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# Financial distress prediction in private firms: developing a model for troubled debt restructuring



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Received 6 December 2022
Revised 22 June 2023
15 September 2023
Accepted 28 October 2023

## Abstract

**Purpose** – This study aims to develop a model based on the financial variables for better accuracy of financial distress prediction on the sample of private French, Spanish and Italian firms. Thus, firms in financial difficulties could timely request for troubled debt restructuring (TDR) to continue business.

**Design/methodology/approach** – This study used a sample of 312 distressed and 312 non-distressed firms. It includes 60 French, 21 Spanish and 231 Italian firms in both distressed and non-distressed groups. The data are extracted from the ORBIS database. First, the authors develop a new model by replacing a ratio in the original Z”-Score model specifically for financial distress prediction and estimate its coefficients based on linear discriminant analysis (LDA). Second, using the modified Z”-Score model, the authors develop a firm TDR probability index for distressed and non-distressed firms based on the logistic regression model.

**Findings** – The new model (modified Z”-Score), specifically for financial distress prediction, represents higher prediction accuracy. Moreover, the firm TDR probability index accurately depicts the probabilities trend for both groups of distressed and non-distressed firms.

**Research limitations/implications** – The findings of this study are conclusive. However, the sample size is small. Therefore, further studies could extend the application of the prediction model developed in this study to all the EU countries.

**Practical implications** – This study has important practical implications. This study responds to the EU directive call by developing the financial distress prediction model to allow debtors to do timely debt



The authors are very thankful to the Editor of the “Journal of Applied Accounting Research” for their support and guidance and the two anonymous reviewers for their helpful comments on earlier versions of this paper. The authors are also thankful to all the participants at the 14th Annual International Risk Management Conference on “Risk Management During and After the Pandemic Storm: Recovery, Resilience and Sustainability”, University of Cagliari, Italy, 1–2 October 2021; the Annual Event of Finance Research Letters on “Frontiers in Credit Risk”, 5–6 July 2021; the ItAIS (Italian Chapter of Association for Information Systems) Junior Faculty and Doctoral Consortium, University of Trento, Italy, 14–15 October 2021; SIDREA (Società Italiana dei Docenti di Ragioneria e di Economia Aziendale) – EAA (European Accounting Association) Doctoral Colloquium, University of Parma, Italy, 20 November 2020, for their fruitful comments on previous drafts of this paper.

*Funding:* This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Journal of Applied Accounting Research
Emerald Publishing Limited
0967-5426
DOI 10.1108/JAAR-12-2022-0325

restructuring and thus continue their businesses. Therefore, this study could be useful for practitioners and firm stakeholders, such as banks and other creditors, and investors.
**Originality/value** – This study significantly contributes to the literature in several ways. First, this study develops a model for predicting financial distress based on the argument that corporate bankruptcy and financial distress are distinct events. However, the original Z"-Score model is intended for failure prediction. Moreover, the recent literature suggests modifying and extending the prediction models. Second, the new model is tested using a sample of firms from three countries that share similarities in their TDR laws.

**Keywords** Financial distress, TDR, Prediction models, EU directive
**Paper type** Research paper

## 1. Introduction

The European Council "Preventive Restructuring" directive, issued on June 20, 2019 (EU/2019/1023), has raised again the scientific debate about the development of financial distress prediction models to incentivize firms and/or debtors in the European Union (EU) member states that experience financial distress. Financial distress prediction is a popular topic among academics and practitioners, and several scholars have developed different models to predict financial distress for firms across the last decades. However, its importance has increased due to the adverse effects of financial crises such as the global financial crisis of 2007–2009 and the current coronavirus (COVID-19) pandemic. This increase is imperative since business firms' survival is essential not only for firms but also for all their stakeholders. For instance, the global financial crisis of 2007–2009 has heavily affected several firms (De Luca and Meschieri, 2017) with a wider impact, and much is expected for this current COVID-19 pandemic. Similarly, scholars argue that the COVID-19 pandemic has raised difficulties for both financial and non-financial institutions due to the economic fallout resulting from this pandemic (Hassan *et al.*, 2022).

In general, the crisis context shows that even strong international firms must be constantly careful about their financial situation (Woodlock and Dangol, 2014). The EU has actively focused on promoting and strengthening the economy since the global financial crisis of 2007–2009. Since 2016, various documents have been issued by the European Commission to facilitate insolvency procedures. Recently, the European Council adopted the "Preventive Restructuring" directive (EU/2019/1023) on June 20, 2019. This new directive focuses on the proper functioning of the internal market (Arias Varona *et al.*, 2020). Mainly, this EU directive focuses on several aspects such as preventive restructuring frameworks, the discharge of debt and disqualifications and measures to enhance the efficiency of procedures regarding restructuring, insolvency and discharge of debt.

The recent EU directive, implemented in all EU member states, aims to provide homogeneous troubled debt restructuring (TDR) laws and procedures at the national level to viable firms and/or debtors that face financial difficulties. This directive presents that restructuring should enable debtors in financial difficulties to continue business. In this perspective, the EU aims to allow debtors to restructure effectively at an early stage to avoid insolvency and the unnecessary liquidation of viable enterprises. For this purpose, this directive requires the development of one or more early warning tool/s that could be developed either by member states or by private entities to incentivize debtors in financial difficulties to take early action.

