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Financial distress prediction: The case of French small and medium-sized firms☆

Nada Mselmi [a,d], Amine Lahiani [a,b,*], Taher Hamza [c,d]

[a] Université d'Orléans, CNRS, LEO, UMR 7322, F-45067 Orléans, France
[b] Montpellier Business School, Montpellier, France
[c] VALLOREM, Université d'Orléans, France
[d] LAMIDED, Université de Sousse, Tunisia.

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ABSTRACT

Financial distress prediction is a central issue in empirical finance that has drawn a lot of research interests in the literature. This paper aims to predict the financial distress of French small and medium firms using Logit model, Artificial Neural Networks, Support Vector Machine techniques, Partial Least Squares, and a hybrid model integrating Support Vector Machine with Partial Least Squares. Empirical results indicate that for one year prior to financial distress, Support Vector Machine is the best classifier with an overall accuracy of 88.57%. Meanwhile, in the case of two years prior to financial distress, the hybrid model outperforms Support Vector Machine, Logit model, Partial Least Squares, andArtificial Neural Networks with an overall accuracy of 94.28%. Distressed firms are found to be smaller, more leveraged and with lower repayment capacity. Moreover, they have lower liquidity, profitability, and solvency ratios. Besides the academic research contribution, our findings can be useful for managers, investors, and creditors. With respect to managers, our findings provide them with early warnings signals of performance deterioration in order to take corrective actions and reduce the financial distress risk. For investors, understanding the main factors leading to financial distress allows them to avoid investing in risky firms. Creditors should correctly evaluate the firm financial situation and be vigilant to signs of impending financial distress to avoid capital loss and costs related to counterpart risk.

1. Introduction

Financial distress is a field of study that does not cease to be relevant. It refers to the situation where a firm's cash flows are not enough to meet contractually required payment. This topic becomes of major interest and is gaining nowadays much more importance mainly after the worldwide recession in 2009 caused by the global credit crunch. Notwithstanding a confirmation that the Eurozone economy had formally left recession, the number of bankrupt firms in France has reached its highest level during the last years. According to the business consultancy Altares, the threshold of 60,000 insolvencies was reached in 2013 for the first time since 2009 to attain 62,300 insolvencies with an increase of 2.8% compared to 2012. Additionally, a 31% rise in the number of medium-sized companies going under is reported between July and September 2013. Distressed firms confront diverse circumstances affecting their value and the welfare of shareholders and creditors, which justifies the vast body of literature devoted to the prediction of financial distress.

Within the context of financial distress prediction, researchers are motivated to detect the first warning signs of financial distress (Altman, Iwanicz-Drozdowska, Laitinen & Suvas, 2016; Liang, Lu, Tsai, & Shih, 2016; Bagher & Milad, 2016; Bauweraerts, 2016; Laitinen & Suvas, 2016; Altman, Iwanicz-Drozdowska, Laitinen, & Suvas, 2014; Bauer & Agarwal, 2014). Various studies have investigated this issue by proposing approaches for predicting financial distress and bankruptcy. Likewise, a large number of empirical studies highlight the importance and the ability of financial ratios in detecting early warnings of corporate financial distress (Amendola, Restaino, & Sensini, 2015).

The objective of this study is to examine the ability of financial ratios to signal financial distress in the French context. We wonder about the main ratios that can discriminate between distressed and non-distressed French small and medium-sized firms one and two years before its occurrence. These ratios are selected such that they maximize the prediction accuracy of financial distress. A descriptive analysis is performed in order to identify the profile of distressed firms. Moreover, since the inquiry of higher accuracy has been a driving force in steering research towards financial distress prediction and machine learning, we compare the predictive accuracy of five prediction models, namely the Logit

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* Corresponding author at: Université d'Orléans, CNRS, LEO, UMR 7322, F-45067 Orléans, France.
E-mail addresses: nada.mselmi@univ-orleans.fr (N. Mselmi), amine.lahiani@univ-orleans.fr (A. Lahiani), taher.hamza@topnet.tn (T. Hamza).

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model, Support Vector Machine (SVM), Artificial Neural Networks (ANNs), Partial Least Squares (PLS), and Partial Least Squares Support Vector Machine (PLS-SVM).[1] It is important to notice that the hybrid PLS-SVM model is proposed as a combination of PLS and SVM to overcome the drawbacks of using each technique separately. While the PLS technique is employed to extract the information from financial ratios and remove the input collinearity, SVM is used to map the nonlinear relationships with better generalization performance than other nonlinear regression methods such as the ANNs (Wang & Yu, 2004). Yeganeh, Shafie Pour Motlagh, Rashidi, and Kamalan (2012) show that both the SVM and the hybrid PLS-SVM models have good prediction ability. Nevertheless, the hybrid PLS-SVM model has better accuracy.

This study aims to answer the following questions: **1) What are the most relevant financial determinants of financial distress? 2) What is the optimal horizon of prediction? 3) What is the most accurate prediction model?**

This study adds to the recent literature in at least four ways. First, while a great majority of studies focus on the five ratios that Altman (1968) uses in his *Z*-Score model, which is considered as the most widely, recognized and applied one in the prediction of financial distress, our study suggests that we can better predict financial distress using a different set of financial ratios. Adopting a backward elimination method, we start with a large battery of financial ratios and select the most discriminant ones. The prediction accuracy of financial distress is similar and even better than that of other studies employing other predictors. Second, our study is among a few number of studies that focus on financial distress prediction in the French context. To the best of our knowledge, there are no published works that predicted French firms' financial distress using SVM and PLS in the French context so far. Third, while the number of studies that construct a hybrid model based on PLS and SVM for classification and prediction tasks are very limited, none of these studies is applied in the context of financial distress nor bankruptcy. Fourth, contrarily to the finding that the prediction accuracy is greater when the prediction horizon is impending (one-year ahead), our findings show that, in the context of French small and medium-sized firms, the prediction accuracy gets better two years prior to financial distress.[2] As such, we consider our research to be an important and timely contribution to this field.

