To Fail or Not to Fail: An Algorithm for SME Survival Prediction Using Accounting Data

José Manuel Pereira, Humberto Ribeiro, Amélia Silva, and Sandra Raquel Alves

5.1 Introduction

The unbalanced environment that economies across the globe faced during the great recession enhanced the occurrence of the corporate insolvency phenomenon. Insolvency and bankruptcy occur on a daily basis.
However, from a long-term view, corporate insolvency tends to be cyclical and to peak during recession periods.

The overleveraged spillover effects from the most recent financial crisis were very significant at the corporate level and even led to the collapse of very large “too big to fail” corporations. Nevertheless, such negative impacts were even more clear and significant on micro and on small and medium-sized enterprises (SMEs). Similarly, one can argue that this financial crisis, to a greater or lesser extent, affected almost every sector of activity. Nevertheless, despite the broad effects across the economy, some particular industries suffered the most, as is the case of financial services and construction-related activities.

The enormous importance of SMEs to the economy is widely recognised (Altman and Sabato 2007; Ayranci 2014; Bantscheff and Britzelmaier 2019). Their impact on employment rates, social unity and economic growth is acknowledged by all political ideologies (Pereira et al. 2017). It is natural for enterprises to have periods of success and failure. However, when a temporary negative period becomes chronic, then it usually leads to bankruptcy (Dengleri et al. 2019). Insolvency, bankruptcy, or business failure, are critical phenomena that attract the public’s and researchers’ interest for a long time, leading to the development of models for business failure forecasting, the pioneering papers of Beaver (1966) and Altman (1968) being noteworthy. They would be soon be followed by a profusion of related research, with successive methodological improvements and the use of various innovative techniques.

Within this framework, and considering more recent methodologies on business failure, such as Pereira (2014), an algorithm that has been constructed for predicting the survival likelihood of a corporation, using financial accounting data, is proposed in this book chapter. Furthermore, due to the more frequent fragility of SMEs, the authors of this book chapter consider this algorithm as a possible tool for assessing their financial condition, providing an immediate insight about their survival odds and therefore

S. R. Alves
CIC.DIGITAL; ESTG, Polytechnic Institute of Leiria, Leiria, Portugal
e-mail: raquel.alves@ipleiria.pt
helping management to support their decision-making processes, namely, the critical ones, that is, the one which may prevent business failure.

In order to test the feasibility of the proposed tool, an algorithm, which was based on an empirical study comprising a set of insolvency proceedings in Portugal involving SMEs, was subjected to a major testing process, with the research being focused on non-financial sectors only. Overall, the results suggest that the proposed algorithm is reliable while forecasting the survival likelihood of SMEs, based on their reported data on financial accounting. Therefore, the authors believe that this algorithm can be regarded as a powerful tool for SME managers to monitor the corporate performance and the outcome of their managerial decisions, particularly with regard to the survival chances of their organisations.

5.2 The Use of Survival Analysis Methodology in Mainstream Literature

The main application of survival analysis in accounting research has been in the area of bankruptcy prediction and the related literature that employs this statistical technique has increased in recent years.

Lane et al. (1986) were the first to employ the Cox model to predict bank failure, using a sample of 130 banks that failed between January 1978 and June 1984, and another sample of 334 non-failed banks. The survival time for each failed bank has been defined as the time (in months) since 31 December of the year considered for the calculation of financial ratios to the date of bankruptcy. Their results indicated that the overall accuracy of the Cox model was similar to the one obtained by using discriminant analysis; however, type I error was lower in the Cox model. Following these findings, many other authors contributed towards the dissemination of this technique in the field of bankruptcy. For instance, Luoma and Laitinen (1991) applied survival analysis while predicting business failure. These authors used a sample of 36 failed companies (24 from industrials and 12 retailing firms) each paired with a not failed company belonging to the same business and of similar size. The results were
compared with models developed from discriminant analysis and logistic regression. The percentage of correct classifications were 61.8%, 70.6% and 72.1%, for survival analysis, discriminant analysis, and logistic regression, respectively. The authors explained the lower accuracy of the model based on survival analysis with the different failure processes found in the data.

