ABSTRACT

Supply chain risk management has received considerable attention in recent years. Financial models that can help predict the probability and timing of supply chain partner failure can bring great benefit to mitigating risks associated with economic instability and financial distress. In this study we compare the predictive bankruptcy classification accuracy of the Cox Proportional Hazards Regression (CPHR) approach to the statistical approaches of Logistic Regression and Discriminant Analysis. Analysis of CPHR versus other models shows competitive results worthy of further consideration.

KEYWORDS: Bankruptcy, Financial Distress, Risk, Supply.

INTRODUCTION

As supply chains continue to stretch further afield in search of the most efficient and cost effective arrangements, the risks to the supply chain increase. The widespread pressures to adopt lean systems and their reliance on customer-driven manufacturing and delivery in conjunction with the disruptive threats of global terrorism, natural disasters, and economic instability increase the risks of supply chain failures and even collapse.

An example is found in the Chrysler injection molding case of 2008. Plastech Engineered Products, a major supplier of injection modeled parts for Chrysler, filed for bankruptcy under Chapter 11 (Gillenwater, 2008). Chrysler had previously bailed the company out to keep it operating while searching for a new supplier. However, they were caught without a new supplier when the bankruptcy announcement was made and had to scramble to keep production interruptions to a minimum while finding a new supplier. While many supply chain risks are not easily mitigated, it is possible to improve on the ability to monitor and predict financial distress of supply chain partners, so that actions may be taken in a timely manner to manage the risks. However, many modeling approaches typically take only a snap shot of financial data at one point in time and make a prediction of failure probability with little information about time frames involved.

The purpose of this research is to investigate whether or not a survival classification method is able to predict potential bankruptcies more accurately than the traditional static classification methods when temporal and dynamic effects are modeled with time series data. An advantage of survival analysis is that it can give a time frame to potential failure. We study the Cox
Proportional Hazards Regression or CPHR model and contrast its decision accuracy with other prominent static classification methods.

LITERATURE REVIEW

Bankruptcy prediction has been an area of interest for many decades. Altman (1968) introduced effective bankruptcy prediction modeling in his seminal work on discriminant analysis using financial ratios. Traditional methods of financial decision support include scorecards for consumer credit (Brill, 1998; Henley, 1995; Mester, 1997; Reichert et al, 1983; Rosenberg & Gleit, 1994) and discriminant models for assessing corporate financial health (Altman et al, 1994; Reichert et al, 1983).

Newer models have emerged in bankruptcy classification modeling, which include neural networks and survival analysis. The reader is referred to Smith and Gupta (2002) and Kumar and Ravi (2007) for a survey of the application of neural networks in a diverse range of research problems that include financial forecasting. In many of the cases the neural networks are reported to provide more accurate bankruptcy prediction capability than the traditional parametric statistical approaches. However, the results are also often mixed (Tam & Kiang, 1992; Coats & Fant, 1993; Altman et al, 1994; Kiviluoto, 1998).

Survival modeling has received significant attention in studies of credit risk modeling and forecasting. While such studies do not directly involve corporate bankruptcy prediction, they are useful for understanding the power of survival models and approaches to using them in business settings that involve default. Survival models work especially well in credit risk analysis because they can give a projected time to default, allowing a forecast of time remaining on the loan and potential loss or profit at default. They also deal well with the inclusion of censored data in the form of debts still being paid.

Survival modeling for use in credit scoring was first introduced by Narain (1992). Building on this work, Banasik et al (1999) studied how survival models in credit scoring could help determine not just if a borrower would default, but also when. They compared several survival models to logistic regression and found Cox Proportional Hazards Regression (CPHR) in particular to be slightly better than logistic regression in predicting default for those defaulting in the first year. Logistic regression was reported to be better at predicting default in the second year. Stepanova and Thomas (2002) proposed improvements to CPHR in its application to credit scoring models and demonstrated survival analysis models to be competitive with logistic regression. They compared the metric of good-versus-bad with match-rate tables and ROC curves and found the latter to be more appropriate in the case of credit risk scoring. They argue that it helps avoid choosing an arbitrary time horizon and also considers the type of failure. These are both important to credit scoring scenarios. Andreeva (2006) extended the use of survival models to the case of revolving credit, using metrics of the area under the ROC curve and the percentage of incorrectly classified accounts. It was found that CPHR and logistic regression gave very similar results. Zhang and Thomas (2012) compared the survival model of CPHR to accelerated failure time models and linear regression in modeling recovery rates and amounts on loan defaults involving consumer credit. Using metrics of $R^2$, the Spearman rank coefficient, MAE and MSE, they found that linear regression generally outperformed survival models for recovery rates when comparing single distribution models. CPHR was the best performing survival model and outperformed Regression for the MAE metric. For recovery amounts, CPHR was best for Spearman and MAE. For mixed distribution models (i.e., segmented consumer groups) CPHR outperformed Linear Regression for Spearman and MAE in both recovery rate and recovery
amount. Therefore the results are mixed, but CPHR is shown to be competitive with linear regression. A survival analysis CUSUM chart was compared to other traditional CUSUM charts by Gandy (2012) for the purpose credit portfolio monitoring. Cusum charts based on survival models were found to perform better than traditional CUSUM charts because they lead to quicker detection and can include more information. Breeden et al (2012) derived a variant of the CPHR model that is tuned to the dynamics of retail loan portfolios. This variant is designed to deal with recent changes in the regulatory capital formula for credit risk. Survival modeling was chosen because it is one of a few modeling approaches suited for capturing the dynamics of retail portfolios. The survival model provides a simple conceptual framework for deriving a formula for capital.