The remaining of the paper is organized as follows. Section 2 presents a literature review highlighting the importance of financial ratios in the prediction of financial distress. In Section 3, we present comparison of the competing models/techniques used in the literature of financial distress prediction and introduce our empirical study. Section 4 describes the sample and the feature selection process. Section 5 presents the empirical results. In Section 6, we compare the predictive performance of the above models. Section 7 concludes.

2. Literature review

Ramser and Foster (1931), Fitzpatrick (1932), Winakor and Smith (1935), and Merwin (1942) are among the early studies that identify the problematic linked to the difference between the values of financial ratios of failing and non-failing firms (Back, Laitinen, Sere, & Wezel, 1996). These studies conclude that the financial ratios of failed firms are poorer. Even though distressed firms have different profiles, they are all characterized by an unstable financial situation. Altman (1968) stipulates that ratios measuring profitability, liquidity, and solvency are the most important in the prediction of bankruptcy. The author adds that the order of their importance is not obvious in consideration of several studies that cite different ratios as being the most efficient in predicting bankruptcy.

Keasey and Mcguinness (1990) suggest that, for a number of years prior to the date of failure, profitability ratio is a significant indicator of failure. Bunn and Redwood (2003) find that increases in capital gearing (the debt to assets ratio) raise the likelihood of firm failure while higher liquidity, as measured by the current ratio, reduces the probability of failure. In addition, low profitability coupled with high debt to assets ratiorises the predicted probability of failure as compared to situations where the two effects occur in isolation. Likewise, Brigham and Ehrhardt (2005) find that financial factors of distress are mainly excessive debt and insufficient capital. Newton (2009) suggests that firms express leaning to overextend debts and consequently become unable to meet their liabilities.

Liang and Wu (2005) support that indicators estimating conditions of cash flow - situation in which there is not enough cash to pay off the debt at term - are essential to identify financial distress. Chen (2011) shows that cash flow ratio and cash flow to total debt ratio contribute significantly to the prediction of financial distress. Pindado and Rodrigues (2004) highlight the importance of detecting firm's insolvency situation since several economic agents hold an interest in the insolvent companies. Closer inspection of insolvency indicators facilitates getting a preventive diagnosis of corporate financial distress. Bellovary, Giacomino, and Akers (2007) trace the literature on bankruptcy prediction from the 1930′s and cite the study of Merwin (1942) who focuses on signs of frailty up to four or five years prior to failure and finds that net worth to total debt is a significant indicator of business failure.

Overall, several experimental researches confirm the role of financial ratios in the prediction of financial distress. Findings show that accounting information can pinpoint firms that would face financial distress.

3. Corporate financial distress prediction models

The application of statistical techniques to bankruptcy prediction began with the univariate analysis of Beaver (1966). The author tests the predictive ability of accounting data and highlights the significant explanatory power of financial ratios in the prediction of failure, howbeit; these ratios do not show similar predictive accuracy. Afterwards, bankruptcy prediction has been studied actively. Altman (1968) uses a multiple discriminant analysis and develops the *Z*-Score model which is considered as a milestone for financial distress prediction research in a period when traditional ratio analysis lost favor with academics. Altman (1968) restricts a list of 22 potentially significant ratios to 5 which are confirmed to be significant in predicting bankruptcy in a sample of 66 firms. The use of this model in the discrimination between the two groups of failing and non-failing firms is justified by the fact that failing firms and financially sound firms manifest dissimilar ratios and financial trends (Caouette, Altman, & Narayanan, 1998). Bemmann (2005) considers the *Z*-score model as a poorly fitted model. In fact, each individual ratio, used as predictor in the model, has a good bankruptcy prediction power. Nevertheless, the ratios' coefficients weaken the predictive power of the model to the point that it performs worse than its best predictor ratio.

Beaver (1966) and Altman (1968) highlight the ability of financial variables in the prediction of bankruptcy. Nevertheless, these traditional methods present at least three drawbacks. First, regarding the univariate analysis of Beaver (1966), it would be better to include variables as predictors rather than to employ them for matching intention. Second, the *Z*-Score model of Altman (1968) imposes some statistical requirements regarding the distribution of predictors. Actually, both groups (failed and non-failed firms) must have identical variance-covariance matrices of the predictors. In addition, the multiple discriminant analysis requires normally distributed predictors, which mitigates against the employment of dummy independent variables. Furthermore, this technique produces a score with a weak intuitive interpretation. Finally, the *Z*-Score model is suitable only for linear classification.

[1] We also compared the prediction accuracy of these five models to that of Decision Tree. Decision Tree gives the worst prediction accuracy. To save space, we do not report results of Decision Tree prediction of financial distress in the French context.

[2] Micha (1984), Neves and Vieira (2006), and Sheikhi, Shams, and Sheikhi (2012) show that the average accuracy of one year before financial distress is higher than that of two years before financial distress.