Another reference research in this area is the one of Shumway (2001). This author draws attention to the need to include multiple observations for each firm by using a discrete time hazard model in the prediction of financial distress and uses an accelerated failure time survival analysis model that outperformed the traditional techniques used in this strand of investigation.

Likewise, Lee (2014) used survival analysis to find the main indicators which could explain the business bankruptcy phenomenon in Taiwan. The sample employed included companies listed on the Taiwan Stock Exchange that were under financial distress between 2003 and 2009. Lee’s research suggested that one does not need to use many ratios to be able to anticipate a potential business bankruptcy.

Finally, it is also noteworthy to mention Gémar et al. (2016) who used survival analysis techniques applied to the Spanish hotel industry. Their findings suggest that the hotels’ survival likelihood depends on their size, location, management and opening timing (preferably in a time of prosperity).

Although some selected research was highlighted in this book chapter, it is important to note that the use of the survival technique can also be observed in many other studies that can be found in recent academic literature. Accordingly, a systematic literature review on the topic was performed in order to assess the most recent contributions in the field.

As for the outset, one should be aware that the medical sciences were the first to develop a systematic literature review, based on the survival methodology used to predict the likelihood of patient survival. Due to the necessity to integrate clinical evidences from different studies, that is, Evidence Based Medicine, meta-analysis became very popular in medicine. More recently, this methodological approach has been increasingly applied to the social sciences. Regardless of the required adaptations, this methodology allows the grouping of a huge volume of literature and the
integration of the different contributions in a field of knowledge. The Clarivate’s Web of Science search engine was selected to perform this review. The following research query was applied:

- Topic: (“survival analysis”) AND Topic: (bankruptcy)
- Publication years: (2019 OR 2014 OR 2010 OR 2018 OR 2013 OR 2017 OR 2012 OR 2016 OR 2011 OR 2015)
- Document types: (ARTICLE)

The search was performed on 30 November 2019, with 32 papers being gathered initially. In order to assess the relevance of each paper, the title and the abstract of each of these papers were examined. From the 32 papers, only one paper was excluded because it dealt with personal bankruptcy and was related to the physical conditions of the individual. The remaining 31 papers were included in the sample and were distributed by years as shown in Fig. 5.1.

In Table 5.1, we summarise the goal of each paper reviewed, ranked by year of publication.

It is interesting to note that, despite the novelty of the introduction of new variables in some studies, most papers use accounting-driven ratios as predictor variables. In the selected sample of collected papers, one could find studies from many different countries around the globe.

![Fig. 5.1](image-url)  
**Fig. 5.1**  
Publication year in web of science about survival analysis in the field of bankruptcy
| Year | Authors | Propose and methodology |
|------|---------|--------------------------|
| 2010 | Hazak and Männasoo (2010) | – Contribute to the research on the indicators that provide a warning of company failure by employing micro and macro variables within a framework of survival analysis  
  – Sensitivity of the results is checked using two complementary event definitions, that is, bankruptcy and negative equity |
| 2011 | Bou-Hamad, Larocque and Ben-Ameur (2011) | – Propose a new survival tree method for discrete time survival data with time-varying covariates  
  – Accommodate simultaneously time-varying covariates and time-varying effects |
| 2011 | Du Jardin and Séverin (2011) | – Show how a Kohonen map can be used to increase the forecasting horizon of a financial failure model  
  – Develop a new way of using a Kohonen map to improve model reliability |
| 2011 | Moon and Sohn (2011) | – Improve a scorecard model to help organisations decide whether or not to grant loans to applicant firms  
  – Propose a survival model that considers not only the time to default but also the total perception scoring phenomenon |
| 2012 | Ding, Tian, Yu and Guo (2012) | – Apply a discrete transformation family of survival models to corporate default risk predictions  
  – Adopt a class of Box-Cox transformations and logarithmic transformations |
| 2013 | Alali and Romero (2013) | – Use survival analysis to determine how early the indications of bank failure can be observed |
| 2013 | Carvalho, J., Divino, J. A., and Orrillo, J. (2013) | – Show that the reduced-form entrepreneurial equilibrium and profit-maximisation entrepreneurial equilibrium, as defined by Magill and Quinzii (1996), are equivalent. In addition, we find an inverse relationship between the economy real interest rate and the probability of default  
  – Propose a Cox proportional hazards model with time-dependent covariates for a sample of sole proprietors’ unsecured credit operations in the Brazilian economy |
| 2013 | Mokarami and Motefares (2013) | – Propose a Cox regression Criteria used for corporate governance are size of Board of Directors, percentage of non-Executive Directors, Chief Executive Officer (CEO) change and major ownership |