The literature also calls for enhancing the accuracy of the prediction models (Sánchez *et al.*, 2013). Recently, researchers have developed models based on a combination of accounting data, stock market data and macroeconomic factors. However, these models have been applied in specific contexts, and their usage on a worldwide level is yet to be confirmed by applying them in other contexts and regions. Therefore, scholars recommend improving the models developed in recent times (Fernández-Gámez *et al.*, 2020; Vo *et al.*, 2019). Altman *et al.* (2017) argue that the Z-Score model is being used worldwide for bankruptcy or financial distress prediction and analysis both in research and practice. They present the original Z"-Score model that performs well in an international context. Yet, they recommend the modification and extension of their developed models as the current business environment is quite different than it used to be in the 20th century.

We aim to develop a model to predict financial distress in an early stage with higher prediction accuracy. We focus on the private large and medium-sized firms of three European economies, namely Italy, France and Spain. These countries are member states of the EU and follow its rules and regulations and share similarities in their TDR laws for debtors/firms that are in financial difficulties.

In Italy, the Article 182-bis restructuring agreements, recently introduced by the Italian bankruptcy law to manage company crisis under 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 (Di Marzio, 2006). In France, the French bankruptcy law introduced a tool known as Article L. 611-3 ad-hoc proceedings of the Commercial Code to manage distressed companies in the law reforms made in 1994 (Wessels and Madaus, 2020) inserted by Article 5, Law No. 2005-845 of July 26, 2005. In Spain, the Spanish insolvency act recently introduced a tool, Article 71bis(1) homologated refinancing agreements to support companies that face financial difficulties under the Royal Decree-Law 4/2014 of 7 March 2014, which introduced the amendments for the adoption of urgent reforms on the refinancing and restructuring of corporate debt, and implemented as Law 17/2014 of 30 September 2014 and effective as of 2 October 2014. All the earlier presented pre-insolvency proceedings in each respective country focus on the agreements between the debtor and the creditors (Chen *et al.*, 1995) to provide a "fresh start." This "fresh start" acts as a lifeline for companies as it provides them with new opportunities to continue business activities and operate in the market, including new out-of-court restructuring instruments that prevent liquidation of the company (De Luca and Meschieri, 2017).

We consider the original Z"-Score model (Altman, 1983) that is based on financial ratios since it performs well in an international context (Altman *et al.*, 2017). Nevertheless, the original Z"-Score (Altman, 1983) is intended for failure prediction. In contrast, our aim is to predict financial distress which allows firms to restore financial equilibrium and keep going concern status. Therefore, we develop a model precisely to predict financial distress, a firm's probability to file for TDR. For this purpose, we modify the Z"-Score model by replacing the working capital to total assets ratio with cash and cash equivalents to current liabilities ratio. We make this replacement as the cash ratio is better able to highlight the financial distress situation as well as the ability of the company to meet its due dates as it compares cash and cash equivalents with current liabilities.

We apply the linear discriminant analysis (LDA) technique and find our developed model (modified Z"-Score) performs well as it depicts higher prediction accuracy and low misclassification errors. We further develop a TDR probability index using the logistic regression model based on our developed model (modified Z"-Score) and calculate the trend of TDR probabilities for both the distressed and non-distressed groups. The results of the TDR probability index depict accurately the trend of TDR probabilities since there is a difference in firms of both distressed and non-distressed groups, indicating the predictive potential for firms' TDR probabilities.

We contribute to the existing literature on financial distress prediction models in the following ways. First, we consider corporate bankruptcy and financial distress as distinct events and develop an early indicator tool (modified Z"-Score model) to predict financial distress precisely, the firm probability of filing for TDR. Second, we obtained our study sample from three EU countries based on similarity in their TDR laws and to the best of our knowledge, this is the first study that considers this aspect for obtaining the study sample.

The rest of the sections are structured as follows. Section 2 discusses the review of literature and hypotheses development, and Section 3 presents the study methodology. Section 4 provides the empirical analysis and discussion, while Section 5 discusses the study's conclusion.

## 2. Review of literature and hypotheses development

In academic literature, considerable attention has been given to corporate financial distress and failure prediction in the area of corporate finance since corporate failure has negative consequences for the company itself as well as its stakeholders (Cultrera and Brédart, 2016).

In the literature, several models have been developed by academic researchers and practitioners considering the accounting information (see Altman, 1968; Altman *et al.*, 2017; Beaver, 1966; De Luca and Meschieri, 2017; Dewaelheyns and Van Hulle, 2006; Gupta *et al.*, 2018; Li *et al.*, 2020; Mselmi *et al.*, 2017; Ohlson, 1980; Ruxanda *et al.*, 2018; Zavgren, 1985; Zmijewski, 1984) and stock market information (see Bharath and Shumway, 2008; Duffie *et al.*, 2007; Vassalou and Xing, 2004). Researchers have further combined both accounting and stock market variables (see Shumway, 2001; Campbell *et al.*, 2008; Vo *et al.*, 2019). Recently, macroeconomic variables are also considered along with accounting and stock market variables (see Vo *et al.*, 2019). Further, the researchers have used regulatory variables along with accounting and macroeconomic variables (see Fernández-Gámez *et al.*, 2020). Moreover, the researchers have considered accounting variables along with network-based variables (see Liu *et al.*, 2019), corporate governance variables (see Chen *et al.*, 2020; Ragab and Saleh, 2021) and auditing variables (see Muñoz-Izquierdo *et al.*, 2020).

