Decision Support Systems 51 (2011) 701–711

Contents lists available at ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

# Predicting corporate bankruptcy using a self-organizing map: An empirical study to improve the forecasting horizon of a financial failure model

Philippe du Jardin [a,*], Eric Séverin [b,1]

[a] Edhec Bussiness School, 393, promenade des Anglais, BP 3116, 06202 Nice Cedex 3, France
[b] Université Lille 1 – USTL, Batiment SHS – N3, BP 179, 59653 Villeneuve d'Ascq Cedex, France

ARTICLE INFO

*Article history:*
Received 15 September 2010
Received in revised form 26 January 2011
Accepted 11 April 2011
Available online 16 April 2011

*Keywords:*
Financial failure prediction
Self-organizing map
Forecasting horizon

ABSTRACT

The aim of this study is to show how a Kohonen map can be used to increase the forecasting horizon of a financial failure model. Indeed, most prediction models fail to forecast accurately the occurrence of failure beyond 1 year, and their accuracy tends to fall as the prediction horizon recedes. So we propose a new way of using a Kohonen map to improve model reliability. Our results demonstrate that the generalization error achieved with a Kohonen map remains stable over the period studied, unlike that of other methods, such as discriminant analysis, logistic regression, neural networks and survival analysis, traditionally used for this kind of task.



## 1. Introduction

A company that fails to fulfill its obligations, and especially to repay its debts, may then face a critical situation that, in the worst cases, leads to its failure. So the ability to predict the bankruptcy of a firm is crucial for an investor or a creditor who wishes to ensure that he will be reimbursed on time. It is for this reason that many banks have developed models to assess the risk associated with their loans or their receivables. These models allow them to decide whether to lend money and on what terms, but also to assess the interest rate depending on the anticipated risk of non-reimbursement.

This issue has been studied for many years by academics of many disciplines, and the very first statistical models were developed in the late sixties [2]. As there is no general theory of business failure, all these models are empirical [1,33] and are designed mainly using data-mining techniques.

Although these models differ greatly, depending on the modeling method, the variables or the samples used [10], they share at least one common characteristic: their forecasting horizon does not usually exceed 1 year. At horizons of more than 1 year, their accuracy falls substantially. Indeed, model accuracy, at horizons of between one and three years, falls by an average of 15%. For example, Altman's [2] model had an accuracy rate of 95% one year before failure and only 48% three years before failure. Altman et al.'s [5] model had an accuracy rate of 97.1% one year before failure and 69.7% three years before failure. With Blum's [14] model, the respective figures are 95% and 70%, with Brabazon and O'Neill's [16] they are 76.7% and 56.7%, with Dimitras et al.'s [24] 76.3% and 50%, with Moyer's [40] model 84.1% and 68.2%, and, finally, with Sharma and Mahajan's [49] model they are 91.7% and 73.9%. Regardless of the modeling technique (linear or non-linear, regression or classification), models always have the same drawback: a very short forecasting horizon.

This drawback is especially severe when the forecasting period does not coincide with the terms of the contract between the debtor and the creditor. Indeed, a creditor who accepts that his debt will be repaid over several years, when his debtor's risk has been assessed over a very short time period (usually 1 year), may face a much higher risk beyond the forecasting horizon of the model.

It is for this reason that we have studied a way to improve model accuracy over time. Our work relies on a very interesting result that has not yet been used to design financial failure models. Research has shown that failure is a dynamic process [21,22,29,32], which may be analyzed over time, hence that the health of a company assessed at a given time depends heavily on its history. Thus, some firms can delay the onset of bankruptcy for many years because they have the resources or because they make a strategic commitment that allows them to change their fate, whereas others cannot. Still others may improve their situation, some more swiftly than others, even though their financial profile, measured at a given time, shows that such an improvement is not possible.

But traditional models rely only on a snapshot of a firm's financial situation measured at time $t$ to predict whether it is likely to fail at time $t+1$ [50,51]. Because these models assume that a firm's history has little or no influence on its future behavior, they are unlikely to make allowances for a struggling firm's ability to recover or muddle

* Corresponding author. Tel.: +33 4 93 18 99 66; fax: +33 4 93 83 08 10.
*E-mail addresses:* philippe.dujardin@edhec.edu (P. du Jardin), e.severin@wanadoo.fr (E. Séverin).
[1] Tel.: +33 3 28 76 73 00; fax: +33 3 28 77 84 77.