(continued)
Table 5.1 (continued)

| Year | Authors                        | Propose and methodology                                                                                                                                                                                                 |
|------|--------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 2013 | Mokarami and Motefares (2013)  | – Propose a Cox regression considering corporate governance  
– Criteria used for corporate governance are size of Board of Directors, percentage of non-Executive Directors, Chief Executive Officer (CEO) change and major ownership |
| 2014 | Dang (2014)                    | – Apply a competing risks approach and an event time dynamic estimation framework to identify the characteristics underlying different insolvency resolutions incurred by US property-casualty insurers during 1998–2010  
– Hazard model relates the time-varying probability of a specific insolvency outcome to insurers’ characteristics and macroeconomic conditions |
| 2014 | De Leonardis and Rocci (2014)  | – Develop a cure model for analysing default time data where two groups of companies are supposed to coexist: those which could eventually experience a default (uncured) and those which could not develop an endpoint (cured)  
– The probability of being uncured is estimated with a binary logit regression, whereas a discrete time version of a Cox’s proportional hazards approach is used to model the time distribution of defaults, accomplished by replacing the discrete time baseline function with an appropriate time-varying system level covariate, able to capture the underlying macroeconomic cycle |
| 2015 | Alves and Dias (2015)          | – Score the credit risk of a financial institution’s clients  
– General framework of survival mixture models (SMMs) that addresses the unobserved heterogeneity of the credit risk of a financial institution’s clients, containing specific cases of aggregate and immune fraction models |
| 2015 | Kim and Partington (2015)      | – Investigate dynamic probability forecasts use of time-varying variables in forecasts from a Cox model  
– Forecast accuracy is evaluated using receiver operating characteristics curves and the Brier Score |
| 2016 | Lado-Sestayo, Vivel-Búa and Otero-González (2016) | – Assess the determinants of survival of Spanish hotel firms |

(continued)
| Year  | Authors                          | Propose and methodology                                                                 |
|-------|----------------------------------|------------------------------------------------------------------------------------------|
| 2016  | Dellana and West (2016)          | - Investigate to what extent differences in legal systems affect cross-border insolvency, that is, What is the relationship between multinational status and firm death rates? To what extent can the legal system affect the pattern of firms’ death across countries? How can the cross-border insolvency legal rules produce firms’ death or survival through corporate restructuring and bailout?  
- Propose a survival method and estimate a discrete time hazard model, looking for the effect of foreign ownership on firm death, controlling for firm- and industry-specific covariates |
| 2016  | Gémar, Moniche and Morales (2016) | - Analyse survival in the Spanish hotel industry  
- Propose an econometric analysis of survival, using the non-parametric Kaplan-Meier estimator of constructed variables, in order to detect the particular influence of each variable  
- Semi-parametric regression was done with the Cox proportional hazards model |
| 2016  | Kim, Ma and Zhou (2016)          | - Propose a Cox proportional hazards model to predict turnaround probability for a distressed firm to remove the Special Treatment cap |
| 2016  | Pittiglio, Reganati and Tedeschi (2016) | - Enrich the understanding of the determinants of foreign-owned firms’ survival in Italy and highlight the important role assumed by the countries’ legal environment  
- Develop a survival model that considers the differences between Common Law countries and Civil Law countries and how it affects cross-border insolvency |
| 2017  | Heim, Hüschelrath, Schmidt-Dengler and Strazzeri (2017) | - Estimate the causal impact of restructuring aid granted by the European Commission between 2000 and 2012 on the survival and financial viability of aided firms |
| 2017  | Patel, Guedes and Pearce II (2017) | - Assess the influence of retail operations characteristics on the survival of new retail ventures  
- Develop a survival model specific for retail ventures |