In respect of methodologies, Beaver (1966, 1968) has employed univariate analysis for selecting financial ratios with good predictive power. Altman (1968) has applied a multiple discriminant analysis (MDA) on five accounting ratios, known as the Z-Score model. However, Zmijewski (1984) argues that the predictive ability of Z-Score estimation could be overstated due to the selection of nonrandom samples. Therefore, he has developed a probit approach. Further, a logit model (Ohlson, 1980) and a Z-Score model for the United Kingdom (Taffler, 1984) are developed. De Luca and Meschieri (2017) have applied multivariate discriminant analysis on accounting ratios. Altman *et al.* (2017) have employed MDA and logistic regression analysis methods on accounting ratios and additional variables (such as year of bankruptcy, size, age, industry and country of the firm). Recent studies have further developed models by employing traditional accounting variables and the logit models (see Apergis *et al.*, 2019; Charalambakis and Garrett, 2019).

Merton's (1974) structural market-based model has also been used for predicting corporate default (see Bharath and Shumway, 2008; Duffie *et al.*, 2007; Vassalou and Xing, 2004). Further, the researchers have employed a discrete hazard model by combining both accounting and market variables (see Campbell *et al.*, 2008; Shumway, 2001). Moreover, Hernandez Tinoco and Wilson (2013) and Vo *et al.* (2019) have applied the logit regression technique by combining accounting, stock market and macroeconomic variables. Fernández-Gámez *et al.* (2020) have used a multilevel logistic model based on accounting, macroeconomic and regulatory variables. Muñoz-Izquierdo *et al.* (2020) have applied a logistic regression model on accounting and auditing variables to predict financial distress.

In addition to statistical models, more recently, artificial intelligence (AI) and machine learning (ML) methods have been widely used by scholars for bankruptcy and financial distress prediction. Scholars provide evidence that ML methods perform better than statistical methods (Barboza *et al.*, 2017; Zelenkov *et al.*, 2017). Cao *et al.* (2022) applied the Bayesian network model, an ML method, to predict corporate bankruptcy. Dube *et al.* (2023) applied the AI method using Artificial Neural Networks (ANN) to predict financial distress. Zhao *et al.* (2023) applied ML methods to predict financial distress. These include supporting vector machine, random forest, extreme gradient boosting (XGBoost) and logistic regression methods. Similarly, Chen *et al.* (2023) used the same ML methods to predict bankruptcy. Nguyen *et al.* (2023) employed ML methods for bankruptcy prediction. These ML methods include the Random Forest, XGBoost, LightGBM (Light Gradient-Boosting machine) and NGBoost (Natural Gradient Boosting for probabilistic prediction).

In prior literature on failure and financial distress prediction, the Z"-Score model (see Altman, 1983) is considered a tool that reliably represents financial statement data confirming Z"-Score's validity and prediction ability (Balcaen and Ooghe, 2006; Laitinen, 1991; Laitinen and Laitinen, 2009; Scott, 1981).

Altman (1968) first developed the Z-Score model to measure predictive power for corporate bankruptcy. This model is based on five financial ratios namely liquidity (working capital to total assets), cumulative profitability (retained earnings to total assets), profitability (earnings before interest and taxes to total assets), leverage (market value of equity to total liabilities) and capital turnover ratio (sales to total assets). However, it can only be applied to publicly traded companies since it uses the market value of equity. Therefore, the original version of Altman's Z-Score model is modified as Z'-Score and Z"-Score (Altman, 1983). In the Z'-Score model, in the fourth ratio, the market value of equity is replaced with a book value of equity. However, there is the issue of potential industry effect due to the capital turnover ratio (sales to total assets). For this reason, in the Z"-Score model, the capital turnover ratio has been excluded to eliminate the industry effect. Therefore, the Z"-Score model is based on four ratios, and it can be applied to both private and public listed firms and to both manufacturing and non-manufacturing firms to predict bankruptcy or financial distress (Altman *et al.*, 2017).

Altman (1983) recommends using the Z-Score model as a guide to financial turnaround in the management of distressed firms. Altman *et al.* (2017) argue that the Z-Score model has been used worldwide for 45 years for bankruptcy or financial distress prediction and analysis both in research and in practice. Nevertheless, some studies show concerns regarding its applicability to other contexts and suggest revising this model considering the current situations and different industries (Begley *et al.*, 1996). Therefore, Altman *et al.* (2017) suggest modifying or extending their developed models for prediction for the contemporary business environment to have better prediction accuracy. Moreover, scholars call for "improving the codification of the qualifications to enhance the accuracy of the model" (Sánchez *et al.*, 2013, pp. 168). More recently, the literature also suggests improving the prediction models (Fernández-Gámez *et al.*, 2020; Vo *et al.*, 2019).

In the literature, corporate bankruptcy and financial distress are mostly considered similar events. For instance, Altman *et al.* (2017) have considered financial distress, failure, default and bankruptcy as equivalents to predict financial distress in an international context. However, Gupta *et al.* (2018) argue that financial distress and bankruptcy are distinct events and therefore, they require separate modeling for improving risk pricing for both events. Similarly, Åstebro and Winter (2012) argue that financial distress prediction should be modeled by distinguishing failure and survival as going concerned and acquisition. De Luca and Meschieri (2017) have considered this aspect and added two more ratios (current and quick ratios) in the Z-Score model to predict financial distress for the listed Italian firms. They conclude that their seven ratios model is more accurate in providing information regarding financial distress since the firms' TDR probability increases when accounting ratios worsen, and firms become distressed. Nevertheless, there is scant literature on this debate, and therefore, this study contributes to this debate and considers failure and financial distress as different events.

