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Innovative Applications of O.R.

Bankruptcy prediction using terminal failure processes

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ABSTRACT

Traditional bankruptcy prediction models, designed using classification or regression techniques, achieve short-term performances (1 year) that are fairly good, but that often worsen when the prediction horizon exceeds 1 year. We show how to improve the performance of such models beyond 1 year using models that take into account the evolution of firm's financial health over a short period of time. For this purpose, we design models that fit the underlying failure process of different groups of firms. Our results demonstrate that such models lead to better prediction accuracy at a 3-year horizon than that achieved with common models.

1. Introduction

For many years, a large number of studies have been focusing on how to improve the accuracy of failure models. Such models are used by financial institutions to assess their credit risk, that is to say the maximal credit loss they may be exposed to if their counterparties do not reimburse their debts. One of the components used to assess this loss is made up of the probability of default of each borrower, usually given a 1-year horizon. The accuracy of the estimation of this probability is a key issue for prudential purposes, since it allows financial institutions to determine the amount of capital needed to cover credit losses. But the accuracy of this estimation at a mid-term horizon (between 2 and 5 years) is also important since risks incurred by financial institutions still exist up until the maturity of the debts owed by their clients. However, most of the time, traditional models used to make mid-term forecasts lead to predictions whose accuracy decreases as the horizon of the prediction increases. One possible explanation of this weakness relies on the fact that these models consider failure based on an erroneous assumption. As these models rely on explanatory variables that are measured over a unique period of time, they assume that the bankruptcy process is the same for all companies, and as a consequence that the warning signs of failure occur in the same way, at the same moment and with the same magnitude for all firms (Laitinen, 1991). Reality, however, is slightly different. One knows that companies follow different strategies of decline, which explains why some firms will go bankrupt extremely quick although they appear to be in rather good health, some others slowly decline before going bankrupt, and yet others will manage to survive even though everything suggests they will not (D'Aveni, 1989).

To improve model ability to correctly forecast the fate of companies not solely at a 1-year horizon, but also at a 2- or 3-year horizon, or more, some authors attempted to take into account these strategies of decline using measures of firm's financial health over several years. Some of them used measures of variation of financial indicators over time (Altman, Haldeman, & Narayanan, 1977; Dambolena & Khoury, 1980). Others designed multi-period models (Berg, 2007; Gepp & Kumar, 2008) that used indicators that were measured over several consecutive years. However, all these works have not led to conclusive results since they did not manage to achieve mid-term forecasts that are as accurate as short-term ones. Still others (du Jardin & Séverin, 2011, 2012) attempted to represent the different paths that firms follow during their lifetime, called trajectories – some leading to bankruptcy, some others not – to forecast their fate. This time, the results are fairly good as the forecasts are rather stable over time. However, this method has a major drawback because it requires a significant amount of historical data; indeed, the models are designed using financial ratios that are collected over 7 consecutive years and, in the real world, it is not uncommon that financial institutions are not able to collect so much data, either because some companies which are of interest are too young, or because data are simply not readily available. This is the reason why we study another way of designing bankruptcy models, using less data than the method mentioned above, but that still relies on this notion of "trajectory". Models rely on a set of "terminal failure processes". These processes represent prototype behaviors of companies that are measured over solely 3 years. Among companies that share the same process, some will finally go bankrupt, some others will not. Once these processes are estimated, companies are classified into groups that share the same process, and then a set of bankruptcy models are designed, one model for each

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Table 1
Main recent studies that have estimated the accuracy of financial failure models over different time horizons.

Studies	Correct classification rates			Differences between correct classification rates		
	1 year prior to failure Y1 (percent)	2 years prior to failure Y2 (percent)	3 years prior to failure Y3 (percent)	Y1–Y2 (percent)	Y2–Y3 (percent)	Y1–Y3 (percent)
Atiya (2001)	74.6	66.7		7.9		
Berg (2007)	78.4	76.0	73.2	2.4	2.8	5.2
Brabazon and Keenan (2004)	80.7	72.0	66.0	8.7	6.0	14.7
Brabazon and O'Neill (2004)	76.7	73.3	56.7	3.4	16.6	20.0
Charalambous, Charitou, and Kaourou (2000)	82.6	73.3	70.9	9.3	2.4	11.7
Charitou, Neophytou, and Charalambous (2004)	83.3	76.2	75.0	7.1	1.2	8.3
Dakovic, Czado, and Berg (2010)	90.1	89.5	89.3	0.6	0.2	0.8
Dewaelheyns and Hulle (2006)	90.1		74.6			15.5
Gepp and Kumar (2008)	95.4	93.0	90.5	2.4	2.5	4.9
Hu and Ansell (2007)	92.7	89.4	88.2	3.3	1.2	4.5
Hu and Chen (2011)	86.2	76.9	70.5	9.3	6.4	15.7
Korol (2013)	96.2	88.7		7.5		
Laitinen and Laitinen (2000)	74.7	65.3		9.4		
Lin, Liang, Yeh and Huang (2014)	81.4	75.1	66.8	6.3	8.3	14.6
Nam and Jinn (2000)	84.4	76.1	76.1	8.3	0.0	8.3
Pompe and Bilderbeek (2005)	80.0	70.0	68.0	10.0	2.0	12.0
Quek, Zhou, and Lee (2009)	92.4	90.9		1.5		
Sun, Jia, and Li (2011)	97.2	87.2	72.5	10.0	14.7	24.7
Xiao, Yang, Pang, and Dang (2012)		87.8	69.0		18.8	
Zhu, He, Starzyk, and Tseng (2007)	86.4	72.2		14.2		
Zopounidis and Doumpos (2002)	63.2	57.9	63.2	5.3	−5.3	0.0