(continued)
Table 5.1 (continued)

| Year | Authors                                      | Propose and methodology                                                                                                                                                                                                 |
|------|----------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 2017 | Shin, Park, Choi and Choy (2017)             | – Investigate internal and external factors affecting the survival of SMEs (small and medium-sized enterprises) in the biotechnology industry in South Korea. Cox hazards model was employed to perform a robust estimation in survival analysis |
| 2017 | Volkov, Benoit and Van den Poel (2017)       | – Incorporate a dynamic view on bankruptcy into bankruptcy prediction modelling  
– Introduce variables based on the Markov for discrimination (MFD) model |
| 2018 | Dendramis, Tzavalis and Adraktas (2018)      | – Test if economic recession and distressed financial conditions as well as political instability constitute the key factors for mortgage default  
– Propose an extension of the discrete time survival analysis model which allows for a structural break in its baseline hazard function and a unique set of individual loan accounts |
| 2018 | Gupta, Barzotto and Khorasgani (2018)        | – Demonstrate that the failure rate of SMEs varies across micro, small and medium-sized categories  
– Estimate univariate hazard models and report average marginal effects (AMEs) for each variable to facilitate the specification of the later multivariate model  
– Estimate multivariate discrete time duration-dependent hazard models with logit link across size categories (for SMEs, micro, small, and medium firms, respectively) for bankruptcy and financial distress, respectively |
| 2019 | Ayadi, Lazrak and Xing (2019)                | – Investigate the determinants of bankruptcy protection duration of Canadian public firms, and also investigate the duration for various bankruptcy outcomes including the liquidation and re-emergence of bankrupt firms  
– Apply duration and survival analyses |
| 2019 | Beretta and Heuchenne (2019)                 | – Extend a semi-parametric proportional hazards cure model to time-varying covariates and propose a variable selection technique based on its penalised likelihood  
– Use a mixture cure model to separate the factors with an influence on the susceptibility to default from the ones affecting the survival time of susceptible banks |

(continued)
Table 5.1 (continued)

| Year | Authors | Propose and methodology |
|------|---------|--------------------------|
| 2019 | Coccorese and Santucci (2019) | – Test the different definitions of “book-value distance to default” (BVDD) to assess whether using downward assets volatility provides some advantage to the index performance or produces adverse impacts on its effectiveness  
– Develop a Cox semi-parametric hazards model where the BVDD is built as a function of a parameter theta, which indicates the percentage of upward assets volatility incorporated in its calculation so as to compare its success in predicting banks’ distress over different levels of theta |
| 2019 | Djeundje and Crook (2019) | – Discuss how survival analysis can be enhanced using generalised additive models (GAMs)  
– Show how GAMs can be used to improve not only the application, behavioural and macroeconomic components of survival models for credit risk data at the individual account level, but also the accuracy of predictions  
– Propose parametrised GAMs for credit risk data in terms of penalised splines, outline the implementation via frequentist and Bayesian MCMC methods, apply them to a large portfolio of credit card accounts |
| 2019 | Gémar, Soler and Guzman-Parra (2019) | – Examine variables influencing resort hotels’ survival in Spain which had not been analysed previously. In this country, determining whether the reasons resort hotels close are different from why other hotels close could be imperative to resort hotels’ survival  
– Develop Cox’s semi-parametric proportional hazards regression to determine which variables influence hotel closure and how much each variable increases risk of closure |
| 2019 | Ivanović, Kufenko, Begović, Stanišić and Geloso (2019) | – Demonstrate that the design of the privatisation process in Serbia allowed rent-seekers to conserve their privileges through asset-stripping, which explains the failure  
– Analyse the determinants of liquidation, merger and bankruptcy of privatised firms |
However, the majority were from European countries. One evidence coming from this literature review is that a sound theoretical approach that may explain corporate bankruptcy broadly is still under development. Figure 5.2 summarises, in the form of keywords, the content of the abstracts of the 31 articles analysed, using a Word Cloud Generator software.