We consider the literature gap for modifying and extending the Z-Score model for better prediction accuracy. For this purpose, following De Luca and Meschieri (2017), we develop an early warning tool by modifying the Z"-Score model for better predictability of financial distress to allow firms facing financial difficulties to request TDR. Therefore, in the modified Z"-Score model, we exclude the working capital to total assets ratio and replace it with cash and cash equivalents to current liabilities ratio. We make this replacement as the working capital to total assets ratio indicates whether a firm has sufficient additional funds to finance operations with respect to the size of the business. This aspect represents that the working capital to total assets ratio is not helpful in measuring financial distress situations in case we refer to TDR. In contrast, the cash and cash equivalents to current liabilities ratio indicates whether a firm has sufficient cash and cash equivalents to meet short-term liabilities. Therefore, the cash ratio is better able to highlight the financial distress situation. Thus, we develop the following hypothesis based on the above literature, which is as follows:

*H1*. The modified Z”-Score model shows higher prediction accuracy to predict financial distress intended as TDR.

## 3. Research methodology

### *3.1 Data and sample firms*

We use Bureau Van Dijk (BvD), specifically the ORBIS database to extract the data for private large and medium-sized firms in Italy, France and Spain.

We place firms into two groups, distressed firms (firms of each respective country that filed for TDR) and non-distressed firms. In ORBIS, data are available for the past ten years. In this regard, we consider the time span from 2011 to 2020. However, we collected data from 2011 to 2019 for both groups. In the case of distressed firms, we assume a firm files for TDR based on the performance of the past financial year. Therefore, we consider the time span from 2015 to 2020 in which firms filed for TDR, and therefore, the data are based on the years 2014–2019. Further, we consider the time span of 3 years prior to firms filing for TDR from 2011 to 2013 to observe the trend of firms’ financial ratios before and after filing for TDR (De Luca and Meschieri, 2017). Our choice of the time period of 3 years before the occurrence of financial distress is supported by the earlier literature (Chen *et al.*, 2020; De Luca and Meschieri, 2017). For non-distressed firms, a control group, we extract the data based on the same number of firms of related size and industry type as the distressed firms based on Standard Industrial Classification (SIC). Therefore, the sample size of the control-to-case ratio was 1.

We set different requirements to obtain the study sample. First, we set up a company that should be active for both distressed and non-distressed groups. Second, we set the owners of a company must have limited liability (therefore, excluding the sole proprietors and partnerships). Third, we set companies should be following local Generally Accepted Accounting Principles (GAAP) as we are considering private large and medium-sized firms, while the listed and large companies follow the International Accounting Standards (IAS) and International Financial Reporting Standards (IFRS). Fourthly, we set firms should be non-financial and therefore, we exclude banks and insurance companies because they require different restructuring laws. Next, we set up firms that must be large and medium-sized and for this reason, we use thresholds for large and medium-sized firms set by the EU (Ref. Ares(2016)956541 - 24/02/2016) (see Table 1). We have not considered small firms because of instability in their financial ratios and hence not useful to include them in the

| Enterprise category | Headcount: annual work unit (AWU) | Annual turnover | | Annual balance sheet total |
|---|---|---|---|---|
| Medium-sized | <250 | ≤ EUR 50 million | or | ≤ EUR 43 million |
| Small | <50 | ≤ EUR 10 million | | ≤ EUR 10 million |
| Micro | <10 | ≤ EUR 2 million | | ≤ EUR 2 million |

**Note(s):** Link to the threshold for companies: https://ec.europa.eu/growth/smes/sme-definition_en
**Source(s):** Table created by author

**Table 1.** Threshold for companies EU (Ref. Ares(2016)956541 - 24/02/2016)

model of failure prediction (Balcaen and Ooghe, 2006). Further, we set legal events related to TDR for firms of each sampling country. For this purpose, we select default, the main legal event and inside the default, we select debt arrangement proceedings for Italian and Spanish firms and French firms, we select rescue plan to obtain the firms that filed for TDR from 2015 to 2020.

We obtained our study sample after setting the earlier presented requirements. We exclude those firms whose data were not available. Therefore, the final sample from three countries is based on 624 firms (312 distressed and 312 non-distressed) as shown in Table 2. In the case of each country, there are 231, 60 and 21 firms in each group (distressed and non-distressed) belonging to Italy, France and Spain, respectively. The sample firms are from 8 different industries based on SIC (see Table 2). The numbers of firms that are financially distressed and filed for TDR are shown in Table 3 year-wise for the overall sample and for each country as well.

### *3.2 Study variables*

We collect data for four independent variables that are financial ratios (see Table 4). Financial distress is our dependent variable which is a dichotomous variable where a distressed firm = 1 and a non-distressed firm = 0 (see Table 4).

We consider TDR as a condition of financial distress rather than bankruptcy or failure. For this purpose, we modify the Z”-Score model intending to develop an early indicator tool that can better predict financial distress situations in an early stage with specific reference to the TDR. For this purpose, we exclude the working capital to total assets ratio and include the cash and cash equivalents to current liabilities ratio in the Z”-Score model (see equation 1). Therefore, we perform the analysis on our modified Z”-Score (M-Z”-Score) model.

$$M - Z” - Score = \beta_1 \times X_1 + \beta_2 \times X_2 + \beta_3 \times X_3 + \beta_4 \times X_4 \tag{1}$$

where $\beta_1, \beta_2, \beta_3, \beta_4$ are coefficients, $X_1$ is Cash and Cash Equivalents/Current Liabilities, $X_2$ is Retained Earnings/Total Assets, $X_3$ is Earnings before Interest and Taxes/Total Assets, $X_4$ is Book Value of Equity/Total Liabilities, *M-Z”-Score* is Modified Z”-Score and it is Overall Index.