0167-9236/$ – see front matter © 2011 Elsevier B.V. All rights reserved.
doi:10.1016/j.dss.2011.04.001

through. They are also unlikely to take into account the effect of some signs of relative weakness which will result in failure only a few years later. For these reasons, these models have very short forecasting horizons.

Although businesses may well take different paths to bankruptcy, the assumption that including this time dimension might improve model accuracy has led to very little research. Pompe and Bilderbeek [46] have compared the performance of models using financial ratios measured over 1 year, with other models using ratios measured over several consecutive years, and have analyzed their performance by forecasting horizons of between one and seven years. Paradoxically, models that incorporate a time dimension do no better than those that do not; indeed, models were not able to stabilize the error with data calculated more than two years before failure.

As a consequence, the aim of this study is to use what some researchers have called the "trajectory of corporate collapse" to examine another way of estimating the changes in firms' financial health. Instead of using financial variables measured at different time intervals to forecast failure, as Pompe and Bilderbeek [46] did, we propose to use these variables as a means to design trajectories, then to use these trajectories to make a forecast.

We used a Kohonen map to design these trajectories. First, the map was used to delimit boundaries between areas representing various stages of company financial health. Second, we analyzed how companies moved over time within these areas to estimate a typology of behavior we called "trajectories". Third, we used this typology to forecast financial failure at horizons of one, two, and three years.

Finally, we compared the results achieved using the trajectories and results estimated using the most common methods of designing financial failure models: discriminant analysis, logistic regression, and neural networks. We also compared the results achieved using the trajectories with those estimated with a survival analysis method. And these comparisons were done at each time horizon.

The remainder of this paper is organized as follows. In Section 2, we present a literature review that explains our research question. In Section 3, we describe the samples and methods used in our experiments. Finally, in Section 4, we present and discuss our results; in Section 5, we summarize our main findings.

## 2. Literature review

Most financial failure models are single-period models. They are estimated using variables (mostly financial ratios) collected at time $t$, and their accuracy is measured at time $t+1$. Since Altman's [2] seminal work a large number of models have been designed in such a way. These models have come in for much criticism, mainly from a statistical point of view [10,24]. Problems such as the ways variables or samples are selected, the influence of exogenous variables on model accuracy, the assumptions required by some methods, and the ways model accuracy is assessed have been highlighted.

However, the approach to failure at the root of these models is also a legitimate target of criticism. First, models assume that the length of the period during which a firm has been exposed to a risk of failure has no influence on its probability of failure, because they do not take into account the history of the company. So the probability of failure does not depend on the age of the company. However, this assumption does not necessarily hold, as age is a major cause of failure [38,46,53].

Second, models assume that failure is the result of a sudden event, as their forecasting timeframe does not usually exceed 1 year. But companies may show signs of relative weakness many years before they fail [22,32,41]. They may survive in the face of evidence that suggests they might not.

Third, models do not take into account the diversity of paths to terminal failure, some of which can be more chaotic or more gradual than others [6,22,32]. Nevertheless, depending on the trajectory taken by the firm or on the way a company moves down a given trajectory, its horizon and its probability of failure may change considerably [32].

Because models fail to account for these factors, their forecasting ability is reduced. Indeed, their accuracy will depend heavily on the frequency of each distinctive path in the sample used to estimate them [10,32]. If firms in the terminal phase of failure are used to design a model, it will perform poorly with firms in an earlier phase.

The consequence of all these factors is presented in Table 1, which shows the studies devoted to designing financial failure prediction systems (failure is usually defined from a legal standpoint as liquidation or reorganization), within a timeframe varying from one to three years, and sometimes beyond 3 years. These studies dealt with models designed using data usually taken from the last accounts published before failure, that is, with an average lag of twelve to eighteen months.

Table 1 clearly shows that only very few models achieved stable results over time. Prediction rates are rather good one year before failure, but less so as the horizon recedes to two and three years.

Table 2 shows the same percentages, but classified as healthy or unsound companies. Overall, prediction rates fall, regardless of the company's status. But the larger the size of the sample used in the study, the lower the prediction rates of failed firms; it seems that, when the sample size is large and selection bias is thus reduced, the future of healthy companies is easier to forecast.