Despite the limitations that this analysis model may present, one can, nevertheless, highlight the predominance of the empirical approach, rather than the use of a theoretical approach to explain the bankruptcy phenomenon.

| Year | Authors                  | Propose and methodology                                                                                                                                                                                                                                                                                                                                                                                                                                                                                   |
|------|--------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| 2019 | Li, Xu, Li and Xu (2019) | – Investigate the symptoms of failure in public corporations with multiple hospitality businesses and examine whether a new case-based deep-layer predictive analysis methodology is more appropriate than conventional approaches to failure analysis  
– A case-based deep-layer predictive analysis of multi-business hospitality failures was conducted using an independently incremental process, a dependent retrieval process, a pre-early-warning process and an early-warning process |

Fig. 5.2  Word cloud resulting from content analysis
5.3 The Proposal of a Predictive Model

5.3.1 The Cox Proportional Hazards Model

According to Collett (1994), the current survival time of an individual $t$ can be regarded as the realisation of a random variable $T$, which may assume any given non-negative value. Therefore, $T$ indicates the time to failure of a firm. $T$ is thus associated with survival time and follows a given probability distribution. $T$ being a continuous probability distribution, and assuming $f$ as the underlying probability density function, the function of distribution is then given by

$$F(t) = P(T < t) = \int_0^t f(u)du$$

which represents the probability of the survival time being inferior to a given value of $t$.

The survival function $S(t)$ is defined as the probability that a firm will survive longer than $t$ times units, being equal or higher than $t$, and assumes the following notation:

$$S(t) = P(T \geq t) = 1 - F(t).$$

The survival function may therefore represent the probability of the survival time of an individual to exceed a given value of $t$.

The hazard function describes the evolution over time of the immediate rate of “death” of a firm. To obtain the hazard function, we assume the probability that the random variable associated with a survival time $T$ is between $t$ and $t + \delta t$, subject to a $T$ value greater than or equal to $t$, which can be shown as

$$P(t \leq T < t + \delta t | T \geq t).$$
The hazard function \( h(t) \) is then the limit of that probability divided by the interval of time \( \delta t \), with \( \delta t \) tending to zero as we can verify below:

\[
    h(t) = \lim_{\delta t \to 0} \left\{ \frac{P(t \leq T < t + \delta t | T \geq t)}{\delta t} \right\}.
\]

The hazard \( h(t) \) is the probability of failure in the next period, given that the firm was alive at time \( t \) (Lane et al. 1986).

The survival function, \( S(t) \), can be obtained from the following equation:

\[
    S(t) = \exp\{-H(t)\},
\]

where

\[
    H(t) = \int_0^t h(u) du.
\]

The function \( H(t) \) is called the cumulative hazard function.

\[
    H(t) = -\log S(t)
\]

The model that can be used as a base for application in this book chapter is the proportional hazards model proposed by Cox (1972), which is also known as the Cox regression model.

The definition of the model is as follows. Assuming that the hazard of “failure” for a given time period depends on the values \( x_1, x_2, \ldots, x_p \) of \( p \) explanatory variables \( X_1, X_2, \ldots, X_p \), the set of values of explanatory variables in the proportional hazard model will be represented by the vector \( x \), so \( x = (x_1, x_2, \ldots, x_p)' \).

We designate \( h_0(t) \) as the hazard function of a company for which the values of all variables that make the vector \( x \) is zero. The function \( h_0(t) \) is called baseline hazard function. The hazard function for \( i \) companies can then be written as:
\[ h_i(t) = \psi(x_i)h_0(t), \]  

where \( \psi(x) \) is the function of the values of the vector of explanatory variables for \( i \) companies.

The function \( \psi(x_i) \) can be interpreted as the risk over time \( t \) for a company whose vector of explanatory variables is \( x_i \), on the risk for a company whose \( x = 0 \).

Since the relative risk \( \psi(x_i) \) cannot be negative it should be written as \( \exp(\eta_i) \), where \( \eta_i \) is a linear combination of \( p \) explanatory variables in \( x_i \).

Therefore

\[ \eta_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_p x_{ip}, \]  

which is equivalent to

\[ \eta_i = \sum_{j=1}^{p} \beta_j x_{ij}. \]  

where \( \beta \) is the vector of coefficients of the \( x_1, x_2, \ldots, x_p \) explanatory variables in the model.