**Table 2.** Sample firms for both distressed and non-distressed group and respective industries

| Sr. No. | Standard industrial classification (SIC) | Distressed firms Italy | Distressed firms France | Distressed firms Spain | Non-distressed firms Italy | Non-distressed firms France | Non-distressed firms Spain |
|---|---|---|---|---|---|---|---|
| 1. | Agriculture, Forestry, And Fishing | 1 | – | – | 1 | – | – |
| 2. | Construction | 19 | 6 | 5 | 19 | 6 | 5 |
| 3. | Manufacturing | 99 | 30 | 9 | 99 | 30 | 9 |
| 4. | Transportation, Communications, Electric, Gas, And Sanitary Services | 30 | 5 | 1 | 30 | 5 | 1 |
| 5. | Wholesale Trade | 13 | 5 | – | 13 | 5 | – |
| 6. | Retail Trade | 15 | 4 | – | 15 | 4 | – |
| 7. | Finance, Insurance, And Real Estate* | 11 | 4 | – | 11 | 4 | – |
| 8. | Services | 43 | 6 | 6 | 43 | 6 | 6 |
| | Total | 231 | 60 | 21 | 231 | 60 | 21 |
| | | 312 | | | 312 | | |
| | | 624 | | | | | |

**Note(s):** * Banks and insurance companies are not included due to their different nature of laws for TDR as compared to non-financial companies. Industries including the Mining and Public Administration have no distressed firms and therefore are excluded from the analysis
**Source(s):** Table created by author

The statistical methods we apply toward data are presented below.

*3.3 Statistical methods*

The AI and ML methods have been generally deemed to outperform the statistical methods in predicting bankruptcy (Barboza *et al.*, 2017; Zelenkov *et al.*, 2017). Nevertheless, scholars argue that there is a need to establish stronger connections and impact on regulators and corporations as existing models have been scantily applied in the real world (Bellovary *et al.*, 2007). Moreover, further financial ratios are recommended by scholars to enhance prediction quality (Zelenkov and Volodarskiy, 2021). Therefore, based on this, we intend to draw on previous studies based on statistical methods and consider an additional financial ratio, cash and cash equivalents to current liabilities ratio, in the Z"-Score model to improve the prediction quality for financial distress by using discriminant analysis and logistic regression.

*3.3.1 Linear discriminant analysis.* LDA is a statistical technique which classifies a single observation into one of various *a priori* groupings dependent upon the individual characteristics of an observation. The groups can be two or more. We employ LDA for classification as well as for making predictions about our dependent variable, financial distress, which comprises two groups, distressed and non-distressed firms, based on independent variables of our study (see Table 4). We apply LDA to the study model (see equation 1). The same technique is applied in earlier studies (Altman, 1968; Altman *et al.*, 2017; De Luca and Meschieri, 2017) for a similar kind of analysis and this technique is more useful for small samples (Altman *et al.*, 2017).

*3.3.2 Logistic regression model for developing TDR probability model: M-Z"-Score$_{i,t}$.* In the next stage, we assess the firm's probability to file for TDR to avoid potential bankruptcy

**Table 3.**
Distressed firms filed for TDR year-wise

| | Overall sample | Italy | France | Spain |
|---|---|---|---|---|
| 2015 | 92 | 28 | 56 | 8 |
| 2016 | 47 | 44 | – | 3 |
| 2017 | 11 | 10 | – | 1 |
| 2018 | 54 | 50 | 2 | 2 |
| 2019 | 45 | 42 | 1 | 2 |
| 2020 | 63 | 57 | 1 | 5 |
| Total | 312 | 231 | 60 | 21 |

**Source(s):** Table created by author

**Table 4.**
Summary of variables

| Variable | Definition/calculation | Source |
|---|---|---|
| Financial distress | Distressed firms = 1, non-distressed firms = 0 | Altman *et al.* (2017), Fernández-Gámez *et al.* (2020) |
| Financial ratios | Retained earnings to total assets ratio | Altman (1983), Altman *et al.* (2017) |
| | Earnings before interest and taxes to total assets ratio | |
| | Book value of equity to total liabilities ratio | |
| | Cash and cash equivalents to current liabilities ratio | Motivation from De Luca and Meschieri (2017) as they have considered other liquidity ratios |

**Source(s):** Table created by author

using the logistic regression model. We use independent variables, the financial ratios (see equation 1), to determine the TDR probability. In earlier literature, Shumway (2001) determined the probability of firm failure by using a logistic regression model. Along with this, in the seminal work by Beaver (1966) and Altman (1968, 1983), they adopted a similar approach for predicting firms' failure based on financial ratios. The financial ratios can predict the probability of business failure and warn about its financial situation before its liquidation (Beaver, 1966). Altman (1968) used five financial ratios and developed a model by using MDA. He presented financial ratios relation for years before and after the bankruptcy. Nevertheless, the focus of these studies was on predicting firm failure. In contrast, in the literature, the only study by De Luca and Meschieri (2017) determined the firm's probability to file for TDR using a logistic regression model.