From the above studies on credit score modeling it is clear that there are many potential benefits of survival models when compared to other regression models such as linear regression and logistic regression. CPHR in particular is found to be competitive to the more widely known and accepted models. Therefore, it is expected that CPHR should exhibit a similar competitiveness in other applications, such as predictions associated with corporate bankruptcy. A review of the related bankruptcy literature follows.

In 1996, Dimitras, et al conducted a comprehensive survey of articles related to business failure and reported only one journal article at that time dealing with survival analysis and bankruptcy prediction. They concluded that survival analysis, although a viable technique, has not been often applied for the prediction of business failure. Balcaen and Ooghe (2006) recently reported on 35 years of studies in business failure. They omitted discussion altogether of survival analysis, stating that it was beyond the scope of their study and needed further research. Thus, very little attention has been paid in the literature to survival analysis as it relates to bankruptcy prediction.

Luoma and Laitinen (1991) studied survival analysis as a tool for predicting company failure. Using a small sample of diverse Finnish failed and non-failed business firms (36 total), they compared their results to those of Lane et al (1986), for discriminant analysis (DA) and logistic regression models. Survival analysis classified both failed firms and non-failed firms correctly 62% of the time. DA classified failed firms correctly 65% of time, while non-failed firms were classified correctly 77% of the time. Logit analysis classified failed firms correctly 74% of time, while non-failed firms were classified correctly 71% of the time. Although survival analysis was not found to outperform DA and Logit, the authors point out that it modeled the dynamic aspects, treated firms as the same population, used more information, and better represented the nature of the failure process. Honjo (2000) examined business failure specifically in new firms using a multiplicative hazards model. The study examined business failure among 2488 new manufacturing firms in Tokyo during the period 1986 to 1994. The hazards regression model was based on age and also on calendar time. By using a regression model based on calendar time, it was found that the firm’s age is related to business failure. No other models were used for comparison in this study. Cochran, Darrat and Elkhal (2006) report on the bankruptcy of internet companies. Using a calendar-time model, they identified three key predictors of company failure; net income to total assets, cash flow to total liabilities, and total assets. In addition, they used an event-time model and found that liquidity became more important as a predictor than profit potential about one year prior to the failure, but that this finding is reversed (i.e. liquidity is less important than profit potential) three years prior to bankruptcy. Their results suggest that for three years prior to bankruptcy, a higher ratio of total liabilities to total assets is associated with lower odds of survival. No other models were compared to CPHR in this study.
The literature on survival analysis as it applies to corporate bankruptcy is fairly limited and reports apparently little success in its application to business failure modeling. However, we believe, based on the other survival analysis applications reviewed here, that there is room for improvement and a place for survival analysis in supply chain risk mitigation. Studies in the past have suffered from the use of primarily static models that do not include time series effects. Metrics employed appear to be limited and experimental methodology sometimes poorly defined. Our study will employ a rigorous methodology of model development, cross-validation, and robust metrics. Our use of quarterly data spanning two years for each company in our dataset will allow the inclusion of time series effects. Dynamic analysis may provide further improvement, but is beyond the scope of the current article. Finally, we will employ a company data set large enough to gain the power needed for analysis of a variety of financial and related variables in the predictive model.