The quantity \( \eta_i \) is called the linear component of the model, also known as risk score or prognostic index for \( i \) firms. The proportional hazard model can generally be expressed as follows:

\[ h_i(t) = \exp\left(\beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_p x_{ip}\right)h_0(t). \]  

### 5.3.2 Proposed Model

Taking into consideration the models offered by the literature, but also employing a specific set of variables that the authors of this book chapter find appropriate to test using a survival function, the proposal of a predictive model of corporate failure follows below.
5.3.2.1 Variables Used

In this research, several economic and financial indicators were used to construct a set of independent variables. Similarly to the procedure used in diverse studies devoted to predicting business failure, the selection of the independent variables was based on its popularity, measured by its use in previous studies. The 22 selected indicators that were collected from the balance sheet and from the income statement of the companies included in the sample are listed below:

\begin{align*}
\text{X1} & \quad (\text{Current assets} - \text{current liabilities})/\text{Total liabilities} \\
\text{X2} & \quad \text{Current assets}/\text{Current liabilities} \\
\text{X3} & \quad \text{Equity}/\text{Total assets} \\
\text{X4} & \quad \text{Equity}/\text{Liabilities} \\
\text{X5} & \quad \text{Cash flow}/\text{Current liabilities} \\
\text{X6} & \quad \text{Cash flow}/\text{Liabilities} \\
\text{X7} & \quad \text{Financing charge}/\text{Operating gains} \\
\text{X8} & \quad \text{Cash}/\text{Total assets} \\
\text{X9} & \quad \text{Cash}/\text{Current liabilities} \\
\text{X10} & \quad \text{Bills payable}/\text{Total assets} \\
\text{X11} & \quad \text{Working capital}/\text{Total assets} \\
\text{X12} & \quad \text{Operating gains}/\text{Current assets} \\
\text{X13} & \quad \text{Operating gains}/\text{Operating costs} \\
\text{X14} & \quad (\text{Net profit before tax} + \text{depreciation expense} + \text{provisions})/\text{Financing charge} \\
\text{X15} & \quad \text{Net profit}/\text{Total assets} \\
\text{X16} & \quad \text{Net profit}/\text{Equity} \\
\text{X17} & \quad \text{Net profit}/\text{Liabilities} \\
\text{X18} & \quad \text{Net profit}/\text{Operating gains} \\
\text{X19} & \quad \text{Net profit}/\text{Sales} \\
\text{X20} & \quad \text{Sales}/\text{Cash} \\
\text{X21} & \quad (\text{Net profit before tax} + \text{financing charge})/\text{Sales} \\
\text{X22} & \quad \text{Net profit before tax}/(\text{Net profit before tax} + \text{financing charge})
\end{align*}
5.3.2.2 The Companies’ Sample

In order to adjust the model, it was necessary to collect a sample of companies where the event of insolvency occurred. Based on the information provided by insolvency administrators it was possible to obtain a sample of 14 companies, whose survival times were known and which could therefore be classified as belonging to the group of failed companies. The survival times for the 14 companies were as follows: 2 companies with 3 months, 1 company with 4 months, 4 companies with 5 months, 2 companies with 6 months, 4 companies with 8 months and 1 company with 10 months. Concurrently, we obtained a sample of 14 companies that did not fail, with survival times obtained from SABI, a database from Bureau Van Dijk, a Moody’s Analytics company.

Taking into consideration the survival times, it was possible to split each company into three sets of observations, which resulted in a group of failed companies with 42 observations, and a group of companies that did not fail with 42 observations as well. Each observation is regarded as a company. To illustrate this situation, one can consider the data from a company that was active until six months after the latest year for which we have data records. Since we collected data for three consecutive years, it was possible to have data for 6, 18 and 30 months prior to the time of business closure. This procedure was repeated for every 28 companies included in the testing sample. The selection method of the explanatory variables followed Collett’s (1994) procedure, and the testing was performed using SPSS software.