We use the following logistic regression model to estimate the firm's probability to file for TDR (see equation 2).

$$\widehat{P}_{i,t} = \frac{e^{M-Z"-Score_{i,t}}}{1 + e^{M-Z"-Score_{i,t}}} \tag{2}$$

where $\widehat{P}_{i,t}$ is TDR probability related to the $i$th firm at time $t$, $e$ is the Euler number, $M\text{-}Z"\text{-}Score_{i,t}$ is a score related to the $i$th firm at time $t$, which is computed through the below formula:

$$M - Z" - Score_{i,t} = 0.62 \times X_{1i,t} + 1.64 \times X_{2i,t} + 3.92 \times X_{3i,t} + 0.33 \times X_{4i,t} \tag{3}$$

where $X_1$ is Cash and Cash Equivalents/Current Liabilities, $X_2$ is Retained Earnings/Total Assets, $X_3$ is Earnings before Interest and Taxes/Total Assets, $X_4$ is Book Value of Equity/Total Liabilities, $_{i,t}$ is the $i$th firm at time $t$, *M-Z"-Score* is the Modified Z"-Score, and it is Overall Index.

$\widehat{P}_{i,t}$ value always ranges between 0 and 1 and indicates the likelihood of a firm filing for TDR. The firm is healthy when the TDR probability is low, while a firm is financially distressed when the TDR probability is high. Thus, $\widehat{P}_{i,t}$ is inversely proportional to the health status of the firm (De Luca and Meschieri, 2017). We calculate $\widehat{P}_{i,t}$ on a year basis. For distressed firms, we consider each of the three years prior to their filing for TDR. In the case of non-distressed firms, we consider all the years from 2011 to 2019.

We estimate the coefficients in $M\text{-}Z"\text{-}Score_{i,t}$ (see equation 3) through LDA based on ratios for each firm, as presented below:

(1) In the case of distressed firms, we use three years of data prior to their filing for TDR.

(2) In the case of non-distressed firms, we use the best ratios of any three years from years 2011 to 2019.

We use this approach to estimate coefficients as it includes the worst ratios of distressed firms and best ratios of non-distressed firms enabling high discriminant potential for ratios and less temporal correlation as data are based on the comparison of different years (De Luca and Meschieri, 2017). Therefore, by doing this, we have an efficient estimation of the $Modified\ Z"\text{-}Score_{i,t}$ model. The LDA fundamental assumption is to have independent sample observations; therefore, we fulfill this assumption by choosing the worst and best ratios years (De Luca and Meschieri, 2017). However, in earlier literature, this assumption has rarely been met (De Luca and Meschieri, 2017).

We observe a difference in coefficients of the modified Z"-Score$_{i,t}$ model if we compare it with the Z"-Score (Altman, 1983) since the same ratios can employ different effects on the formula. This aspect distinguishes bankruptcy/failure and financial distress events. Hence, these ratios can affect a firm's choice related to accessing a TDR agreement (De Luca and Meschieri, 2017). Further, the modified Z"-Score$_{i,t}$ model is estimated based on multi-industry and multi-year analysis of three European countries. On the contrary, the Z"-Score is for multi-industry; however, it is based on one-year data interval (De Luca and Meschieri, 2017). Moreover, the modified Z"-Score$_{i,t}$ model is estimated to determine $\widehat{P}_{i,t}$, the probability of a firm filing for TDR. In contrast, the Z"-Score was developed for determining a cut-off value (De Luca and Meschieri, 2017).

We further calculate the average of TDR probabilities for each year for both distressed and non-distressed firms to show the trend of TDR probabilities for both groups. We assume a firm files for TDR to overcome the temporary state of crisis and therefore, the following two hypotheses should be satisfied for the time series analysis of $\widehat{P}_{i,t}$ (De Luca and Meschieri, 2017).

*H2.* In the case of distressed firms, the probability should be increasing until a year before the TDR request and in the following years, it should become stationary or even decrease.

*H3.* In the case of non-distressed firms, there should be stationary in the time series, and it should be following a nearly constant trend over the years.

The next section presents the empirical analysis and discussion.

## 4. Empirical analysis and discussion

We present descriptive statistics of independent variables used in the study for both distressed and non-distressed firms in Table 5. We observe a difference in the mean values of both groups for all independent variables, including retained earnings to total assets ratio, earnings before interest and taxes to total assets ratio, the book value of equity to total liabilities ratio and cash and cash equivalents to current liabilities ratio. Overall, for the distressed group, the mean values are pretty low, and in the case of non-distressed firms, the mean values of each ratio are quite good. This represents that one group is of financially healthy firms while the other group is facing financial difficulties. Hence, the results support our choice of groups for the healthy and distressed firms. Moreover, the standard deviation values indicate no extreme volatility for any of the independent variables.