**Table 1**
Results of the main studies dealing with financial failure prediction at forecasting horizons of between one and three years.

| Studies | % of correct classification | | | Sample size | | |
|---|---|---|---|---|---|---|
| | All companies | | | Healthy | Failed | Total |
| | Years before failure | | | | | |
| | 1 | 2 | 3 | | | |
| Altman [2] | 95.0% | 72.0% | 48.0% | 33 | 33 | 66 |
| Altman et al. [5] | 97.1% | 88.2% | 69.7% | | 34 | 34 |
| Altman et al. [3] | 91.0% | 89.0% | 84.0% | 53 | 58 | 111 |
| Altman et al. [4] | 93.2% | | 91.1% | 404 | 404 | 808 |
| Atiya [7] | 74.6% | 66.7% | | 716 | 444 | 1160 |
| Aziz et al. [8] | 91.8% | 84.7% | 78.6% | 39 | 39 | 78 |
| Back et al. [9] | 97.3% | 73.0% | 83.5% | 37 | 37 | 74 |
| Barniv and Hershbarger [11] | 89.3% | 87.7% | | 77 | 70 | 147 |
| Barniv and McDonald [12] | 83.7% | 80.0% | 71.9% | 153 | 141 | 294 |
| Betts and Belhoul [13] | 90.1% | 72.4% | 64.7% | 39 | 93 | 132 |
| Blum [14] | 95.0% | 80.0% | 70.0% | 115 | 115 | 230 |
| Brabazon and Keenan [15] | 80.7% | 72.0% | 66.0% | 89 | 89 | 178 |
| Brabazon and O'Neill [16] | 76.7% | 73.3% | 56.7% | 89 | 89 | 178 |
| Charitou et al. [17] | 83.3% | 76.2% | 75.0% | 51 | 51 | 102 |
| Coats and Fant [18] | 92.9% | 86.2% | 81.9% | 188 | 94 | 282 |
| Dambolena and Khoury [23] | 91.2% | 84.8% | 82.6% | 23 | 23 | 46 |
| Dimitras et al. [24] | 76.3% | 60.5% | 50.0% | 40 | 40 | 80 |
| Doumpos and Zopounidis [25] | 71.1% | 60.5% | 57.9% | 59 | 59 | 118 |
| Gombola et al. [28] | 89.0% | 86.0% | 72.0% | 244 | 77 | 321 |
| Kotsiantis et al. [30] | 71.8% | 71.1% | 68.8% | 100 | 50 | 150 |
| Lacher et al. [31] | 94.7% | 89.4% | 84.1% | 188 | 94 | 282 |
| Laitinen and Laitinen [34] | 86.6% | 68.3% | | 41 | 41 | 82 |
| Laitinen and Laitinen [35] | 74.7% | 65.3% | | 85 | 85 | 170 |
| Laitinen and Kankaanpaa [33] | 86.9% | 65.8% | 71.1% | 38 | 38 | 76 |
| Lau [36] | 80.0% | 79.0% | 85.0% | 700 | 100 | 800 |
| Lee et al. [37] | | 78.6% | 76.2% | 84 | 84 | 168 |
| Moyer [40] | 84.1% | 79.6% | 68.2% | 22 | 20 | 42 |
| Nam and Jinn [41] | 84.4% | 76.1% | 76.1% | 46 | 46 | 92 |
| Piramuthu et al. [45] | 89.1% | 87.0% | | 91 | 91 | 182 |
| Pompe and Bilderbeek [46] | 80.0% | 70.0% | 68.0% | 1800 | 1800 | 3600 |
| Sharma and Mahajan [49] | 91.7% | 78.3% | 73.9% | 23 | 23 | 46 |
| Tam and Kiang [52] | 85.2% | 88.8% | | 81 | 81 | 162 |
| Yim and Mitchell [55] | 92.0% | 90.0% | | 80 | 20 | 100 |
| Zurada et al. [56] | 81.6% | 76.6% | 68.1% | 253 | 92 | 345 |

Figures presented in this table correspond to the best results when many results were computed.
Empty cells correspond to results that were not mentioned.