The explanatory variables that contributed significantly to the reduction of statistics $-2\log L$ are shown in Table 5.2.

| Variables | B   | SE  | Wald | df | Sig.  | Exp(B) |
|-----------|-----|-----|------|----|-------|--------|
| X1        | 0.452 | 0.199 | 5.137 | 1  | 0.002 | 1.571  |
| X2        | -1.269 | 0.335 | 14.317 | 1 | 0.000 | 0.281  |
| X5        | -0.393 | 0.219 | 3.210 | 1  | 0.003 | 0.675  |
| X22       | 0.229 | 0.061 | 13.863 | 1 | 0.000 | 1.257  |
5.4 The Survival Algorithm

In Table 5.3 are shown the values of the survival function relative to the average of the variables’ values.

The survival analysis provides quantitative information about the probability of a company failing at the end of a time period $t$ and not only whether it will, or will not, fail. The compiled data, shown in Table 5.3, made it possible to develop an algorithm using Matlab, which allows to deliver a company’s performance forecast and a survival function value for the time considered. The time period considered for the study was 12 months. The values of the survival function, for each firm, were based on the respective figure for the nearest time frame obtained in the survival model developed earlier (ten months). In order to calculate the forecast for each company, a cut-off point of 0.5 was used, that is, the model considers 1 for a company when the likelihood to survive is greater than 0.5, and 0 otherwise. The combination of these criteria and data allowed to produce the algorithm, which is show below in italic.

| Time | Baseline cum hazard | At mean of covariates | Survival | SE | Cum hazard |
|------|---------------------|-----------------------|----------|----|------------|
| 3    | 0.018               |                       | 0.994    | 0.006 | 0.006      |
| 4    | 0.074               |                       | 0.978    | 0.011 | 0.023      |
| 5    | 0.112               |                       | 0.966    | 0.014 | 0.035      |
| 6    | 0.192               |                       | 0.943    | 0.019 | 0.059      |
| 8    | 0.276               |                       | 0.918    | 0.024 | 0.085      |
| 10   | 0.345               |                       | 0.899    | 0.027 | 0.106      |
| 15   | 0.373               |                       | 0.891    | 0.028 | 0.115      |
| 16   | 0.461               |                       | 0.867    | 0.032 | 0.142      |
| 17   | 0.523               |                       | 0.851    | 0.035 | 0.161      |
| 18   | 0.653               |                       | 0.818    | 0.039 | 0.201      |
| 20   | 0.793               |                       | 0.783    | 0.044 | 0.244      |
| 22   | 0.908               |                       | 0.756    | 0.047 | 0.280      |
| 27   | 0.997               |                       | 0.735    | 0.051 | 0.307      |
| 28   | 1.291               |                       | 0.672    | 0.058 | 0.398      |
| 29   | 1.506               |                       | 0.629    | 0.063 | 0.464      |
| 30   | 2.016               |                       | 0.537    | 0.067 | 0.621      |
| 32   | 2.685               |                       | 0.437    | 0.069 | 0.828      |
| 34   | 3.275               |                       | 0.364    | 0.069 | 1.010      |
**Algorithm**  Survival function and forecast’s description

```matlab
function survival

% estimated values of the coefficients
b1 = 0.452;
b2 = -1.269;
b5 = -0.393;
b22 = 0.229;

% for ten months
H0 = 0.345;

% read table from excel
T = xlsread('table.xls');

d = size(T, 1);

for k = 1:d
    es(k) = exp(b1 * T(k, 3) + b2 * T(k, 4) + b5 * T(k, 5) + b22 * T(k, 6));
end

es = es';
H = es * H0;

% survival function
ST = exp(-H);

% forecast (0 or 1)
for k = 1:d
    if ST(k) > 0.5
        result(k) = 1;
    else
        result(k) = 0;
    end
end
```
result=result';

for k=1:d
fprintf('Company %g at 10 months: survival function = %g, forecast = %g
',T(k,1),ST(k),result(k));
end

A=[T(:,1) ST(:,1) result(:,1)];
save forecast A-double

As the authors had the information for the last year before the failure of 72 companies in the sample, another sample of 72 non-failed companies was collected from the SABI database.