In the next step, we perform the LDA. We split the data sample into training (80%) and testing (20%) sets for the goodness of fit of our study model. The relevance of the testing set is

**Table 5.** Descriptive statistics (overall sample)

| | RETA | | EBITTA | | BVOETL | | CR | |
|---|---|---|---|---|---|---|---|---|
| | NON-D | DIS | NON-D | DIS | NON-D | DIS | NON-D | DIS |
| Mean | 0.326 | 0.0022 | 0.087 | −0.040 | 1.025 | 0.259 | 0.232 | 0.098 |
| Median | 0.296 | 0.046 | 0.069 | 0.016 | 0.626 | 0.150 | 0.078 | 0.035 |
| S.D. | 0.194 | 0.375 | 0.086 | 0.187 | 1.236 | 0.546 | 0.434 | 0.194 |
| Lower quartile | 0.181 | −0.045 | 0.035 | −0.051 | 0.351 | 0.028 | 0.0094 | 0.011 |
| Upper quartile | 0.463 | 0.174 | 0.116 | 0.035 | 1.228 | 0.390 | 0.286 | 0.093 |
| Minimum | −0.281 | −5.418 | −0.066 | −1.884 | 0.011 | −0.723 | 0.000000498 | 0.0000275 |
| Maximum | 0.874 | 0.719 | 0.789 | 0.280 | 9.599 | 9.888 | 3.882 | 1.844 |

**Note(s):** RETA is retained earnings to total assets ratio, EBITTA is earnings before interest and taxes to total assets ratio, BVOETL is book value of equity to total liabilities ratio and CR is cash and cash equivalents to current liabilities ratio. NON-D is non-distressed firms, DIS is distressed firms, and S.D. is standard deviation
**Source(s):** Table created by author

that the data in this set are unseen by the model. Therefore, the results of the testing set must be similar to or better than the training set. We split data for the overall sample and each country. We consider data from three years for each group. In the case of distressed firms, data is based on three years before their filing for TDR, and in the case of non-distressed firms, we use three years of best-performing ratios from 2011 to 2019.

Table 6 shows the coefficients of the study model (see equation 1) for the entire sample and each country. According to the results, the ratio of earnings before interest and taxes to total assets shows a high discriminant power.

We predict the study model (see equation 1) based on the estimated coefficients and present prediction results of the testing data set for the entire sample and each country in Table 7. First, we check the misclassification errors and determine the prediction accuracy of the study model. Interestingly, the results indicate higher prediction accuracy with lower misclassification errors for the entire sample as well as for each country for the study model which we modified to predict financial distress.

Table 7 further shows that there are no misclassification errors for distressed firms in the case of Spain. The reason for no misclassification errors is that we have a small sample size for Spain. The results in Table 7 are based on the testing data set (20% of total sample). Although in the case of the training data set (80% of the total sample) (see Appendix A), we find misclassification errors for both distressed and non-distressed firms. The LDA results of the training data set (see Appendix) indicate a similarity with respect to the testing data set for the overall sample and each country. This shows the goodness of fit of our study model.

The findings of LDA reveal that our modified model of the Z”-Score shows higher prediction accuracy and low misclassification errors for the overall sample and for each country including Italy, France and Spain. This justifies our selection of sampling countries since there is a similarity in their TDR laws. The results further justify our assumption about the replacement of a ratio in the Z”-Score, as discussed in Section 1 and 2. Moreover, the results justify the argument that failure prediction and financial distress prediction are not

| | Overall sample | Italy | France | Spain |
|---|---|---|---|---|
| RETA | 1.636 | 1.698 | 1.179 | 1.059 |
| EBITTA | 3.918 | 3.397 | 6.594 | 5.517 |
| BVOETL | 0.327 | 0.322 | 0.378 | 0.279 |
| CR | 0.620 | 0.867 | −1.537 | 1.769 |

**Note(s):** RETA is retained earnings to total assets ratio, EBITTA is earnings before interest and taxes to total assets ratio, BVOETL is book value of equity to total liabilities ratio and CR is cash and cash equivalents to current liabilities ratio
**Source(s):** Table created by author

**Table 6.** Coefficients of study model

| | Misclassification errors: Distressed firms | Misclassification errors: Non-distressed firms | Prediction accuracy |
|---|---|---|---|
| Overall sample | 9.43 | 8.57 | 82.00 |
| Italy | 6.30 | 10.37 | 83.33 |
| France | 13.11 | 11.48 | 75.41 |
| Spain | 0.00 | 19.05 | 80.95 |

**Note(s):** All values are presented in percentages
**Source(s):** Table created by author

**Table 7.** Results of LDA for testing data

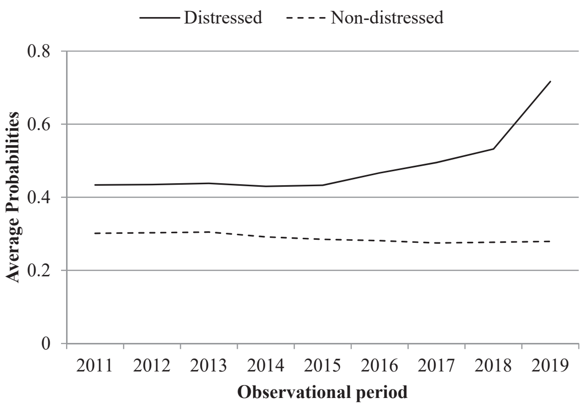
similar events (Åstebro and Winter, 2012; Gupta *et al.*, 2018) as we develop a model for distress prediction and based on the findings it depicts higher prediction accuracy. Our results for hypothesis H1 are in line with the literature (De Luca and Meschieri, 2017).

In the next stage, we develop a TDR probability model (see equation 2) for firms, as discussed in Section 3. We determine probabilities based on our modified Z”-Score model (see equation 1) for both distressed and non-distressed firms by using the estimated coefficients (see Table 6).