Note: Classification rates that are presented in this table correspond to the best results that were assessed by each study when many results were estimated.

group, using traditional modeling methods (discriminant analysis, logistic regression, survival analysis and a neural network). Thereby, for each combination of failure process and each modeling method, a forecasting model is designed. Models are then used with test data to assess their prediction ability over three time horizons: 1, 2 and 3 years. Results are then compared to those achieved with traditional models commonly used.

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 study. In Section 4, we present and discuss the results and, in Section 5, we conclude.

2. Literature review

2.1. Prior studies

Traditional failure models ensure optimal predictive ability when the forecasting horizon is short, and their accuracy decreases severely beyond 1 year. All studies conducted on this topic since Altman (1968) to date (Lin et al., 2014) clearly show that this is the case. Indeed, the more the horizon increases, the more these models are not be able to capture the different underlying patterns that characterize firms which will go bankrupt. Table 1 presents a list of studies, published between 2000 and 2014, that assessed model accuracy at a 1-, 2- and 3-year horizons. This table indicates a general trend where accuracy decreases as the horizon of a prediction increases. As it happens, Berg (2007), while studying this issue, confirms this relationship between model accuracy and the horizon of a prediction.

Several factors seem to explain the phenomenon. The first one lies in the way models are estimated and optimized. Indeed, in general, they are designed using data that are measured over a period t to achieve a prediction over a period $t + 1$, with an average lag of 1 year between t and $t + 1$. This time period actually materializes at the point in time when the difference between the distributions of data that characterize the two groups of companies (failed and non-failed) is the largest—therefore the instant when the discrimination between the two groups is the easiest (Beaver, 1966). As a consequence, if a model is built to forecast an event such as bankruptcy, with data that are collected solely 1 year before this event occurs, its optimal forecasting horizon cannot exceed this timeframe in the future. Therefore, intrinsically, models are ill-suited to make mid-term forecasts that are as accurate as short-term forecasts they are used to make. This is probably the reason why El Hennawy and Morris (1983) had the intuition that a model designed using a large time lag between the moment when model parameters are estimated and that when the prediction is achieved (5 years) might have greater informational content than a model built using a shorter lag (1 year). This is precisely the result they obtained.

The second factor is due to the fact that the relationships between independent variables and the dependent variable of a model are supposed to be stable over time (Zavgren, 1983). However, this assumption is not consistent with reality (Charitou et al., 2004) because conditions that govern firms' economic environment (market competitive structure, technological cycle, inflation rate, growth rate, etc.), and that may strongly influence the relationships between variables (Mensah, 1984; Platt, Platt, & Pedersen, 1994), are hardly completely stable. Indeed, some firms that might survive in a favorable economic environment are sometimes unable to do so when economic conditions worsen. This is why, when large macro-economic changes occur, it becomes much more difficult to forecast the fate of unsound firms than that of sound companies (Pompe & Bilderbeek, 2005). Actually, the larger the time interval between the period during which a model is designed and that when it is used, the more models are likely to be influenced by macro-economic changes that affect companies, and as a consequence, the more they may lose a significant part of their accuracy. A few studies have demonstrated that, when economic fluctuations occur over different years, one may observe a phenomenon known as population drift (Balcaen & Ooghe, 2006). This phenomenon results in the fact that the boundary between failed and non-failed firms moves (Pompe & Bilderbeek, 2005) and the distributions of explanatory variables change (Pinches, Mingo & Caruthers, 1973) from one period to another, thereby causing a decrease in model prediction ability. Experimental results clearly state that variations in the economic environment, that occur between the period during which a model is estimated and that when it is used for forecasts, is a key factor in explaining variations in model accuracy