DATA AND MODELS

Description of the dataset

A bankruptcy dataset was constructed by the authors from Standard and Poor’s Compustat financial files. Explanatory variables for this part of the study were limited to the five key financial ratios from research by Altman et al (1994). These ratios, constructed from quarterly financial statement information spanning approximately a decade from 1996 to 2005, include: working capital/total assets, retained earnings/total assets, earnings before interest and taxes/total assets, market value of equity/book value total liability, and sales/total assets. We also included information on company age and a monthly index of US economic health in the PMI index published by the Institute for Supply Management. The dataset has a total of 143 companies, consisting of 74 bankrupt companies and 69 healthy companies. The original data set was larger with an equal number of bankrupt and non-bankrupt companies. However, outlier values were detected in some of the original data and a number of bankrupt and non-bankrupt companies were dropped from the study. The original non-bankrupt company data were matched as closely in time as possible to the bankrupt companies, so that the two groups are close to equally represented by time period. The financial information is available as quarterly data for each company. Ratios were obtained going back eight quarters starting one year prior to bankruptcy for the bankrupt companies. The same ratios were obtained for the healthy companies going back eight quarters during a similar time frame as for matched bankrupt companies.

Discriminant analysis (DA)

Multiple Discriminant Analysis can be used to classify an observation into one of several a priori groupings. In this research we limit this analysis to the two binary classifiers of bankrupt and non-bankrupt, thus employing simple discriminant analysis or DA. This classification is based on the individual characteristics of the observation. DA attempts to derive a linear combination of the characteristics which best discriminates among groups (Altman, 1968). In our study, the groupings are bankrupt and non-bankrupt. The discriminate function of the form,

\[ Z = v_1 x_1 + v_2 x_2 + \ldots + v_n x_n \]  

where  \( v_1, v_2, \ldots, v_n \) = Discriminant coefficients  
and  \( x_1, x_2, \ldots, x_n \) = Independents variables
transforms individual variable values to a single discriminant score of \( Z \) value which is then used to classify the object. The DA computes the discriminate coefficients, \( v_j \), while the independent variables \( x_j \) are the actual values, where, \( j = 1, 2, \ldots n \). DA allows the analysis of the entire variable profile of the object simultaneously rather than sequentially examining its individual characteristics. In a financial health application, this allows combinations of financial ratios to be considered together (Altman, 1968).

For the purpose of Discriminant Analysis, our independent variables included the five Altman quarterly financial ratios, quarterly PMI index, and company Initial Public Offering (IPO) date. The PMI index was chosen as the ending month for the quarter being considered in each case. The IPO date was chosen as the number of quarters before or after the last quarter of 1995 (depending on company age). The number could be negative or positive depending on the IPO date in relation to the start date. We examined interactions of these variables as well as time-dependent versions of the variables. For example, during any given 1-2 year span, the difference between the starting value and the ending value was modeled. This is considered in our analysis as a temporal component and the involved models are referred to as temporal models.

**Logistic regression (LR)**

Logistic Regression (LR) is a statistical model based on a discrete probability distribution which takes the value 1 with success probability \( p \) and the value 0 with failure probability \( q = 1 - p \). It is a generalized linear model that uses the logit as its link function. The model takes the following form (Agresti, 2002):

\[
\text{Logit} \ (p_i) = \ln \left( \frac{p_i}{1 - p_i} \right) = \alpha + \beta_1 x_{1,i} + \cdots + \beta_k x_{k,i}
\]

\[i = 1, \ldots, n, \quad \text{where there are } n \text{ units with covariates } X \text{ and}
\]

\[p_i = E(Y | X_i) = \Pr(Y_i = 1)
\]

The logarithm of the odds (the probability divided by one minus the probability) of the outcome is modeled as a linear function of the explanatory variable, \( X_i \). This can be written equivalently as

\[p_i = \Pr(Y_i = 1 | X_i) = \frac{e^{\alpha + \beta_1 x_{1,i} + \cdots + \beta_k x_{k,i}}}{1 + e^{\alpha + \beta_1 x_{1,i} + \cdots + \beta_k x_{k,i}}}
\]

The interpretation of the \( \beta \) parameter estimates is as a multiplicative effect on the odds ratio. In the case of a dichotomous explanatory variable, for instance bankrupt versus non-bankrupt, \( e^\beta \) is the estimate of the odds-ratio of having the outcome for bankrupt compared with non-bankrupt. The parameters \( \alpha, \beta_1, \ldots, \beta_k \) are usually estimated by maximum likelihood.