We further calculate the average of TDR probabilities year-wise for the overall sample to observe the general trend of TDR probabilities for both groups as presented in Figure 1. In Figure 1, there are two trends related to distressed and non-distressed firms. The black solid line depicts the trend for distressed firms which indicates the trend of TDR probabilities increases with increasing proximity to the critical period. Further, it presents the trend has reached its maximum in the last 3 years, in which we have a total of 162 (out of 312) TDR requests. The interesting fact is the trend started increasing from 2014 since we consider the years 2015–2020 in which firms requested TDR and the data are based on the years 2014–2019. Another interesting fact is the TDR probabilities of distressed firms are higher even three years prior to their TDR request than the non-distressed firms. The results represent that our developed model can signal financial distress even three, two and/or one year before the firms face severe financial difficulties and request TDR. In contrast, the black dashed line presents the trend for non-distressed firms which depicts a lower but constant trend in TDR probabilities since these are healthy firms and did not request for TDR.

The results of the TDR probability model reveal that firms of both distressed and non-distressed groups differ in terms of their TDR probabilities year-wise, as shown in Figure 1. In the case of distressed firms, the TDR probability has an increasing trend whereas, the trend is stationary and constant for non-distressed firms. The findings support our choice of sample firms as we select firms that are in financial difficulties and request for TDR, labeled as distressed firms, and firms that are healthy and did not request for TDR, labeled as non-distressed firms. The results further justify the replacement of a ratio we make in the Z”-Score model (see equation 1) to predict financial distress. The findings for H2 and H3 are in line with the earlier literature (De Luca and Meschieri, 2017).

We perform an independent sample *t*-test on firms TDR probabilities, $\widehat{P}_{i,t}$, year-wise as a robustness test. The results in Table 8 depict there is a significant difference between the




**Source(s):** Figure created by author

**Figure 1.**
Trend of average TDR probabilities to file for TDR for overall sample

TDR probabilities for each year for both distressed and non-distressed groups. We also observe increasing differences in TDR probabilities from 2014 to 2019. The interesting insight is the TDR probabilities are significantly different for both groups even three years prior to TDR request by the distressed firms. The results of robustness analysis confirm the predictive accuracy of TDR probabilities and the predictive ability of our developed model that is able to warn firms of potential financial distress situations. Thus, firms can request TDR in an early stage to restore financial equilibrium (De Luca and Meschieri, 2017).



## 5. Conclusion

Financial distress and failure prediction are enormously debated topics in the literature in the field of corporate finance. However, both are distinct events and therefore, we aim to predict financial distress, namely a firm's probability to file for TDR to overcome a temporary state of crisis. For this purpose, we develop a model based on financial ratios. Specifically, we develop a model where we modify the Z"-Score model by replacing the ratio of working capital to total assets with cash and cash equivalents to current liabilities. We consider private large and medium-sized firms of three European countries, including Italy, France and Spain, since there is a similarity in their TDR laws. We find higher prediction accuracy for our developed model. We further find that the firms of both distressed and non-distressed groups differ concerning their TDR probabilities.

Our study has several practical implications. This study responds to the EU call by developing a financial distress prediction model. Thus, it could allow firms that are in financial difficulties to timely restructure their debt and continue their businesses. Overall, the findings of this study are helpful for firms' management and their stakeholders. Mainly the management's objective is to save a firm from bankruptcy and liquidation. Therefore, they can measure the firm health status regularly by using our developed model for earlier indication of financial distress. They can take early action by requesting for TDR agreement in case a firm faces financial distress. Therefore, it could help them to overcome financial distress situations, restore financial equilibrium and avoid potential bankruptcy and liquidation since, with this tool, they can enter into TDR agreements in an early stage. Moreover, banks and other creditors can use this tool to measure the health status of their debtor firms for credit assessment. Along with this, investors also need to be aware of the company's financial status. Therefore, this tool can help them with their investment decisions. In the case of social implications, our study model can probably help protect firms from failure and lower the risk of adverse effects on the economies and societies of the sampling countries since it would maintain employment rates.

| Observational period | *t*-statistics |
|---|---|
| 2011 | 5.356*** |
| 2012 | 6.178*** |
| 2013 | 7.738*** |
| 2014 | 6.714*** |
| 2015 | 9.628*** |
| 2016 | 11.365*** |
| 2017 | 13.426*** |
| 2018 | 11.721*** |
| 2019 | 13.816*** |

**Note(s):** *** represent significance level at 1%
**Source(s):** Table created by author

**Table 8.** Independent sample *t*-test of probabilities to file for TDR between distressed and non-distressed firms for overall sample

The findings of this study are conclusive. However, there is still room for further extension, such as the sample size of this study is small. Hence, future studies could apply the developed model of this study to large samples to predict financial distress and TDR probabilities. Moreover, future research could investigate the extent to which the adoption of alternative methods for financial distress prediction, such as AI and ML, could help in improving the prediction accuracy, and provide companies and practitioners with reliable and "ready to use" tools to better support their decisional processes.

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## Appendix
## LDA for training data

| | Misclassification errors | | Prediction accuracy |
|---|---|---|---|
| | Distressed firms | Non-distressed firms | |
| Overall sample | 9.86 | 10.07 | 80.07 |
| Italy | 6.68 | 9.46 | 83.86 |
| France | 12.73 | 11.27 | 76.00 |
| Spain | 6.67 | 16.19 | 77.14 |

**Note(s):** All values are presented in percentages
**Source(s):** Table created by author

**Table A1.** Results of LDA for training data

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