With the sample of failed companies, it was verified that the survival function value for the considered time was higher than expected (type I error) in four situations. With the sample of non-failed companies, the survival function value was less than expected in two cases (type II error). Based on these results the type I error was 5.55%, and the type II error was 2.86%.

An extract of the algorithm output can be seen below, showing the algorithm running commands and output for a number of selected companies in italic. According to the algorithm, using this selected sample, only six companies were forecast to survive.

**Algorithm**  Survival function and forecast’s output

**Command Window**

```
>> survival
Company 6000 at 10 months: survival function = 1.51142e-12, forecast = 0
Company 6003 at 10 months: survival function = 0.417195, forecast = 0
Company 6009 at 10 months: survival function = 0.437352, forecast = 0
Company 6016 at 10 months: survival function = 0.537961, forecast = 1
Company 6002 at 10 months: survival function = 0.0969574, forecast = 0
Company 6015 at 10 months: survival function = 0.568619, forecast = 1
Company 6007 at 10 months: survival function = 0.764383, forecast = 1
Company 6008 at 10 months: survival function = 0.121495, forecast = 0
```
Company 6014 at 10 months: survival function = 0.241082, forecast = 0
Company 6018 at 10 months: survival function = 0.00191624, forecast = 0
Company 6004 at 10 months: survival function = 0.592384, forecast = 1
Company 6012 at 10 months: survival function = 0.945657, forecast = 1
Company 6017 at 10 months: survival function = 0.786941, forecast = 1
Company 6019 at 10 months: survival function = 0.308932, forecast = 0

5.5 Conclusions

Small and medium-sized enterprises are the bulk of any economy. Nevertheless, they are mostly vulnerable and are prone to face several constraints that often result in some relevant issues that may even lead to insolvency proceedings. Besides being more susceptible to the surrounding environment, SMEs often lack control and quality information, which could eventually prevent them from being involved in dramatic failure processes. In this book chapter, the very significant negative effects of the financial crisis were examined, in particular on micro and small and medium-sized enterprises (SMEs). The issue of corporate bankruptcy has been, and keeps being, a topic of significant interest for a broad set of economic agents. Accordingly, an algorithm that has been constructed for predicting the survival likelihood of a corporation, with a particular focus on SMEs, was proposed here.

On the one hand, this chapter focused on examining SME data in order to perceive whether a sample of these companies could be facing serious financial difficulties, but, on the other, it focused on trying to understand whether they could have benefited from an early diagnosis in order to try preventing business failures with proper monitoring, together with some other eventual support. Taking into account recent data, this research examined insolvency processes, involving SMEs, that have taken place recently in Portugal. A specific tool was constructed and proposed: a survival algorithm that was based on financial accounting data from a set of SMEs. The reliability of this tool was subject to testing, while employing an empirical study comprising a set of insolvency proceedings.
Overall, the results of this research suggest that the proposed algorithm is reliable while forecasting the survival likelihood of SME, based on financial accounting data. Decisions need to be based on reliable information and sound forecasting tools. Therefore, the authors believe that this algorithm can be regarded as a powerful tool for SME managers to monitor both the corporate performance and the outcome of their managerial decisions, particularly with regard to the assessment of the survival chances of their organisations.

Current economic conditions, driven by the Covid-19 pandemic containment measures and uncertainty, are certainly very challenging for corporations. SMEs, as usual, continue to be the main victims of the negative economic cycles. Despite the massive support that is being offered by governments and monetary authorities to ensure the survival of corporations, the fact of the matter is that, in general, SMEs are not attractive enough or financially sound to be able to capture such support, as financial institutions often prefer backing large companies.

As many SMEs will likely be forced to continue to manage their financial issues on their own during the Covid-19 pandemic period, it is believed that the tool presented in this chapter may effectively help managers, while supporting their decision-making processes, particularly with regard to critical decisions that may, ultimately, result in the future success or failure of the organisation. SMEs cannot fully rely on bailouts from governments and financial institutions. They lack size and mediatic importance, so they can be easily disregarded, forgotten even. They are “too small to save”. Survival is a matter of fate. Not a matter of faith. To fail, or not to fail: another Shakespearean drama that perhaps can be unveiled with an algorithm.

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