For the purpose of Logistic regression we ran the same sets of independent variables as in the case of DA. This included interactions of the variables as well as time-dependent versions of the variables. As with DA, model runs that included the temporal component are referred to as temporal models.
Cox proportional hazards regression (CPHR)

Survival analysis models the time it takes for events to occur, focusing on the distribution of survival times. While DA and LR can be used to classify firms according to financial health, the CPHR model allows estimation of a firm’s probability of failure. DA and LR are also limited to static or cross-sectional data, while CPHR can be used to study time-varying data as well. The CPHR approach enjoys fewer basic assumptions and can be performed without having to define the baseline hazard function. A major distinction of CPHR is its ability to include censored data in the model. These data represent firms that might not fail during the sample period. Thus, companies that remain financially healthy during the sample period can be included and modeled in the regression (Cox, 1972; Cox & Oakes, 1984).

Survival analysis, as applied to analysis of organizational financial health, allows the estimation of time to business firm failure (i.e., bankruptcy). The survival is measured by the hazard rate using a hazard function (Zhang & Lyn, 2012). The hazard function \( h(t) \), giving the intensity to fail, is defined as the limit of the conditional probability

\[
h(t) = \lim_{\Delta t \to 0^+} \frac{P(t \leq T < t + \Delta t | T \geq t)}{\Delta t}
\]

(5)

where \( T \) is the random variable describing the moment of failure for a firm and \( P(t \leq T \leq t + \Delta t | T \geq t) \) the survival function (Cochran et al, 2006). This expression gives the instantaneous conditional probability of failure provided that the firm's survival is longer than time \( t \). This can be estimated by

\[
h(t, x_i) = h_0(t) \exp \left[ \beta^T x_i \right]
\]

(6)

where \( h_0(t) \) is referred to as the baseline hazard function, which is a nonparametric function of time alone and is assumed to be the same for all firms (Noh et al, 2005). The \( \exp \) part of the equation represents the parametric portion of the Cox model. The term \( X \) denotes a vector of \( p \) explanatory variables. The vector \( X \) contains individual firm characteristics and helps predict the survival of the firm in the index.

The CPHR model is semi-parametric (Simonoff & Ma, 2003) since the baseline hazard function is not pre-specified but allows for the incorporation of any chosen survival function. According to Efron (1977) the effect of the baseline hazard function loss is negligible in almost all instances. While the baseline hazard can take any form, the covariates enter the model linearly. For example, consider two observations \( i \) and \( i' \) that differ in the \( x \)-values, with corresponding linear predictors

\[
\eta_i = \beta_1 x_{i1} + \cdots + \beta_p x_{ik}
\]

(7)

and

\[
\eta_{i'} = \beta_1 x_{i'1} + \cdots + \beta_p x_{ik}
\]

(8)

The hazard ratio for these two observations
\[
\frac{h_i(t)}{h_0(t)} = \frac{h_0(t)e^{n_i}}{h_0(t)e^{n_i}} = e^{n_i} \tag{9}
\]

is independent of time \(t\). Consequently, the Cox model is a proportional-hazards model (Fox & Weisberg, 2011). Although the baseline hazard is unspecified, after fitting the model, it is possible to extract an estimate of the baseline hazard.

For the purpose of survival modeling with CPHR we ran the same sets of independent variables as in the case of DA and LR (the Altman financial ratios, PMI and IPO). This included interactions of the variables as well as time-dependent versions of the variables (i.e., temporal). Two model types were run with CPHR, which included: static and temporal static. Static modeling involved using the same single starting point in time for all firms. Temporal models included temporal variables that represented the change in static values over the horizon studied. Another modeling approach possible with CPHR is the dynamic approach. Dynamic models take advantage of the time-series modeling capability of CPHR by using a different starting point for data analysis in the case of each company. This starting point in each case is the quarter in which data becomes available for each firm. This approach was beyond the scope of the current paper. In all cases of static and temporal analysis, the data spanned eight quarters.

The assignment of a firm as bankrupt versus non-bankrupt was based on two metrics. These included cutoffs based on measures of Median Survival Time (MST) and Median Skewness (MS) of the survival functions.

**EXPERIMENTAL DESIGN**

The experimental design for the study involves the analysis and comparison of the three different models of DA, LR and CPHR from the perspective of data that are static, and static with time trend (referred to as temporal). Use of dynamic models is beyond the scope of the current study and will be addressed in a future study. In addition, the models are run for cases of 4, 6 and 8 quarters prior to bankruptcy. The expectation is that better predictive power will be observed in models with temporal effects for LR and DA. In addition, the interaction of model terms was included in this study, but was not found to be significant in any of the cases. Therefore, the results reflect only the main effects.

Appropriate statistical tests were conducted to assess compliance with underlying parametric model assumptions, as appropriate. A cross-validation “leave-one-out” approach was used to assess the errors in each model. This means that the model was run 143 times, with each model building run leaving out one of the companies from the dataset. This one company was then used to test the model’s ability to predict its outcome as either bankrupt or non-bankrupt. The percentage of correct outcomes was then tallied in the case of both bankrupt and non-bankrupt companies.

