity to suggest TDR at the correct time.

Further research could assess the efficiency of the TDR procedure in pursuing the legislator's aims in reforming the bankruptcy law, ie, a reduction in the company failure rate during periods of financial crisis.

DECLARATION OF INTEREST

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

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