**RESULTS AND ANALYSIS**

All models were run in SAS 9.2 statistical software with model parameters for individual runs exported in excel files. These files were then consolidated into a single excel file for construction of the predictive models from each cross-validation run. Each model was then tested using the corresponding hold-out company data to compare the model prediction to the actual outcome.
for each hold-out company. Summary results of these hold-out tests are shown in Table 1 for the three modeling approaches.

Table 1 shows each model’s predictive ability as the percentage of bankrupt and non-bankrupt companies incorrectly classified as well as the overall misclassification rate. All three models did very well in general. Examination of bankruptcies 4 quarters out indicates that the CPHR Static and LR Temporal models have the lowest overall misclassification rates at 4.9%. Both models were very good at classifying healthy companies (misclassification at 2.9%) and fairly good at classifying bankrupt companies (misclassification at 6.76%). However, the DA model was slightly better at classifying Bankrupt companies (misclassification at 5.41%). Examination of bankruptcies 6 quarters out indicates that the CPHR Temporal Static model had the lowest overall misclassification rate at 9.09%. This was followed closely by the DA model with a misclassification rate of 9.79%. The DA model was better at classifying bankrupt companies while the CPHR model was better at classifying healthy companies. Examination of bankruptcies 8 quarters out indicates that the CPHR Static model had the lowest overall misclassification rate at 13.29%. This was followed by the DA Temporal model with a misclassification rate of 15.38%. The CPHR model was substantially better at classifying healthy companies while the DA model was somewhat better at classifying bankrupt companies.

It is interesting to note that CPHR is competitive in the shorter time frame of 1 year prior to bankruptcy, but is substantially better than the other models as the time before bankruptcy

<table>
<thead>
<tr>
<th>Quarters before Bankruptcy</th>
<th>Model</th>
<th>Bankrupt Errors</th>
<th>%</th>
<th>Healthy Errors</th>
<th>%</th>
<th>Total Errors</th>
<th>Overall %</th>
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<tr>
<td>4</td>
<td>CPHR-Static</td>
<td>5</td>
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<td>LR</td>
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*Temporal variables did not enter the model
increases to 2 years. The misclassification rate is also very low 1 year out from bankruptcy (2.9-6.76%) and fairly low two years out from bankruptcy (11.59-14.86%). The inclusion of temporal variables did help improve the classification ability for the LR models. For the DA models, the inclusion of temporal variables gave mixed results. In two cases their inclusion improved classification results and in one case it diminished classification results. Temporal variables had little effect aiding the CPHR models, but neither did they detract.

**DISCUSSION AND CONCLUSIONS**

We have shown, using cross-sectional data only, that Cox Proportional Hazards Regression modeling performs better overall than both Logistic Regression and Discriminant Analysis in the outcome prediction related to company bankruptcy. The CPHR model overall misclassification rates based on data four quarters, six quarters and eight quarters ahead of potential bankruptcy averaged about 9%. This compares to average misclassifications of 10.5% for Logistic Regression and 10.7% for Discriminant Analysis. This finding suggests that the CPHR model is well-suited to predictions regarding future financial health of a company and may be useful in providing a time-frame for potential company failure. Time to company failure is especially useful information that is not provided by the other modeling approaches. Thus, survival analysis using CPHR may provide substantial benefit to supply chain members in the assessment of financial risk within the supply chain. This may allow supply chain partners to take early action to minimize costly disruptions to their operations and possibly even avoid being critically damaged by the unexpected loss of a supply chain partner.

As mentioned previously, the experimental design for the full study will add CPHR models that include dynamic effects. We expect this will serve to further enhance the classification capability of CPHR over other models. Model runs will also be conducted for 1, 5 and 7 quarters prior to bankruptcy for CPHR, LR and DA. This will provide additional information to more fully characterize the classification capabilities of CPHR modeling as well as the other modeling approaches. Interaction terms will also be considered in the full study. We will also make predictions using CPHR of the time to failure for firms in the data that went bankrupt as a further demonstration of the capabilities of CPHR modeling to aid in risk mitigation in the supply chain. Future research, beyond this basic study, might focus on extending this work to include comparison to various neural network models. However, we do not expect these to perform significantly better given the data are not characterized as highly non-linear or dynamic.

**REFERENCES**


classic statistical methodologies and their related problems. [Electronic version]. *The British Accounting Review, 38*(1), 63-93.


